12th IFAC International Symposium on
Advanced Control of Chemical Processes
July 14-17, 2024. Toronto, Canada

Smart Monitoring and Predictive Maintenance for an Offshore Natural Gas Dehydration Unit

Leonardo M. De Marco*, Jonathan W. V. Dambros*, Thiago K. Anzai, Jorge O. Trierweiler*, and Marcelo Farenzena***

**Group of Intensification, Modeling, Simulation, Control, and Optimization of Processes (GIMSCOP) – UFRGS, CEP 90040-040, Rua Engenheiro Luiz Englert, s/n° - Prédio 12204, Porto Alegre, Brazil (e-mails: leo.mandler@gmail.com, dambros@enq.ufrgs.br, jorge@enq.ufrgs.br, farenz@enq.ufrgs.br).*

***Centro de Pesquisas e Desenvolvimento Leopoldo Américo Miguez de Mello – CENPES, Petrobras CEP 21941-915, Rio de Janeiro, Brazil (e-mail: tanzai@petrobras.com.br)*

Abstract: This work highlights the importance of dehydration in natural gas production, especially in offshore units, and tackles the challenges associated with adsorption processes. The main contribution is implementing digital solutions to monitor a Brazilian operational offshore natural gas dehydration unit. Bayesian inference and robust regression are utilized to determine the Remaining Useful Life (RUL) of the adsorbent in fixed beds. Furthermore, a mass balance in fixed beds provides valuable process insights, such as the adsorbed volume of water, a crucial variable for assessing the fixed bed's performance. Bayesian inference and the logistic function yielded the most accurate predictions for the end of the fixed bed's useful life. The proposed methodologies have been successfully integrated into a real-time monitoring dashboard at a Brazilian oil and gas plant.

Keywords: natural gas, dehydration, adsorption, RUL, Bayesian inference, robust regression.

1. INTRODUCTION

Natural gas has gained significant attention as a clean and efficient fossil energy source, leading to a surge in demand (Daniel and Kemp, 1998; John, 2003). Dehydration, a crucial step in natural gas production, removes water vapor from the gas, preventing corrosion and hydrate formation in pipelines (Mokhatab et al., 2006; Santos et al., 2017). This process is essential for subsequent operations like Natural Gas Liquids (NGL) extraction and Liquefied Natural Gas (LNG) production (Aleghafouri and Davoudi, 2018).

Adsorption beds are commonly used in refineries and petrochemical plants to ensure the desired water humidity specificity (Terrigeol and Trifilieff, 2015). Several studies have explored methods to optimize and extend the lifetime of adsorption beds in natural gas dehydration processes. Aleghafouri and Davoudi (2018) modeled a Pressure-Temperature Swing Adsorption (PTSA) process in a two-layer commercial adsorption system. Dalane *et al.* (2019) evaluated a membrane contactor with triethylene glycol (TEG) for natural gas dehydration and regeneration. Marco *et al.* (2019) assessed techniques to estimate the number of remaining useful cycles (NRC) of fixed beds, and Terrigeol (2012), and Terrigeol and Trifilieff (2015) identified factors that shorten the adsorbent lifetime. Therefore, optimizing adsorption and regeneration times is crucial for maximizing bed lifetime, as premature or delayed completion of these steps can reduce the bed's lifetime.

To address the issue of premature adsorbent failure in natural gas dehydration units, this work proposes digital monitoring solutions for an offshore unit located on the Brazilian coast. The goal is to determine the RUL of the adsorbent in the fixed bed where dehydration occurs, thereby enabling timely maintenance and cost optimization. Due to limited failure data for critical equipment, degradation advancement analysis is employed, which involves monitoring variables responsible for system deterioration (Nikulin et al., 2010; Tang et al., 2014). Two methods are used for RUL estimation: Bayesian inference approach proposed by Wang *et al.* (2018) and a robust regression method with automatic parameter update algorithm proposed in this paper in a simplified manner. The motivation for comparing these methods lies in the fact that one is more complex and probabilistic (Bayesian inference), while the other is more intuitive and simpler (robust regression). This work also presents a mass balance for the fixed beds in natural gas dehydration units, providing valuable insights into the process that are not readily available from current instrumentation. One of the key variables obtained from this mass balance is the adsorbed volume at breakthrough, which is crucial for evaluating unit performance and determining the RUL of the fixed bed.

