A Hybrid Ensemble-Based Approach for Process Parameter Estimation and Degradation Assessment in Offshore Oil Platforms

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Abstract: In offshore oil platforms, choke valve erosion is a major issue. An indicator of the choke valve health state is the valve flow coefficient, which is a function of measured and allocated parameters. The allocated parameters are typically provided by a physics-based model which has been proved to be inaccurate for some operating conditions. As a consequence, inaccuracies are introduced in the evaluation of the health indicator, undermining the possibility of using it for prognostics. In this paper, we overcome this hurdle by resorting to hybrid modelling which integrates the physics-based model into an ensemble of data-driven models built using Kernel Regression (KR) methods. A local procedure which uses the historical performance of the physical and data-driven models is adopted to aggregate the different model outcomes. The proposed hybrid ensemble-based approach is verified on real measurements performed on offshore choke valves located topside at different wells.

Keywords: *offshore oil platforms, hybrid ensemble, health state assessment, Kernel Regression*

1. Introduction

Health assessment of choke valve in offshore oil platforms is a major issue to grant high production and low maintenance costs. Physics-based and data-driven models can be used for health assessment [1]. In physics-based models, the relationship between the measured parameters and the health state of the system is derived from a combination of first principles and empirical laws. On the other side, data-driven models do not have any physical basis, but are purely mathematical representations of relationships between parameters built considering a set of representative data. Physics-based models rely on a deep understanding of the system behaviours and detailed knowledge of geometry, material properties and other characteristics of the system. Also, their development requires substantial engineering time and in many cases is not capable of accurately reproducing system non-linearities [2]. On the other hand, data-driven approaches are only accurate when applied to the same, or similar, operating conditions for which data have been collected.

In practice, it is usually difficult to decide whether one particular model is more effective than another in the entire operational range of interest. According to [3], it is agreed that no single method is best in every situation: real-world problems are often complex in nature and any single model may not be able to capture different patterns equally well. By combining different methods, the problem of model selection can be bypassed. In particular, the combinations of physics-based and data-driven models are usually termed hybrid models. Interesting overviews of these methods can be found in

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[4,5]. Hybrid modelling has gained considerable interest in the field of chemical engineering due to the lack of accurate physics-based models of complex chemical reactions. In the field of prognostics and health management (PHM), given the variety of information and data sources and types, this approach is becoming more and more attractive [6]. The result of combining the estimates of physics-based and process sensor data-driven PHM methods is to balance out their different errors and to augment the robustness and interpretability of physics-based models with the sensitivity of process sensor data-driven models [7]. The modelling framework underpinning hybrid methods is certainly more complicated, but offers clear advantages on the reliability and accuracy of the predictions.

In this paper, we extend the work presented in [8] by developing and applying an hybrid model for assessing the erosion level of choke valves located topside at wells on the Norwegian Continental Shelf [9,10]. The difference between the actual valve flow coefficient and its theoretical value is traditionally retained as the indicator of the choke valve erosion state. This health indicator is analytically calculated on a daily basis as a function of two measured parameters (the opening and the pressure drop through the choke) and three allocated parameters (oil, gas and water flow rates), whose values are obtained from a physics-based model, as a function of the measured total production from a number of wells and of physical parameters (*e.g.*, pressures and temperatures) related to the specific well. In practice, the allocated values of oil, gas and water flow rates indicators are affected by large inaccuracies and uncertainties, so that the resulting choke valve health state indicator is very noisy and lacks the physical monotonicity expected in the erosion process [11]. In this work, we consider the opportunity of combining the physics-based model and an ensemble of Kernel Regression (KR) models. KR is a data-driven regression algorithm estimating the parameters of a test pattern based on its distance from the training patterns [12]; an ensemble of multiple KR models is used to avoid the need of selecting the optimal model and to reduce the uncertainty of the estimate [11]. Diversity is injected in the ensemble by differentiating the predictor parameters for each KR model. The aggregation of the outcomes of the KR models and of the physics-based model is performed taking into account the single model performance on historical patterns closed to the test pattern. This approach can be found in literature under the name of local fusion [13].

The performance of the hybrid approach is evaluated on real data collected during the operation of 27 choke valves in 5 different wells, and compared to those of the physics-based model and the KR ensemble.

