27th ABCM International Congress of Mechanical Engineering
December 04-08, 2023, Florianópolis-SC, Brazil

COB-2023-2225
Control Performance Improvement of Light Cut Naphtha Removal via Model-free Adaptive Filter

Lucas Moura Gomes
Automation and Control Group (GRACO), Dpt. of Mechanical Engineering, University of Brasília, Brasília, Federal District, Brazil
lucasmouragomes@ieee.org

Luis Longhi
PETROBRAS – UO REFAP – Alberto Pasqualini Refinery-Optimization, Brazil
longhi@petrobras.com.br

José Oniram de Aquino Limaverde Filho
Eugênio Fortaleza
Automation and Control Group (GRACO), Dpt. of Mechanical Engineering, University of Brasília, Brasília, Federal District, Brazil
joseoniram@ieee.org
efortaleza@unb.br

Abstract. *Hydrotreated naphtha is a complex hydrocarbon used to produce gasoline and it is composed of heavy and light naphtha based on sulfur content. The heavy cut must go through hydrodesulfurization (HDS), while the light cut meets the sulfur requirements of gasoline and should be removed to decrease load on HDS reactors. Prior to this study, a filter derived by the authors was introduced in several feedback control loops of an industrial oil refinery plant with a 30,000 m³/d average throughput of oil, whose results were promising in terms of reducing actuator wear while keeping an equivalent output performance as compared to the unfiltered case. In the present work, we propose to slightly modify the filter tuning process to further reduce the impact of measurement noise without compromising the controller action of a closed-loop control system used in light naphtha extraction. Data were collected from 16 days before and 15 days after the addition of the filter in the feedback control loop. Control performance indexes were then computed to assess the robustness and effectiveness of the proposed approach. The inclusion of the filter led to a reduction of approximately 20% in the average Integral Absolute Error (IAE), showing considerable improvement in reference tracking of the output. Furthermore, actuator Travel in percentage was reduced by 60%, indicating less stress on the actuator and fewer reversions. The experimental findings achieved with a slight modification of the tuning parameters of this filter show that its usage can be expanded with minimal implementation effort to improve output performance of industrial control plants and reduce the excessive use of the actuator over time. These results encouraged the process engineers to carry on the application of the filter in the same control loop, as well as research other possibilities inside the industrial oil refinery plant.*

Keywords: *Industrial Plant, Adaptive Filter, Model-Free Method, Process Control, Exponential Moving Average*

1. INTRODUCTION

Petroleum Naphtha is a generic term that refers to the volatile fraction of crude oil, mainly regarded as a solvent or a precursor to gasoline (Speight, 2020). Its refinement is done by catalytic naphtha reforming, which is an important part of modern plants in producing aromatic hydrocarbons (Nabgan et al., 2018). During this process, sulfur impurities have a general negative impact leading to less efficiency. The removal of sulfur species from naphtha is done by hydrodesulfurization (HDS) (Sánchez-Delgado, 2007).

Naphtha can be categorized based on sulfur impurity levels as heavy naphtha (higher sulfur content) and light naphtha (lower sulfur content). Before the reaction, light cut naphtha is commonly extracted from the compound to prevent overload of the HDS reactor. This separation can be done in a distillation column, with the light cut being withdrawn from the top while the heavy cut is fed into the reactor. Since the light cut meets the sulfur requirements for catalytic reforming, it generally does not need to go through HDS.

Distillation columns, first analyzed by Skogestad and Morari (1988), are known have complex dynamics due to large input-output interactions, non-linearities, uncertainty and lack of reliable measurements. On the other hand, Lee et al. (1997) explained that reliable control strategies for these systems can allow operation at points close to the economic optimum. Recently, many studies seek to improve disturbance rejection and set point tracking by introducing modeling methods using artificial neural networks, such as Shin et al. (2020) and Gizaw et al. (2023). Previous works focused on robust approaches by applying model predictive control (MPC) as exemplified by AlGhazzawi and Lennox (2009), Yamashita et al. (2016) and Cheng et al. (2019), some of them providing practical results from crude oil refineries such as Martin et al. (2019). Lastly, proportional-integral (PI) controllers and its variations are commonly used in industrial processes including distillation columns (see Sharma and Singh (2010) for a review). Although designing robust control strategies is a frequent research topic, these systems can benefit from filtering techniques that are able to mitigate the effect of measurement noise on control performance.