The proposed digital solutions, integrated within a real-time monitoring dashboard, assist in identifying the depletion point of adsorption beds. This enables predictive maintenance, thereby minimizing costs, environmental and operating risks, and production losses resulting from unforeseen shutdowns.

This paper is organized as follows: Section 2 introduces the dehydration unit. In Section 3, the methodology based on mass balance is presented. Section 4 introduces the methodologies for predicting RUL. Section 5 presents the results, and conclusions are provided in Section 6.

2. ACTUAL OFFSHORE DEHYDRATION UNIT

2.1 Temperature Swing Adsorption (TSA) Process

The Natural Gas Dehydration Unit studied in this work was presented by Marco *et al.* (2019). In natural gas production, the undesirable presence of water is a problem because it can cause corrosion and lead to the formation of hydrates, which can obstruct well pipelines. The TSA method with adsorption using molecular sieves is employed to remove water from natural gas due to the need to achieve low water concentrations.

Adsorption dehydration involves altering the adsorption equilibrium conditions to desorb molecules and regenerate the adsorbent. This regeneration step is essential and requires high temperatures. Multiple parallel adsorption beds maintain high flow rates (Terrigeol, 2012). The TSA method, widely used for mixture separation, involves adsorption at room temperature followed by regeneration at high temperatures, resulting in a longer cycle than Pressure Swing Adsorption (PSA) (Fonseca, 2011).

The TSA process consists of at least two fixed beds operating in parallel in cycles. One bed adsorbs at room temperature, while the other regenerates at high temperatures (Nastaj and Ambrozek, 2015). The optimal timing of adsorption and regeneration steps is crucial for maximizing bed lifetime. Premature or delayed completion of these steps can shorten the bed's lifetime.

The TSA method is recommended for strongly adsorbed components, while PSA is more suitable for weakly adsorbed components and products requiring high purity, such as hydrogen purification (Fonseca, 2011; Santos et al., 2017).

The TSA unit used in this work consists of three fixed beds, each undergoing adsorption and regeneration. At any given time, two beds are in adsorption while one is in regeneration, so the adsorption-regeneration cycle time needs to consider this switching.

2.2 Contaminants that affect the lifetime of molecular sieves

Adsorption beds in natural gas dehydration processes can experience several operational issues that reduce their performance and molecular sieve lifetime. Liquid contaminants like water and impurities cause these issues in the feed gas. Contaminants affect the adsorption process through adsorption competition, structure degradation, partial bed blockage, and side reactions like carbonyl sulfide (COS) formation (Terrigeol, 2012; Terrigeol and Trifilieff, 2015).

Some dehydration units operate with a fixed cycle time, while others use breakthrough conditions, meaning the adsorption step ends when impurities are detected in the outlet stream. In the latter case, the cycle time gradually decreases until the bed's lifetime ends due to adsorbent property loss from fouling and degradation (Terrigeol, 2012).

A well-designed molecular sieve can maintain the required adsorption capacity throughout its lifetime. However, contaminants affect the bed's lifetime, causing premature breakthroughs and a rapid increase in pressure drop. This significantly impacts the natural gas dehydration process and implies an earlier adsorbent replacement (Terrigeol and Trifilieff, 2015).

A premature breakthrough occurs when the adsorbent fails to meet the specified water concentration before the projected adsorption step's end. Reasons for premature breakthrough include coking, adsorbent degradation, and preferential paths. Preferential paths can reduce total capacity due to "dead volumes" and lead to improper regeneration, causing residual water in the bed (Terrigeol, 2012; Terrigeol and Trifilieff, 2015).