The paper is framed as follows. The traditional procedure for the construction of a health indicator assessing the choke valve erosion state is presented in Section 2; in Section 3, an hybrid modelling strategy is proposed to improve the accuracy of the allocated flow rates; Section 4 shows the results of the application of the method to the choke valves dataset; finally, conclusion and potential perspectives for future work are drawn in Section 5.

2 Choke Valve Erosion Assessment

In oil and gas industries, choke valves are normally located on top of each well and are used to balance the pressure on several wells into a common manifold to control flow rates and protect the equipment from unusual pressure fluctuations.

In Figure 1, left, a choke valve is sketched. The throttle mechanism consists of two circular disks, each with a pair of circular openings to create variable flow areas. One of the disks is fixed in the valve body, whereas the other is rotated either by manual operation or by an actuator, to vary or close the opening. For large pressure drops, the well streams which contain gas, liquid and sand particles can reach 400-500 m/s and produce heavy metal loss mainly due to solids, liquid droplets, cavitation and combined mechanisms of erosion-corrosion, resulting in choke lifetimes of less than a year. In Figure 1, right, the picture of an eroded choke valve is shown. The main parameters determining erosion potential in the chokes are the fluid velocity and the resulting angle of sand through the choke discs. Erosion management is vital to avoid failures that may result in loss of containment, production being held back, and increased maintenance costs. Moreover, several chokes are located subsea, where the replacement cost is high. Then, the need has increased for reliable models to estimate erosion and lifetime of choke valves, in order to allow implementing effective maintenance strategies [14].

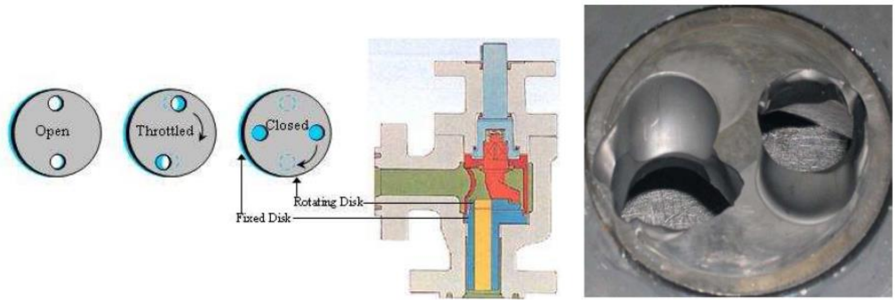

Figure 1: Typical Choke Valve of Rotating Disk Type (http://www.vonkchokes.nl/) (left). Example of eroded choke disk (right).

A common indicator of the valve flow capacity is the flow coefficient CV, which is related to the effective flow cross-section of the valve. For a specific valve opening θ, erosion produces a gradual increase of the valve area available for the flow transit, thus determining an increase of CV (eq. 1). For this reason, knowing the value of the flow coefficient is fundamental for assessing the health state of the choke. During operation, CV is not directly measured but computed, for a two-phase flow, as [14]:

$$C_V = \frac{\dot{m}_{tot}}{27.3 \cdot F_p \sqrt{\Delta P \cdot \rho_{mix}}} \; ; \; \rho_{mix} = \left(\frac{f_g}{\rho_g \cdot J^2} + \frac{f_w}{\rho_w} + \frac{f_o}{\rho_o} \right)^{-1} \quad (1)$$

where $\dot{m}_{o,w,g}$ are the oil, water and gas flow rates, respectively, $f_{o,w,g} = \dot{m}_{o,w,g} / \dot{m}$ the corresponding fluid fractions and $\rho_{o,w,g}$ the corresponding densities, ρ_{mix} the mixture density, $\dot{m}_{tot} = \dot{m}_o + \dot{m}_w + \dot{m}_g$ the total mass flow rate of the oil-water-gas mixture, J the gas expansion factor, $F_p(\theta)$ the piping geometry factor accounting for the geometry of the valve/pipe reducer assembly and ΔP the pressure drop through the choke. Eq. (1) and the values of $\rho_{o,w,g}$, J and $F_p(\theta)$ are derived from fluid dynamics; parameters ΔP, θ, $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ are measured or allocated during operation, *i.e.*, calculated by a physics-based model of the piping process.