Studies of filters applied to these systems are generally pointed towards solving the state estimation problem. This is necessary in most control advanced control strategies because unfortunately it may not always be cost-effective to measure all the states required to control the system. Within this context and considering the nonlinearity observed in distillation columns, the most prominent filtering approaches seem to be the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF), as exemplified in the works of Oisiovici and Cruz (2000); Guo and Huang (2015); Purohit et al. (2015). Although Kalman filters can provide optimal state estimation, its implementation in industrial plants can be a hard task due to model-dependent assumptions associated with the filter design. For that reason, simpler versions of PI controllers are still widely applied to these systems, along with frequency-based approaches that can increase lag in the control loop.

Recently, inspired by the findings reported in Filho et al. (2022), a model-free adaptive filter was proposed in Fortaleza et al. (2022) based on the statistical behavior of the measured signal and filter output. Its findings are supported by industrial results of oil refinery control loops, in which additive measurement noise was partially suppressed to reduce variations in the control signal without compromising the performance of the controller regarding the system output. The addition of their filter led to reduced actuator usage and wearing. It is interesting to note that the the filter design only depends on knowledge of the standard deviation of the sensor measurement noise.

In this paper, we propose to slightly modify the filter tuning process presented in Fortaleza et al. (2022) to further reduce the impact of measurement noise without compromising the controller action of a closed-loop control system of a distillation column in an operational plant using PID control loop with additive white Gaussian noise. The system response in both unfiltered and filtered cases were observed and quantified by the performance indexes used at the plant such as Integral Absolute Error (IAE), Travel and Reversions.

The remainder of the article is organized as follows. Section 2 presents a review of the adaptive filter, including the proposed modification of the filter tuning process. In Section 3 we display the performance achieved with the adaptive filter after applying it to the closed-loop control system of light naphtha extraction in a distillation unit. The conclusions and suggestions for further research are given in the last section.

2. MODEL-FREE ADAPTIVE FILTER

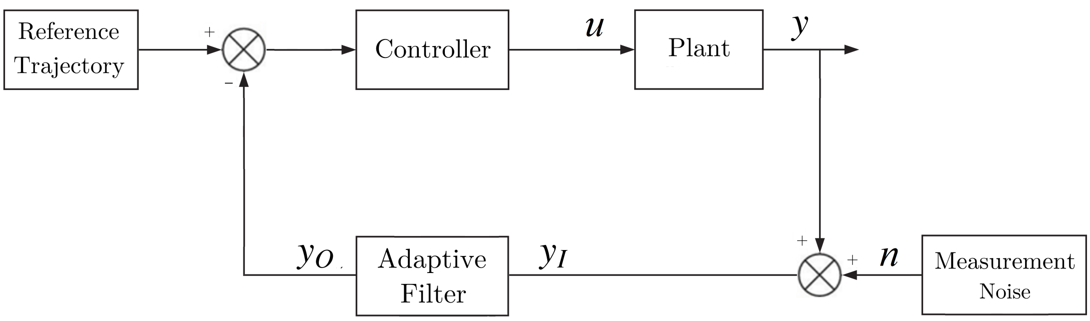

Figure 1. Block diagram of measurement noise propagation in the presence of the adaptive filter. Extracted from Fortaleza et al. (2022).

As described in Fortaleza et al. (2022), the basic functionality of the model-free adaptive filter (see Fig. 1) is that it analyzes how the current sample of the measured variable and the last sample of the filter output are statistically different according to the standard deviation σ_n of the measurement noise (n), which is assumed to be an additive white Gaussian noise (AWGN).

More precisely, if the filter detects the current sample of the measured output as a relevant modification of the process output (y), the corresponding changes are propagated to the controller (u). Otherwise, the filter attempts to minimize the impact of noise propagation on the control signal due to small changes in the process output without bringing significant changes to the original closed-loop performance (i.e., unfiltered case). It is also important to note that the filter in question can be used regardless of controller structure or knowledge of the plant model.

As stated by the authors in Fortaleza et al. (2022), the dynamic behaviour of the adaptive filter is based on an exponential moving average algorithm (EMA) (Brown, 1956). The main reasons are because the EMA is computationally efficient and it is more responsive to new information for the same level of white noise attenuation when compared to the simple moving average.