Pressure drops in natural gas dehydration typically range from 0.2 to 0.5 bar at the start of the bed's lifetime. The pressure drop gradually increases with cycles due to fouling from hydrocarbon deposits and light dust from thermal stress and friction. An accelerated pressure drop can occur in severe cases with coking, liquid reflux, and heavy dust accumulation, potentially leading to preferential paths and flow restriction (Terrigeol and Trifilieff, 2015).

Adsorbent lifetime is affected by regeneration, as inadequate regeneration, such as too fast heating, can cause liquid water reflux, while excessively long regeneration can cause thermal stress on the molecular sieve (Terrigeol, 2012; Terrigeol and Trifilieff, 2015). The decrease in cycle time, as the fixed bed degrades, affects the amount of water adsorbed by the column; therefore, the adsorbed volume by the adsorbent in the adsorption step when breakthrough occurs is used to evaluate the dehydration unit's performance.

3. MASS BALANCE

This Section presents a methodology based on mass balance to estimate the adsorbed volume by the molecular sieve until the breakthrough instant. It is used to monitor the dehydration unit's performance.

An algorithm was developed in this paper to perform a mass balance, focusing on humidity accumulation within the fixed beds. The algorithm operates through two main sections: adsorption and desorption. Each Section calculates the alteration in the volume of humidity captured within the columns over time using a simple mass balance model. When a humidity sensor is installed, it can be used to calculate the amount of water in the inlet stream. Otherwise, when this sensor is not working or even available, the amount of water can be estimated using a specific humidity model such as the Khaled model (Aimikhe and Adeyemi, 2020; Khaled, 2007).

In the adsorption section, the algorithm starts by checking the previous state. If the previous state was desorption, the bed volume is initiated (set to zero), and the accumulated humidity in the step is added. If the previous state was adsorption, the algorithm checks for a breakthrough when the adsorbent becomes saturated and cannot capture humidity. The algorithm checks for a breakthrough by comparing the average humidity of the last hour and checks if it exceeds 5 ppm. If a breakthrough is detected, the volume is not updated, and the maximum volume of humidity is recorded. If no breakthrough is detected, the volume is updated with the mass balance. The humidity content in the gas is determined by the Khaled model, which considers the pressure at the inlet and the temperature. The volume of humidity held in each bed is updated by:

$$V_i = V_{i-1} + F_{per\ bed}.Humidity.\Delta t \qquad (1)$$

where $F_{per\ bed}$ is the global flow entering into the two fixed beds in the adsorption stage divided by two.

The desorption section calculates the humidity based on the desorption pressure and temperature at the outlet. The flow rate undergoes a similar conversion as in the adsorption phase, representing the humid gas being released. The volume of water in the bed is updated by subtracting the product of flow, time step, and humidity. If the volume calculation yields a negative value, it is adjusted back to zero. Marco et al. (2024a) provide a detailed description of this mass balance.

4. METHODS TO ESTIMATE RUL

Two methods are proposed to monitor the Natural Gas Dehydration Unit's performance and estimate the fixed beds' RUL. The first method is based on Bayesian inference and was presented by Wang *et al.* (2018). The second method uses robust linear regression and the logistic function with a robust optimization method along with an automatic parameter update algorithm for regression models.

4.1 Bayesian Inference

Wang *et al.* (2018) proposed a Bayesian inference-based methodology for estimating real-time RUL. The methodology employs a Wiener Process-based degradation model, incorporating deterministic and stochastic components for standard and individual equipment characteristics. This degradation model can accommodate systems with varying degradation rates under different operating conditions and applies to both linear and nonlinear degradation scenarios.

The Bayesian methodology comprises two phases: offline and online. The offline phase involves using maximum likelihood estimation to determine the hyperparameters of the prior distribution for the stochastic parameter and the deterministic parameters based on historical degradation data from M identical systems. In the online phase, Bayesian inference is used to update the mean and the variance of the stochastic parameter and estimate RUL. The mean time to the remaining useful life is calculated using Equation (2).

$$mean_{RUL} = \int_0^{+\infty} l_k\, f_{Lk}(l_k) dl_k \qquad (2)$$

where l_k is the vector of RUL, and the probability density function (PDF) $f_{Lk}(l_k)$ is calculated.