For a correct assessment of the choke erosion state, it is fundamental to obtain frequent and reliable measurements or estimates of the parameters ΔP, θ, $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ used to compute the flow coefficient C_V. Nevertheless, only the pressure drop ΔP across the choke and the valve opening θ are measured during standard daily inspections (SI), whereas measures of water, oil and gas flows rates are taken downstream of the choke only during well tests (WT) with a multiphase flow separator. On a daily basis, the values of $\dot{m}_o$, $\dot{m}_w$ and $\dot{m}_g$ are allocated for a single well by a physics-based model accounting for the measured total production from a number of wells and on physical parameters (pressures and temperatures) related to the specific well. Figure 2 schematizes the procedure for the estimation of the flow coefficient.

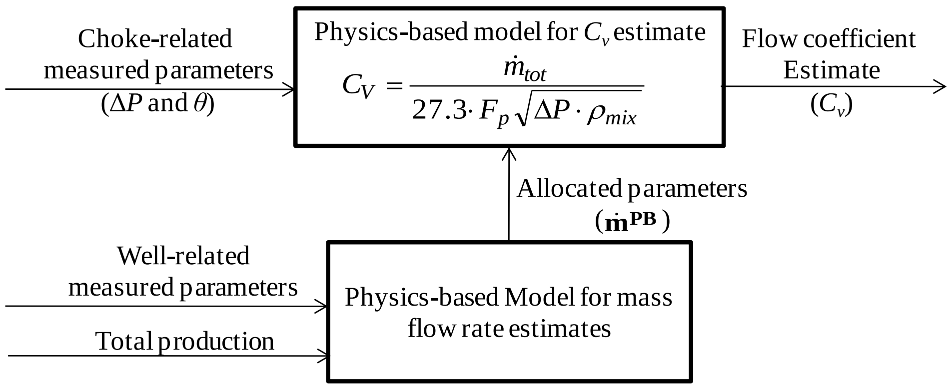

Figure 2: Schematic of the Procedure for the Estimate of Cv.

The value of the parameters in input to the physics-based model is not recorded. Only the values of the choke-related parameters ΔP, θ, $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ collected during WT and SI have been recorded during a protracted period for five different wells. Table 1 outlines the available information: the daily allocated values $\dot{\mathrm{m}}^{\mathrm{PB}} = [\dot{m}_o^{PB}, \dot{m}_w^{PB}, \dot{m}_g^{PB}]$ of the flow rates, the daily measured value of ΔP and θ and the real values of $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ measured during well tests.

Table 1: Available Information

	Standard Inspections (SI)	**Well Test Inspections (WT)**
ΔP and θ	Measured	Measured
$\dot{m}_o$, $\dot{m}_w$ and $\dot{m}_g$	Allocated	Measured

3 Improving the Quality of the Allocated Parameters: a Hybrid Modeling Approach

Since the allocated values of $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ are noisy and unreliable [11], an on-line procedure aiming at improving the accuracy of their estimates is here proposed. The procedure is based on a hybrid approach combining the physics-based model with an ensemble of data-driven models which learn from a training set the relationships between the parameters and provide estimates of $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ in output.

According to [15], there are two major approaches to hybrid modelling: the series and the parallel approaches. In the series approach (Figure 3, upper), data-driven models are used to model parameters of the physics-based model. In the parallel approach (Figure 3, bottom), data-driven models are trained to predict the residuals not explained by the physics-based model.

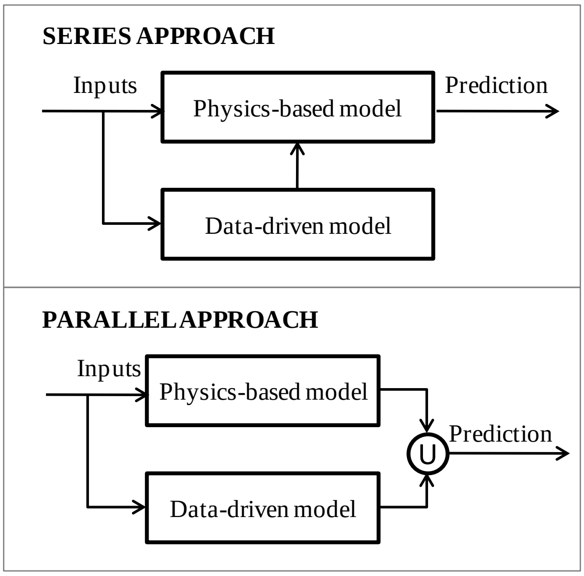

Figure 2: Schematic of Series (upper) and Parallel (bottom) Hybrid Approaches.