By defining y_O as the filter output and y_I as the filter input (i.e., measured output), the exponential moving average is recursively given as follows:

$$\begin{cases} y_O[0] &= y_I[0] \\ y_O[k] &= y_O[k-1] + \alpha[k](y_I[k] - y_O[k-1]), \quad k > 0 \end{cases} \tag{1}$$

where $0 \leq \alpha \leq 1$ is a weight coefficient, whose value determines the smoothing of y_I.

In Fortaleza et al. (2022), the filter parameter α is used to represent how statistically confident we are that the filter output reflects the same direction of the process output at each sampled time k. Mathematically speaking, this statistical confidence is defined as the difference of the probability that the filter is acting so that y_O approaches y, minus the probability that it is not.

For example, in case $y_I[k]$ is just slightly larger than $y_O[k-1]$, both probabilities are close to 50% since one cannot guarantee that y is increasing or that this difference is only due to the measurement noise, so $y_I[k]$ will not have a significant impact on $y_O[k]$ (i.e., $\alpha \approx 0$). On the other hand, in the case the measured output is considerably different from the filter output according to σ_n, the filter has no effect (i.e., $\alpha = 1$), making the closed-loop response for large disturbances identical with the one without the filter.

The filter parameter α is obtained at each sampled time k through the following probability equation:

$$\begin{aligned} \alpha[k] = & \, P\left(\text{sign}(Y_O[k-1] - Y_I[k]) = \text{sign}(\mu_{Y_O[k-1]} - \mu_{Y_I[k]})\right) \\ & - P\left(\text{sign}(Y_O[k-1] - Y_I[k]) \neq \text{sign}(\mu_{Y_O[k-1]} - \mu_{Y_I[k]})\right) \end{aligned} \tag{2}$$

where Y_O and Y_I are random processes that represent the filter input and output, respectively. In addition, $Y_O[k-1] \sim \mathcal{N}(\mu_{Y_O[k-1]},\ \sigma^2_{Y_O[k-1]})$ and $Y_I[k] \sim \mathcal{N}(\mu_{Y_I[k]},\ \sigma^2_{Y_I[k]})$ are observations of Y_O and Y_I, respectively. Here sign(x) represents the sign function, which is defined as:

$$\text{sign}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \tag{3}$$

Now, let Y_{OI} be a random process, in which an observation at instant k has mean and variance given by:

$$\mu_{Y_{OI}[k]} = \left|\mu_{Y_O[k-1]} - \mu_{Y_I[k]}\right| \tag{4}$$

$$\sigma^2_{Y_{OI}[k]} = \sigma^2_{Y_O[k-1]} + \sigma^2_{Y_I[k]} + 2Cov\left(Y_O[k-1], Y_I[k]\right) \tag{5}$$

where $\sigma^2_{Y_O[k-1]}$ and $\sigma^2_{Y_I[k]}$ are variances of $Y_O[k-1]$ and $Y_I[k]$, respectively.

It is straightforward to show that (2) can be rewritten as follows:

$$\alpha[k] = 2P\left(Y_{OI}[k] \geq 0\right) - 1 \tag{6}$$

which provides the theoretical value of the weight coefficient of (1) that reflects how statistically confident we are that the filter output reflects the same direction of the process output at each sampled time k.

In order to ease its implementation for practical usage, it is reasonable to assume first that the source of the sensor measurement noise is composed of statistically independent elements (e.g., sensor resolution and unknown environment disturbances). From the central limit theorem, the total contribution of these elements tends towards a normal distribution even if the original variables themselves are not normally distributed. Consequently, the random variable $Y_{OI}[k]$ can be approximated by a normal distribution with mean $\mu_{Y_{OI}[k]}$ and variance $\sigma^2_{Y_{OI}[k]}$.

Next, by considering an additive zero-mean measurement noise, it is feasible to use the samples $y_O[k-1]$ and $y_I[k]$ to estimate $\mu_{Y_O[k-1]}$ and $\mu_{Y_I[k]}$, respectively. In addition, the variance of the measured output is usually significantly higher than the variance of the filter output. Finally, both high frequency and random behavior of the measurement noise imply that the observations $Y_O[k-1]$ and $Y_I[k]$ can be considered approximately statistically independent of each other. Mathematically, it implies that $Cov\left(Y_O[k-1], Y_I[k]\right) \sim 0$.