4.2 Linear Model

The first regression model is the most straightforward function for fitting, which is the linear model, characterized by being a straight line, i.e., given by:

$$y(x) = ax + b \qquad (3)$$

where a is the slope coefficient, b is the intercept, x is the current measure, and $y(x)$ is the predicted degradation value. The coefficients a and b are responsible for the slope and intercept of the line, respectively.

4.3 Logistic Model

Nonlinear models are a viable option for data modeling because they capture a wide range of functions. It can provide a better fit for specific applications due to their reduced number of parameters, facilitating a more straightforward interpretation. Moreover, nonlinear models offer more robust predictions than polynomial models, particularly for extrapolation scenarios (Archontoulis and Miguez, 2015).

The sigmoid curve is a promising nonlinear model for degradation fitting due to its S-shaped form that aligns with patterns observed in life cycles and various phenomena. Widely used in fields like demography, biology, and economics, the sigmoid curve comprises three distinct phases: the base phase, the growth or logarithmic decay phase, and the stabilizing mature phase (Forouzanfar et al., 2010). Variants of the sigmoid model exist, including the logistic function. Forouzanfar *et al.* (2010) proposed using the logistic function to predict natural gas consumption in Iran. Equation (4) presents the logistic model.

$$y(x) = \frac{a}{1+ e^{-b(x-c)}} \quad (4)$$

where a is the maximum value of the logistic curve, b is the slope of the curve, c is the curve's inflection point, x is the current measure, and $y(x)$ is the predicted value by the logistic function. Regarding fitting the logistic curve for degradation, the parameter c is critical as it determines the midpoint of the logarithmic phase.

Linear and logistic models are used together with the automatic parameter update algorithm for regression models to estimate the RUL of fixed beds of natural gas dehydration. This algorithm is based on a reference degradation with reference parameters for each regression model used. Based on tolerance parameters, the algorithm decides whether to update the regression model parameters or not. This algorithm is presented in detail in Marco et al. (2024b).

5. RESULTS

This Section presents the results obtained for the performance monitoring and estimation of RUL of fixed adsorption beds in an Offshore Natural Gas Dehydration Unit in Brazil. The method uses the adsorbed volume at breakthrough, which is a critical variable for the performance of the dehydration unit.

To obtain the hyperparameters of the Bayesian methodology proposed by Wang *et al.* (2018) and to obtain the reference degradation model to linear and logistic models, data between 2018 and 2019 are considered. Tests are conducted on data between 2022 and 2023. The entire implementation was done in Python. To protect confidentiality, the data was normalized, and the units of the obtained parameters were omitted.

5.1 Adsorbed Volume Calculated Between 2018 and 2019

The dataset of adsorbed volume at breakthrough spans from January 1, 2018, to November 1, 2019. Figure 1 depicts the adsorbed volume data for each fixed bed. As illustrated in Figure 1, a gradual decrease in adsorbed volume is evident as the fixed bed degrades. There were 377, 324, and 456 breakthrough occurrences throughout this period, with the final measurements recorded on October 24, 2019, November 1, 2019, and October 30, 2019, for fixed beds A, B, and C, respectively.

Figure 1. Adsorbed Volume Between 2018 and 2019.

Additionally, Figure 1 reveals that the sampling intervals are not uniform. This means that a fixed bed may experience one breakthrough per week in the initial period, while it may experience one breakthrough per day in the subsequent period, for example. Another noteworthy aspect is the presence of outliers in the dataset. These outliers arise from uncertainties primarily associated with calculating inlet stream humidity and inlet flow. As detailed in Section 2, inlet humidity is calculated based on temperature and pressure measurements of the inlet stream, and there is no direct measurement of the individual flow entering each fixed adsorption bed. Consequently, the respective flow is assumed to be half of the total flow entering the fixed adsorption beds.

