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Advanced State Estimations for Gravitational Oil/Water Separator Tanks using a Kalman Filter and Multi-Model Hypothesis Testing

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Abstract

This paper presents a new application of the Kalman filter with hypothesis testing for a fast and robust model-based estimator for measuring level interfaces of atmospheric gravitational oil-water separator tanks. A newly developed semi-empirical linearized model is applied in the estimator algorithm. A multi-model hypothesis-testing algorithm for covering more scenarios was deployed. The proposed method provides a cost-effective and straightforward solution for estimating all state variables in an oil-water separator. Our evaluation results demonstrate that the proposed algorithm achieves high accuracy with an observation error of less than 2% and a false alarm rate of 3.3% under 50-70% working conditions. Furthermore, the estimator can effectively handle process noise with a 10% feed offset. The proposed platform requires only a few installed sensors yet can accurately estimate unknown parameters. The proposed approach offers a robust and practical soft sensor solution for gravitational oil-water separators.

Keywords: semi-empirical model, multi-model hypothesis testing, Kalman filter, gravitational oil-water separation, state estimation, measurements

I. INTRODUCTION

Despite renewable energy's rising popularity [1], oil is still one of the primary energy sources, accompanied by coal and biomass fuel [2], especially in developing countries [3]. Petroleum is one of the most valuable commodities in the world due to its value as a transportable, dense energy source, the primary ingredient in many industrial chemicals, and the power source for the great majority of vehicles [4]. The limited oil resources, or the energy sources in general, encourage oil producers to adjust strategies and increase production efficiency for all their facilities [5], [6].

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One of the primary production processes is the gravitational separation process. The role of an oil production facility is to separate the oil well stream into its three phases (oil, gas, and water), and to either convert these phases into commercially viable products or dispose of them in an environmentally responsible way. Oil-specific gravity and oil sourness are the two parameters used to evaluate the quality of the produced oil. Higher specific gravity and less sourness indicate higher oil quality, which means larger oil prices and higher oil sales earnings [7].

Gravitational separator tanks are commonly used in primary oil production facilities to separate water from crude oil, as illustrated in Figure 1. This technology can minimize the water contents; hence, the following secondary facility can eliminate the remaining water. Most of the gravitational tanks are manually operated in the batch separation process due to continuous operation

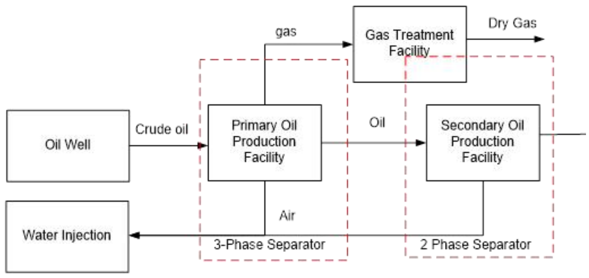

Figure 1. Oil Production Process Flow

requiring a high-end and complex controlling system, leading to expensive instrumentations [8]. Such investment is avoided due to the low economic value of the primary production facilities despite their population being far more significant than secondary production facilities.

Continuous water separation systems are the most efficient methods to achieve separation compared to the batch separation technique [9]. The drawback was that these systems required instruments to measure the oil-water interface level and control the final oil production quality. For example, interface measurement using an automatic tank gauge is one of the standard methods in the industry [10]. The main challenge of this method is the high investment and maintenance costs. Alternatively, Arvoh et al. [11] proposed using multiple pressure sensors and a minimum variance technique to estimate the level interface. Despite the approach being more economical than another industrial-grade sensor, considerable pressure sensor numbers must be installed to obtain high accuracy. Another challenge for interface measurement is the requirement of a water content sensor to ensure the quality of the separation process [12]. The standard water content sensor's accuracy usually drops as the water content significantly changes. Ultrasonic sensors for measuring the interface or emulsion can be a solution by employing tomography methods, but it is not too practical because it requires complex imaging equipment [13], [14]. In brief, the highly accurate level measurement using physical sensors can only be achieved using a relatively high number of sensors [15].

A state estimator, as one of the soft sensor methods, can be a cheaper solution by predicting the level interface by installing minimum sensor numbers. If reducing cost is the primary concern, it can be a suitable choice by reducing the need for measurement devices [16]. For example, Backi et al. [17] investigate to determine the in-flow measurement on a three-phase gravity separator. The same research group also proves that the estimation technique can estimate unmeasured disturbance in the separation process [18]. Chonwattana et al. [19] attempted to measure and control the interface level of the palm oil and water separator system using a state estimator within its model predictive control (MPC) system. Even though the separation process differs from that of crude oil separation system, the model-based control system works well. However, the MPC remains questionable in terms of noise and robustness. Therefore, an alternative algorithm is needed to increase the estimator's adaptability against process disturbances.