By investigating (6) under the above technical assumptions, it follows that (6) can be simplified into:

$$\alpha[k] = \text{erf}\left(\frac{|y_O[k-1] - y_I[k]|}{\sigma_{Y_I[k]}\sqrt{2}}\right) \tag{7}$$

where erf$(\bullet)$ represents the Gauss error function.

Lastly, for a stable control system, the following relation is valid in steady-state closed-loop operation:

$$\frac{y}{n} = -|G|, \qquad |G| \leq 1, \tag{8}$$

where G is the plant transfer function. In other words, the gain of the noise component propagated into the system must not exceed the unitary value when reaching the output signal. Otherwise, the system tends to become unstable as noise is amplified.

Thus, in terms of variance, the influence of the measurement noise on the measured output can be represented as:

$$\sigma_{Y_I}^2 = (1-G)^2\sigma_n^2, \qquad 0 \leq \sigma_{Y_I}^2 \leq 4\sigma_n^2 \tag{9}$$

In their previous work, Fortaleza et al. (2022) show that assuming the worst-case scenario to express $\sigma_{Y_I}^2$ in terms of σ_n^2, the final expression for α is given by rewriting (7) as

$$\alpha[k] = \mathrm{erf}\left(\frac{|y_O[k-1] - y_I[k]|}{2\sigma_n\sqrt{2}}\right) \tag{10}$$

showing that the filter parameter only depends on knowledge about the measurement noise standard deviation and stating its model-free characteristic.

Inspired by the results achieved when introducing the filter, we suggest the following change of variables:

$$\alpha[k] = \mathrm{erf}\left(\frac{|y_O[k-1] - y_I[k]|}{2\tau_n\sqrt{2}}\right), \qquad \tau_n = C\sigma_n, \quad C > 0 \tag{11}$$

such that by manually increasing or decreasing C, we can respectively increase noise attenuation while adding lag or reduce lag while decreasing noise attenuation. Increasing this value allows the filter to react slower to changes in the process variable, making it particularly useful for stable systems where a slower response does not affect the system output heavily. Depending on the gains of the controller, a slower response may as well increase the performance by reducing the impact of noise on the control action.

Remark 1 *Whenever the system output has a derivative statistically significant regarding the expected measurement noise, the parameter alpha goes to 1, essentially removing the effect of the filter in the loop. Modifying C in (11) leads to changes in how the filter assesses this statistical significance for values relatively close to the expected measurement noise. However, the characteristic of nullifying its effect is maintained for sufficiently high derivative values.*

3. INDUSTRIAL RESULTS

This section presents the results obtained from the application of the filter with the proposed modification of its tuning process in the light naphtha extraction control-loop of a distillation unit belonging to a Brazilian oil refinery with an average throughput of 30,000 m3/d (188,700 bpd) of oil. Diesel is the main refinery product (50% of production), followed by gasoline (25%). The remainder production is divided into jet fuel (kerosene), fuel oil, liquefied petroleum gas, asphalt, petrochemical naphtha and propylene. The distillation unit started its operation in 1993, being able to process 125,000 bpd of crude. Its current capacity is 132,000 bpd and feed switches occur 3 to 4 times per week. The unit has six product draws (Liquified Petroleum Gas, Light Naphtha, Heavy Naphtha, Kerosene, Light Diesel and Heavy Diesel) plus the atmospheric residue which is sent to a Residue Fluid Catalytic Cracking Unit. The simplified flow diagram of the plant is shown in Fig. 2.