To address the issue of outliers in the dataset, we propose an algorithm that employs a moving window technique. If a given data point j exceeds the mean of the moving window data plus s times its standard deviation, data point j is replaced with the mean of the moving window data plus s times its standard deviation. Conversely, if a given data point j is less than the mean of the moving window data minus s times its standard deviation, data point j is replaced by the mean minus s times its standard deviation. For this dataset, the moving window size was set to 10, and s with the value equals 0.1.

As the time data is in date format, applying the proposed methodologies requires some mathematical transformations. The first one is to convert the measurement date into a numerical value. The next step in pre-processing the dataset is dealing with non-constant sampling with linear interpolation with 1000 points between the first and the last measurement for each fixed bed. Finally, after all these steps, the FILTFILT function in the scipy library is utilized to smooth the data and improve prediction quality. Figure

2 presents the dataset after undergoing all these mathematical transformations.

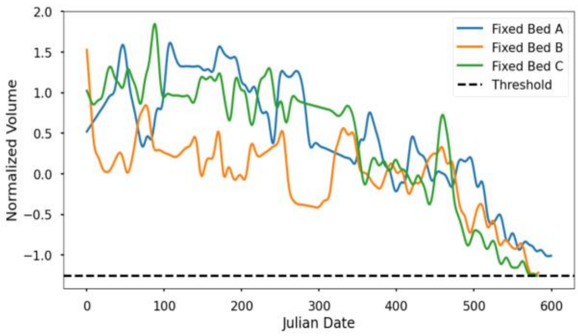

Figure 2. Adsorbed Volume after pre-processing and mathematical transformations.

For convenience, the threshold of adsorbed volume, X_f, was considered the last value of the filtered adsorbed volume for fixed bed C, which equals 6.64 m³. Therefore, the date of October 30, 2019, is considered as the end of the useful life for fixed bed C.

The datasets from fixed beds A and B are used to obtain the hyperparameters of the prior distribution of the stochastic parameter of the Bayesian degradation model, and the dataset from fixed bed C is used to test the Bayesian methodology and its ability to update the stochastic behavior for fixed beds of adsorption. The dataset from fixed bed C is used to obtain the reference degradation model to linear and logistic functions. Appendix A shows the hyperparameters of the Bayesian degradation model and the reference regression parameters for each model used. The vector l_k has a start value of 0 and a stop value of 3000, with 500 samples. More details are provided by Marco et al. (2024b).

5.2 Prediction of RUL for the adsorbed volume dataset between 2018 and 2019

The dataset from fixed bed C was employed to assess the methodologies for predicting RUL of fixed beds of natural gas adsorption. Fixed bed C attained the defined X_f threshold on October 30, 2019, which consequently marks the end-of-life date for this fixed bed. The methodologies for predicting RUL compute the lifetime l_k and, hence, the end-of-life time, t_{end}, which is defined as $t_{end} = t_k + l_k$, where t_k denotes the current measurement time.

Two measurements of adsorbed volume per adsorption cycle in fixed bed C are analyzed to evaluate the quality of prediction of the presented methodologies. The first measurement was on December 31, 2018, and the second measurement on August 30, 2019. Fixed bed C showed 149 and 345 premature breakthroughs for these measurements, respectively. On the last measurement data analyzed, fixed bed A presented 280, while fixed bed B gave 196 early breakthroughs, which indicates that fixed bed C is degrading more rapidly.

Table 1 presents the estimated end-of-life date for each of the proposed methodologies. The logistic function was the most accurate method for predicting the end-of-life of fixed bed C, outperforming other proposed methodologies. This is likely because data from fixed bed C between 2018 and 2019 was used to fit the logistic function. Linear regression, despite utilizing the same reference data, yielded unsatisfactory results due to the process's nonlinear nature. On the other hand, Bayesian inference continuously updates its end-of-life prediction with each new measurement, bringing it closer to the actual end-of-life date. However, it is essential to note that Bayesian inference based on the Wiener process exhibits Markov characteristics, implying that degradation depends solely on the current measurement. This can lead to misleading results in processes with significant noise.