In this work, the values $\dot{m}^{PB}$ provided by the physics-based model and the two measured parameter *ΔP* and *θ* are fed in input to a data-driven model, trained using the values of the five parameters ΔP, θ, $\dot{m}_o$, $\dot{m}_w$, and $\dot{m}_g$ collected during WT. The output of this data-driven model is a new empirical estimate $\dot{m}^{DD}$ of the allocated parameters which is, then, aggregated to the output of the physics-based model, $\dot{m}^{PB}$, through a hybrid ensemble (HE) approach. In practice, a parallel hybrid approach combining the outcomes $\dot{m}^{PB}$ of the physics-based model with the outcomes $\dot{m}^{DD}$ of the data-driven model is used to obtain improved estimates of the allocated flow rates $\dot{m}^{HE}$; these allocated values $\dot{m}^{HE}$ are, then, used by another physics-based model estimating the flow coefficient in a series hybrid configuration (Figure 3).

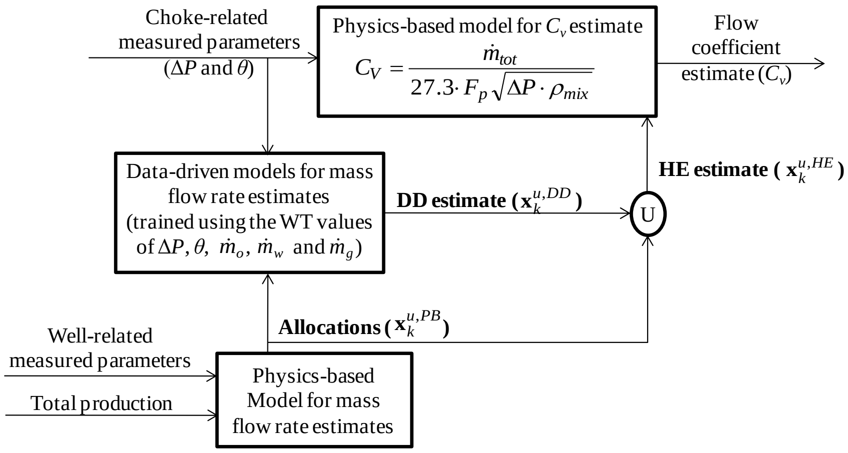

Figure 3: Schematic of the Proposed Hybrid Modelling Approach.

3.1 Data-Driven Model

Different data-drive techniques such as those based on the use of principal component analysis [16], artificial neural networks [17], support vector machines [18] have been used for estimating physical parameters. In this work, we resort to nonparametric Kernel Regression models [12] to build data-driven models for improving the quality of the estimate of the allocated values of oil, water and gas mass flow rates. Compared to parametric methods, which are defined by sets of parameters and predefined functional relationships, nonparametric methods have the advantage that they do not require any assumption about the mathematical structure of the regression model.

KR modeling develops local models in the neighborhoods of the test patterns they are fed with. Estimates are obtained as weighted averages of the training patterns, with weights decreasing as the distance between the test and the training patterns increases. In practice, training patterns closer to the test pattern are conjectured to be more similar to the test pattern, thus giving the most relevant contribution to its estimate.

Let $X_{trn}=\{\boldsymbol{x}_k\}$, k=1,…, Ntrn be the training set used for the estimate of the test pattern $\boldsymbol{x}_{tst}$. To develop the KR model, the input parameters used by the physical-based model for the estimate of the flow coefficient are divided into a predictor group (PG) and a response group (RG) (with the two groups possibly overlapping). For the estimate of x_{tst}, the KR algorithm assigns to each training pattern $\boldsymbol{x}_k$ a weight w_k=K[$d_{PG}(\boldsymbol{x}_{tst},\boldsymbol{x}_k)$], where K is the kernel function which produces the weight for a given distance $d_{PG}(\boldsymbol{x}_{tst},\boldsymbol{x}_k)$], between the training and the test patterns, computed considering only the parameters of the predictor group. The estimate $\hat{x}_{tst}^{RG}$ of the RG parameters of the test patterns is obtained as a weighted average of the RG parameters of the training patterns:

$$\hat{\mathbf{x}}_{tst}^{RG} = \frac{\sum_{k=1}^{N_{trn}} w_k \cdot \mathbf{x}_k^{RG}}{\sum_{k=1}^{N_{trn}} w_k} \tag{2}$$