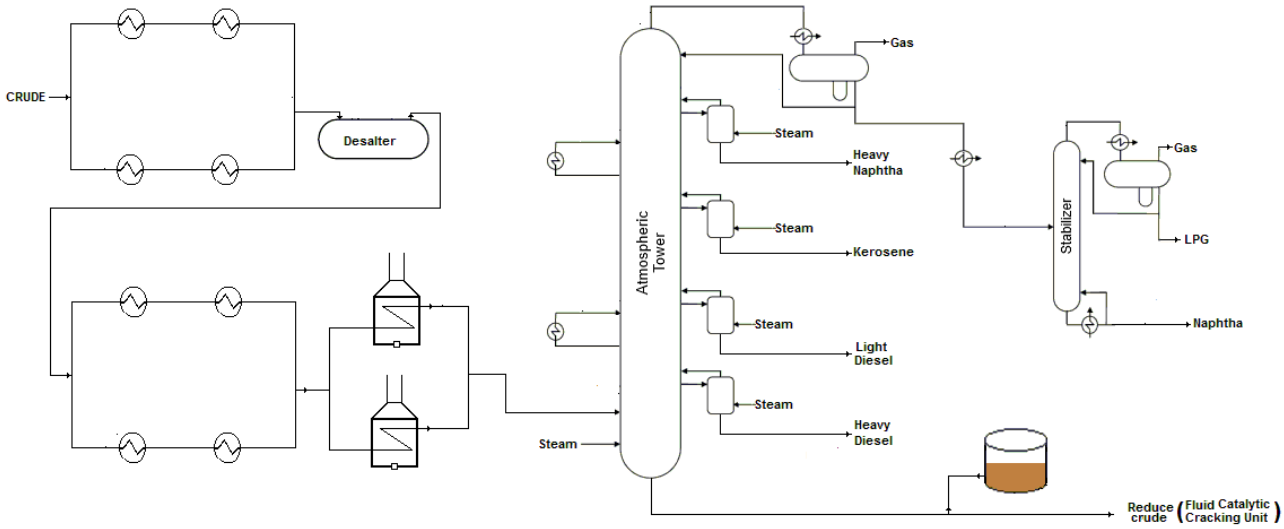

Figure 2. Distillation Unit simplified scheme. Extracted from Fortaleza et al. (2022).

The adaptive filter was implemented in a single loop of the atmospheric distillation tower, which is not detailed due to confidentiality reasons. Data from 16 days prior and 15 days subsequent to the addition of the filter were collected and analyzed. Reports were generated and indexes calculated every 12 hours with the plant in full operation. The filter algorithm has been implemented in the supervisory system to analyze the effects of the filter on the control signal and output performance. The standard deviation σ_n of the output was obtained from output measurements.

Figs 3 and 4 show the Travel and IAE curves of the control signal and the process variable, respectively. The average Travel of the actuator was reduced from 837.12% per day to 330.134% per day, a reduction of approximately 60%. Output performance was also improved, with average IAE reducing by 20% after applying the filter in the control loop. Lastly, it is important to note that no faults occurred during data collection.

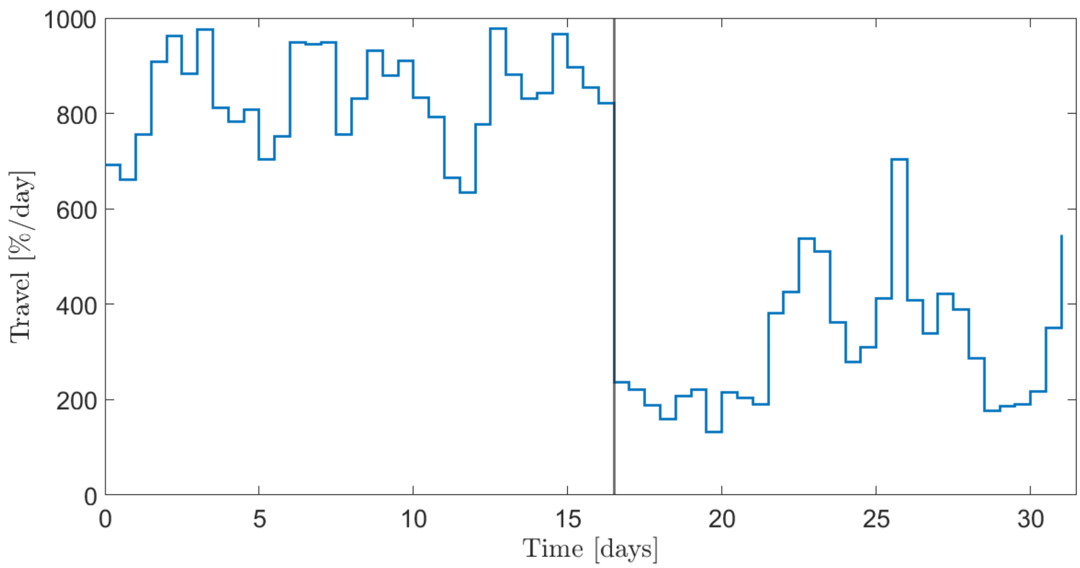

Figure 3. Travel of the actuator before and after the addition of the filter, depicted by a vertical line.