Table 1. End of Life predicted for data from fixed bed C between 2018 and 2019.

Date of measurement	Model	Predicted End of Life	Actual End of Life
31-12-2018	Linear	25-01-2020	30-10-2019
	Logistic	02-11-2019	
	Bayesian	10-07-2020	
30-08-2019	Linear	25-01-2020	30-10-2019
	Logistic	02-11-2019	
	Bayesian	17-11-2019	

5.3 Prediction of RUL for the adsorbed volume dataset between 2022 and 2023

The second dataset analyzed covers the period from August 2022 to May 2023. In this Section, the fixed bed A is analyzed. Table 2 presents the prediction of the end of useful life for this fixed bed. Three measurements of the adsorbed volume were chosen. It is evident that fixed bed A is degrading faster than the other columns according to the methodologies, because with each new measurement, the estimated end-of-life for this column is updated to a more recent date.

Table 2. End of Life predicted for data from fixed bed A between 2022 and 2023.

Date of measurement	Model	Predicted End of Life	Actual End of Life
01-11-2022	Linear	01-06-2024	Second Semester of 2023
	Logistic	09-03-2024	
	Bayesian	11-12-2023	
01-01-2023	Linear	01-06-2024	Second Semester of 2023
	Logistic	21-07-2023	
	Bayesian	25-09-2023	
25-02-2023	Linear	01-06-2024	Second Semester of 2023
	Logistic	26-06-2023	
	Bayesian	16-08-2023	

The proposed algorithm for updating the parameters of regression models effectively enabled the logistic function to dynamically adjust its estimates and adapt to the degradation of fixed bed A. This is evident from Table 2. Notably, fixed bed A underwent maintenance in the middle of 2023. Consequently, the logistic function, in conjunction with the proposed algorithm and Bayesian inference, accurately predicted the end-of-life for fixed bed A. The estimates of the methods are close to the date when fixed bed A underwent maintenance, corroborating the prediction. Linear regression, on the other hand, failed to produce satisfactory results due to the nonlinear nature of the process.

It is important to note that these methodologies are already integrated into a dashboard that monitors the performance of an Actual Offshore Natural Gas Dehydration Unit in real-time.

6. CONCLUSIONS

This work presents digital solutions for monitoring the performance of an Offshore Natural Gas Dehydration Unit. A mass balance is developed for the unit's fixed beds, providing access to process information that is unavailable through the unit's instrumentation, such as the adsorbed volume by the fixed bed when a breakthrough occurs. This information is valuable for monitoring the unit's performance and estimating the RUL of the fixed beds. Two methods were used to determine RUL: Bayesian inference and an algorithm for automatic updating of parameters of regression models. These methodologies could estimate and update the end-of-life date for each fixed bed in the dehydration unit. The proposed methods for evaluating the unit's performance are implemented in a real-time dashboard that monitors the unit, helping reduce environmental, operational, and production loss risks.

REFERENCES

Aimikhe, V.J., Adeyemi, M.A., 2020. A Critical Evaluation of Natural Gas-water Formula Correlations. J Sci Res Rep 1–20. https://doi.org/10.9734/jsrr/2019/v25i630206

Aleghafouri, A., Davoudi, M., 2018. Modeling and simulation of a pressure–temperature swing adsorption process for dehydration of natural gas. Adsorption 24, 121–133. https://doi.org/10.1007/s10450-017-9924-z

Archontoulis, S. V, Miguez, F.E., 2015. Nonlinear regression models and applications in agricultural research. Agron J 107, 786–798. https://doi.org/10.2134/agronj2012.0506

Dalane, K., Hillestad, M., Deng, L., 2019. Subsea natural gas dehydration with membrane processes: Simulation and process optimization. Chemical Engineering Research and Design 142, 257–267. https://doi.org/10.1016/j.cherd.2018.12.027

Daniel, W., Kemp, A., 1998. Engineering Data Book, Gas Processors Suppliers Association (GPSA), 11th ed. Tulsa.