The kernel function K typically assigns large weights to the training patterns with small distances from the test pattern and vice versa. Among the several functions which satisfy this criterion, the Gaussian kernel is commonly used [11]:

$$K(d_{PG}) = \frac{1}{\sqrt{2\pi h^2}} \exp\left(-\frac{{d_{PG}}^2}{2h^2}\right) \tag{3}$$

where the parameter h defines the kernel bandwidth and is used to control how close training patterns must be to the test pattern to be assigned a large weight. In order to compute d_{PG}, the *PG* parameters are rescaled in the range [0, 1].

In the present case study, the choices of the training dataset and the predictor parameters are critical. In principle, both the WT and the SI patterns can form the training dataset; in this work, only the WT are used for training the KR models, due to their greater reliability. In particular, only the patterns concerning the same well of the current test pattern xtst are considered. This is done since the well behavior and the relationships among the observed parameters can vary from one well to another; as a consequence, patterns collected from other wells do not provide useful information on the behavior of the well under study. In practice, when estimating the test pattern $\boldsymbol{x}_k$ for a specific well w, only the patterns x_j, j=1,…, k-1 previously collected during the life of the w-th well are retained as training patterns.

Concerning the predictor parameters, many different models can be developed by differentiating the parameters used to compute the distances in the KR algorithm. In this work, the four models listed in Table 2 have been used for the construction of the ensemble. The choice of the four sets of predictor parameters is motivated by the quality of the information conveyed by the different parameters: the reliable parameters θ and ΔP are used in all four models. Furthermore, we have verified that a model using as input parameters only the pressure drop ΔP and the opening θ performs very poorly in the estimate of the mass flow rates, and, thus, it has not been considered.

Table 2*:* Predictor Parameters used in the Four Different Models of the Ensemble.

Model	**Predictor Parameters**				
	ΔP	θ	$\dot{m}_o$	$\dot{m}_w$	$\dot{m}_g$
1	X	X	X	X	X
2	X	X	X		
3	X	X		X	
4	X	X			X

In order to verify the performance of the different models, we have considered a test set made by the N_{WT} SI patterns collected during the same day of a well test for which an accurate measure of the process parameters under estimation is available. The total number of available well tests patterns used for training and the number of well tests used for testing is given in Table 3. Patterns collected during choke valve degradation from five different wells are considered. Since degraded valves are replaced, patterns collected for a single well refer to different chokes.

Table 3: Number of Training and Validation WT Patterns for each Choke.

Well	N_{WT}	***Ntst***
1	87	68
2	96	59
3	39	20
4	96	54
5	71	36

Finally, the response group is formed by the unreliable parameters that need to be estimated $\mathrm{x}_k^{RG} = \dot{\mathrm{m}} = [\dot{m}_o, \dot{m}_w, \dot{m}_g]$.

It has been verified that the performance of the single models depends on the characteristics of the parameter to be estimated and the intensity of the noise affecting the input pattern, so that it is difficult to identify a single best model (Baraldi *et al*., 2011), . Moreover, due to the great uncertainty affecting the input pattern, a robust approach is required to estimate the output. Using all models, within an ensemble approach, in a parallel configuration with the physics-based model (Figure 5), allows both overcoming the dilemma of selecting the optimal model, and increasing the robustness of the final estimate, since the diverse outcomes average out their errors. The result is a hybrid ensemble of five models, four KR and one PB.

3.2 Aggregation

Figure 5 shows that the estimates of the flow rates provided by the four KR models and the physics-based one have to be aggregated. Different techniques for the aggregation of the outcomes of the individual models into the ensemble outcome have been proposed in the literature, from statistics methods like the simple mean and the median [9,16] to weighed averages of the model outcomes based on the global or local performances of the individual models [8]. In the latter ones, the aggregation is guided by the local performance of each model, *i.e.*, its reconstruction accuracy on patterns of training similar (and for this reason also called neighbors) to the test pattern. These methods rely on the idea that each model can perform well in some regions of the parameter space and poorly in others. In this work, local performance-based techniques are applied for estimating the mass flow rates. This allows exploiting the four data-driven models only when they actually outperform the physics-based model, thus avoiding affecting its accuracy when it actually outperforms the KR models.