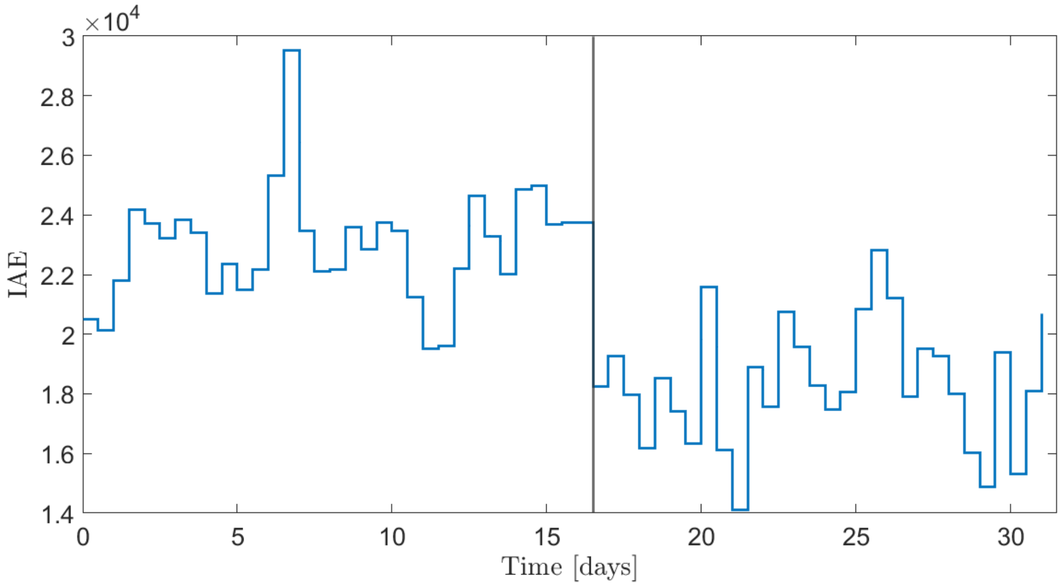

Figure 4. IAE of the process variable before and after the addition of the filter, depicted by a vertical line.

4. CONCLUSION

In this paper, a model-free statistical-based adaptive filter was applied to the closed-loop system of light naphtha extraction in a distillation unit of an oil refinery. The findings show that modifying the tuning process of the adaptive filter to further attenuate the measurement noise in stable systems can significantly reduce actuator Travel and even improve output performance by reducing the impact of reinjected noise. This can allow more flexibility for the control engineer by tuning the filter to react slower in the presence of measurement noise and low gain disturbances, while keeping its property of nullifying the presence of the filter when high gain disturbances are observed.

Further analysis include the development of statistical-based filtering strategies for fault detection during dynamic processes. A continuous assessment of an actuator operating under influence of the filter would also be useful to quantify the long-term financial impact in maintenance costs. The results were approved by the control engineers of the industrial plant, motivating its application in other control loops of the same unit.

5. ACKNOWLEDGEMENTS

The authors would like to acknowledge Petrobras (ANP Project No. 21418-9) and ANP for supporting the present study, as well as the support from CAPES (Coordination for the Improvement of Higher Education Personnel).

6. REFERENCES

AlGhazzawi, A. and Lennox, B., 2009. "Model predictive control monitoring using multivariate statistics". *Journal of Process Control*, Vol. 19, pp. 314–327. ISSN 09591524. doi:10.1016/j.jprocont.2008.03.007.

Brown, R., 1956. *Exponential Smoothing for Predicting Demand*. Little, Cambridge.

Cheng, Y., Chen, Z., Sun, M. and Sun, Q., 2019. "Active disturbance rejection generalized predictive control for a high purity distillation column process with time delay". *The Canadian Journal of Chemical Engineering*, Vol. 97, No. 11, pp. 2941–2951.

Filho, J.O.A.L., Fortaleza, E.L.F., Silva, J.G. and de Campos, M.C.M.M., 2022. "Adaptive Kalman filtering for closed-loop systems based on the observation vector covariance". *International Journal of Control*, Vol. 95, No. 7, pp. 1731–1746.

Fortaleza, E.L., Gomes, L.M., de A. Limaverde Filho, J.O., de Campos, M.C., Longhi, L.G.S., de Lima, M.L. and Tognetti, E.S., 2022. "Model-free adaptive filter to mitigate actuator wear". *ISA Transactions*. doi: https://doi.org/10.1016/j.isatra.2022.02.026.