Fonseca, N.A.A., 2011. Simulação do processo de adsorção PSA para separação da mistura etanol-água 141.

Forouzanfar, M., Doustmohammadi, A., Menhaj, M.B., Hasanzadeh, S., 2010. Modeling and estimation of the natural gas consumption for residential and commercial sectors in Iran. Appl Energy 87, 268–274. https://doi.org/10.1016/j.apenergy.2009.07.008

John, M., 2003. Technical Assistance Service for the Design Operationand Maintenance of Gas Plants. John Campbell and Company, Oklahoma.

Khaled, A., 2007. A prediction of water content in sour natural gas. King Saud University, Riyadh, Saudi Arabia.

Marco, L.M. De, Dambros, J.W. V., Anzai, T.K., Trierweiler, J.O., Farenzena, M., 2024a. Digital Solutions for Performance Monitoring and Remaining Useful Life Estimation of an Actual Offshore Natural Gas Dehydration Unit. Unpublished.

Marco, L.M. De, Trierweiler, J.O., Farenzena, M., 2024b. Automatic Parameter Update Algorithm for Regression Models to Estimate Remaining Useful Life: Application in an Offshore Natural Gas Dehydration Unit. Unpublished.

Marco, L.M. De, Trierweiler, J.O., Farenzena, M., 2019. Determination of Remaining Useful Life in Cyclic Processes. Ind Eng Chem Res 58, 22048–22063. https://doi.org/10.1021/acs.iecr.9b03182

Mokhatab, S., William, AP., Speight, J., 2006. Handbook of natural gas transmission and processing. Elsevier, Burlington.

Nastaj, J., Ambrozek, B., 2015. Analysis of gas dehydration in TSA system with multi-layered bed of solid adsorbents. Chemical Engineering and Processing: Process Intensification 96, 44–53. https://doi.org/10.1016/j.cep.2015.08.001

Nikulin, M.S., Limnios, N., Balakrishnan, N., Kahle, W., Huber-carol, C., 2010. Advances in Degradation Modeling. Springer Science & Business Media. https://doi.org/10.1007/978-0-8176-4924-1

Santos, M.G.R.S., Correia, L.M.S., de Medeiros, J.L., Araújo, O. de Q.F., 2017. Natural gas dehydration by molecular sieve in offshore plants: Impact of increasing carbon dioxide content. Energy Convers Manag 149, 760–773. https://doi.org/10.1016/j.enconman.2017.03.005

Tang, S., Yu, C., Wang, X., Guo, X., Si, X., 2014. Remaining Useful Life Prediction of Lithium-Ion Batteries Based on the Wiener Process with Measurement Error. Energies (Basel) 7, 520–547. https://doi.org/10.3390/en7020520

Terrigeol, A., 2012. Gas Processors Association-Europe Molecular Sieves Contaminants: Effects, Consequences and Mitigation.

Terrigeol, A., Trifilieff, O., 2015. Practical Considerations For The Design Of Adsorbent Beds-Molecular Sieve Lifetime Optimization.

Wang, Z.Q., Hu, C.H., Fan, H.D., 2018. Real-Time Remaining Useful Life Prediction for a Nonlinear Degrading System in Service: Application to Bearing Data. IEEE/ASME Transactions on Mechatronics 23, 211–222. https://doi.org/10.1109/TMECH.2017.2666199

Appendix A

Table A1. Hyperparameters of Bayesian Inference.

Hyperparameter	Optimal Value	Standard Deviation
$\mu_{a}0$	0.4000	0.0019
$\sigma_{a}0^2$	$5.06.10^{-8}$	$6.93.10^{-10}$
β	0.5961	0.0009
σ	0.0090	$6.06.10^{-7}$

Table A2. Optimal parameters of the models.

Model	Parameter	Optimal Value	Standard Deviation
Linear	a	-0.0200	0.0000
	b	20.00	0.0592
Logistic	a	20.00	0.0574
	b	-0.0078	0.0002
	c	494.34	2.3023