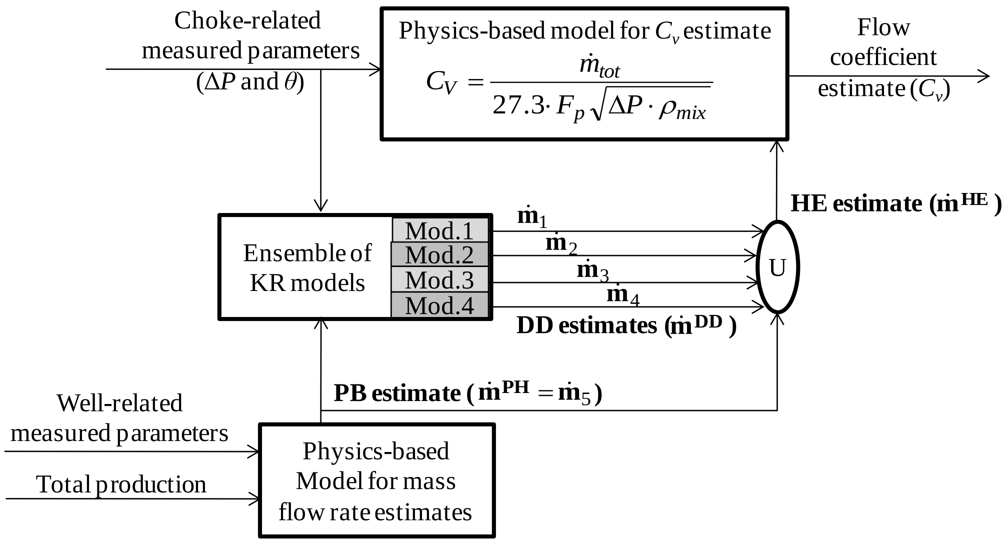

Figure 4: Schematic of the Hybrid Ensemble of Models.

For each parameter p to be estimated, the local performance aggregation approach here adopted assigns to the generic model b of the ensemble a weight $w_{p,b}$ proportional to the model performance evaluated on the N_n=3 training samples closest to the test pattern x_{tst}. The estimation error made by model b in providing the estimate $\hat{x}_i^{p,b}$ of the p-th parameter is, then, obtained by comparing $\hat{x}_i^{p,b}$ to the corresponding WT measurement $x_i^{p,WT}$; the local weight $w_{p,b}$ assigned to model b is taken as the inverse of its mean square estimation error over the N_n patterns closest to x_{tst}:

$$w_{p,b} = \left[\frac{1}{N} \sum_{i=1}^{N_n} \left(\hat{x}_i^{p,b} - x_i^{p,WT} \right)^2 \right]^{-1} \tag{4}$$

where the parameter h defines the kernel bandwidth and is used to control how close
The final estimate $\hat{x}_{tst}^{p}$ of parameter p is obtained as the weighted average of the multiple model estimates $\hat{x}_{tst}^{p,b}$.

$$\hat{x}_{tst}^{p} = \frac{\sum_{b=1}^{5} w_{p,b} \hat{x}_{tst}^{p,b}}{\sum_{m=1}^{4} w_{p,b}} \tag{5}$$

4 Results

The hybrid approach is here applied to the choke valve case study to obtain estimates of the mass flow rates $\dot{m}_o$, $\dot{m}_w$ and $\dot{m}_g$. Models performances are evaluated by considering the root mean square error (RMSE) between the estimates of the mass flow rates $\dot{m}_o$, $\dot{m}_w$ and $\dot{m}_g$ and the corresponding well test measurements, normalized in the range [0,1]. The performance of the hybrid ensemble is compared with those of the physics-based model and the KR ensemble.
Table 4 compares the RMSE of the physics-based model with respect to that obtained by the data-driven ensemble.

Table 4: Comparison of the Performance of the Hybrid Ensemble with that of the Physics-based Model and of the Data-driven Ensemble

	RMSE (10^{-2})					
	Well 1	Well 2	Well 3	Well 4	Well 5	average
Physics-based	7.118	2.742	1.056	3.248	5.796	4.435
KR ensemble	4.438	3.892	3.395	4.208	6.277	4.441 (+0.1%)
Hybrid ensemble	3.877	2.984	1.194	3.665	5.480	3.623 (-18%)

Results show that the KR ensemble outperforms the physics-based model only in the case of the first well, producing a 38% reduction of the RMSE; in all the other four wells the physics-based models generates more accurate estimates than the ensemble. The hybrid ensemble mediates between the physics-based and data-driven models by conserving, and even enhancing, the good performance in case of well 1 and well 5 and at the same time keeping the error low also in the case of the other wells.