Gizaw, D.G., Periyasamy, S., Kumar, P.S., Salilih, E.M., Redda, Z.T., Velusamy, K. and Rangasamy, G., 2023. "Artificial neural network based identification of process dynamics and neural network controller design for continuous distillation column". *Sustainable Energy Technologies and Assessments*, Vol. 57, p. 103168. ISSN 22131388. doi: 10.1016/j.seta.2023.103168.

Guo, Y. and Huang, B., 2015. "State estimation incorporating infrequent, delayed and integral measurements". *Automatica*, Vol. 58, pp. 32–38. ISSN 0005-1098. doi:https://doi.org/10.1016/j.automatica.2015.05.001.

Lee, J., Kesavan, P. and Morari, M., 1997. "Control structure selection and robust control system design for a high-purity distillation column". *IEEE Transactions on Control Systems Technology*, Vol. 5, No. 4, pp. 402–416. doi: 10.1109/87.595921.

Martin, P.A., Zanin, A.C. and Odloak, D., 2019. "Integrating real time optimization and model predictive control of a crude distillation unit". *Brazilian Journal of Chemical Engineering*, Vol. 36, pp. 1205–1222. ISSN 1678-4383. doi:10.1590/0104-6632.20190363s20170578.

Nabgan, W., Rashidzadeh, M. and Nabgan, B., 2018. "The catalytic naphtha reforming process: hydrodesulfurization, catalysts and zeoforming". *Environmental Chemistry Letters*, Vol. 16, pp. 507–522. ISSN 1610-3653. doi: 10.1007/s10311-018-0707-x.

Oisiovici, R. and Cruz, S., 2000. "Sensor locations and noise reduction in high-purity batch distillation control loops". *Brazilian Journal of Chemical Engineering*, Vol. 17, No. 4-7, p. 671–684. ISSN 0104-6632. doi:10.1590/S0104-66322000000400031. URL https://doi.org/10.1590/S0104-66322000000400031.

Purohit, J.L., Patwardhan, S.C. and Mahajani, S.M., 2015. "Performance evaluation of bayesian state estimators for nonlinear dae systems using a moderately high dimensional reactive distillation column model". In K.V. Gernaey, J.K. Huusom and R. Gani, eds., *12th International Symposium on Process Systems Engineering and 25th European Symposium on Computer Aided Process Engineering*, Elsevier, Vol. 37 of *Computer Aided Chemical Engineering*, pp. 1763–1768. doi:https://doi.org/10.1016/B978-0-444-63577-8.50139-X.

Sharma, N. and Singh, K., 2010. "Control of reactive distillation column: A review". *International Journal of Chemical Reactor Engineering*, Vol. 8, No. 1. doi:doi:10.2202/1542-6580.2260. URL https://doi.org/10.2202/1542-6580.2260.

Shin, Y., Smith, R. and Hwang, S., 2020. "Development of model predictive control system using an artificial neural network: A case study with a distillation column". *Journal of Cleaner Production*, Vol. 277, p. 124124. ISSN 09596526. doi:10.1016/j.jclepro.2020.124124.

Skogestad, S. and Morari, M., 1988. "Understanding the dynamic behavior of distillation columns". *Industrial & Engineering Chemistry Research*, Vol. 27, No. 10, pp. 1848–1862. doi:10.1021/ie00082a018.

Speight, J.G., 2020. "Chapter 3 - hydrocarbons from crude oil". In J.G. Speight, ed., *Handbook of Industrial Hydrocarbon Processes (Second Edition)*, Gulf Professional Publishing, Boston, pp. 95–142. Second edition edition. ISBN 978-0-12-809923-0. doi:https://doi.org/10.1016/B978-0-12-809923-0.00003-5. URL https://www.sciencedirect.com/science/article/pii/B9780128099230000035.

Sánchez-Delgado, R., 2007. *Hydrodesulfurization and Hydrodenitrogenation*. Elsevier. doi:10.1016/B0-08-045047-4/00029-7.

Yamashita, A.S., Zanin, A.C. and Odloak, D., 2016. "Tuning the model predictive control of a crude distillation unit". *ISA Transactions*, Vol. 60, pp. 178–190. ISSN 00190578. doi:10.1016/j.isatra.2015.10.017.

7. RESPONSIBILITY NOTICE

The authors are solely responsible for the printed material included in this paper.