In Figure 6, the measured values of oil, water and gas flow rates for the test patterns are compared with the estimates obtained by the physics-based model and by the hybrid ensemble. The obtained results show that the hybrid ensemble and the physics-based model estimates are in general very similar except for the oil flow in well 1, where the ensemble significantly outperforms the physics-based model. This confirms that the hybrid ensemble is able to distinguish when the physics-based model works properly and when, instead, the greatest weight must be assigned to the data-driven models of the ensemble.

5 Conclusions

In this work, we have considered the problem of improving the quality of the estimates of some process parameters used in offshore oil platforms for assessing the health state of degrading choke valves. In order to improve the estimates provided by a physics-based model, we have proposed a hybrid method based on an ensemble of models. In practice, the physics-based model is combined with multiple data-driven models based on Kernel Regression. In order to inject diversity into the models of the ensemble, the data-driven models consider different input parameters. The aggregation of the outcomes of the different models is performed by a local performance-based technique.

The results obtained from the application of the approach on several degrading choke valves have confirmed that in those circumstances in which the physics-based model is inaccurate, an ensemble approach with data-driven models can increase the accuracy of the estimates and that the hybrid ensemble correctly favors the most accurate between the data-driven and physics-based models in the ensemble.

The physics-based, KR and ensemble estimates derived in this paper need to be complemented with a measure of uncertainty. A traditional measure of this uncertainty is the average error of the models on a validation dataset. For the physics-based estimates this can be obtained by comparing the allocated parameters with the corresponding values obtained during well tests. This would provide an estimate of the average error over different input data and working conditions. Local models relating the uncertainty to the input data could provide a more accurate quantification of the uncertainty of the specific estimates. The uncertainty of KR estimates is typically estimated using bootstrapping and cross validation; more advanced approaches may resort to the Dempster Shafer theory and fuzzy numbers for the treatment of data and models uncertainty. Finally, the uncertainty of the ensemble estimates has to be obtained by aggregating the uncertainties of the different model. This is likely to be a challenging task, since the estimates of the different models are not independent. Future work will be devoted to the reliable quantification of the uncertainty of the hybrid ensemble estimates.

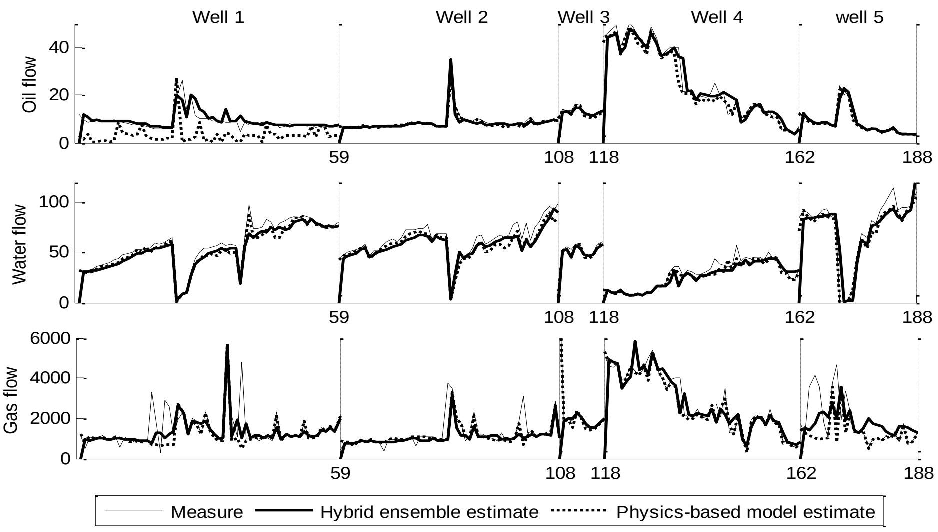

Figure 5: Comparison of the Measured Values of Oil, Water and Gas Flow Rates with the Estimates obtained by the Physics-based Model and the Hybrid Ensemble.

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