The model-based estimator can be accurate to a certain degree since it is heavily related to its model accuracy. The system's nonlinearity reduces estimation accuracy on process parameter changes, such as inlet flow rates, concentrations, and other disturbances [20]. The existing works for the oil-water separation process model mainly focused on a three-phase pressurized separator tanks system [17]·[18] and ultrafiltration process [21]. However, the models are complex and highly nonlinear, so they are prone to estimation errors due to process disturbances or changes. Moreover, the types of equipment used in oil production facilities are limited due to high investment costs. The models may offer highly accurate predictions for pressurized tanks.

The pressurized part adds to the computational burden, considering the model's complexity. There never be a deep study for a continuous oil-water gravitational separation in an atmospheric tank model despite the high population of that equipment in the field. The development of this equipment's mathematical model can serve as the basis for developing a soft sensor, which is expected to help increase the effectivity of the existing gravitational oil-water separator tank.

An algorithm for the soft sensor must be developed for fast, robust, and accurate level estimation using a simplified semi-empirical atmospherically gravitational separator-type model with a two-phase separation can be developed. For fast state estimation, the Kalman filter can be employed for fast and robust estimation [22]. This algorithm must also increase estimation accuracy even when using simplified mathematical models. Hypothesis testing can cover various scenarios, such as process variances, disturbances, and out of ranges [23]. A combination of the abovementioned methods can be employed to achieve the demands. However, applying Kalman filters with hypothesis testing with a linearized mathematical model in an atmospheric gravitational separator is rarely found in the literature.

Therefore, this study aims to develop a new estimator system for measuring all level interfaces in a continuous atmospheric gravitational separator system using the Kalman filter and hypothesis testing algorithms. A simplified linear mathematical model of the separator with a two-phase separation approach is also proposed as a basis of the estimator algorithm. Model simplification is a common practice in the process control systems with low frequency or very long time constant [24]. This research can support low computational burden algorithms with relatively low-cost instrumentation. The method's accuracy and adaptability from a process disturbance are evaluated using a numerical simulation and compared with its nonlinear counterparts in several operations conditions.

This research contributes to developing simplified mathematical models of gravitational separator tanks with a two-phase separation approach. The model is constructed by combining analytical and empirical approaches. The experiment was conducted to determine the model's parameters under several operating conditions. These models estimate all variables, including water, emulsion, and oil, using relatively low-cost and basic instrumentation in the industry. Therefore, the proposed method is expected to enhance the efficiency of overall oil production facilities.

In the following sections, the discussion of constructing the proposed process model and the state estimation algorithm is carried out. The simulation scenario is also discussed in Section 2. Section 3 explains the experiments conducted to obtain process parameter models, as well as the simulation results in under various operation scenarios. Last, the conclusion of our research is explained.

II. Material and Methods

The estimation algorithm consists of several parts: the mathematical models, Kalman filter, and hypothesis testing algorithm, as shown in Figure 2. The suggested method aims to reduce the expense of purchasing complete measurements for continuous oil-water separators. This method eliminates requiring specialized instruments to detect interface levels while retaining measurement precision. The estimation technique used a linear approach to simplify the mathematical model and reduce the need for additional computing power. We included a hypothesis testing method to overcome the restriction of linearized models by detecting whether the estimator remains within the designed operational range.

A. Oil-Water Separation Process Model

This study simplifies the process by combining emulsion and dense-packed zone into a single state variable shown in Figure 3(b). The build-up of water at the tank's bottom was regarded as a first-order system response [25], as shown in Equation 1:

$$\frac{dV_e}{dt} = \beta \frac{1}{\tau_c} V_e \tag{1}$$

where V_e is the emulsion volume, τ_c is the residence time, and β is the separator velocity constant. Assuming the cross-section area of an atmospheric tank is uniform at all heights, the residence times and the separation velocity are all constant. The rate of emulsion level (h_e) decreasing can be represented using a first-order

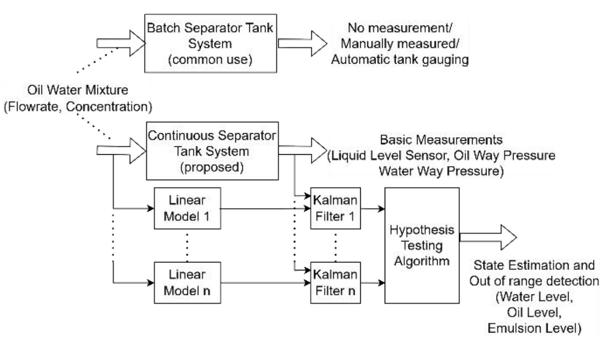

Figure 2. Proposed Estimation Algorithm in this Research

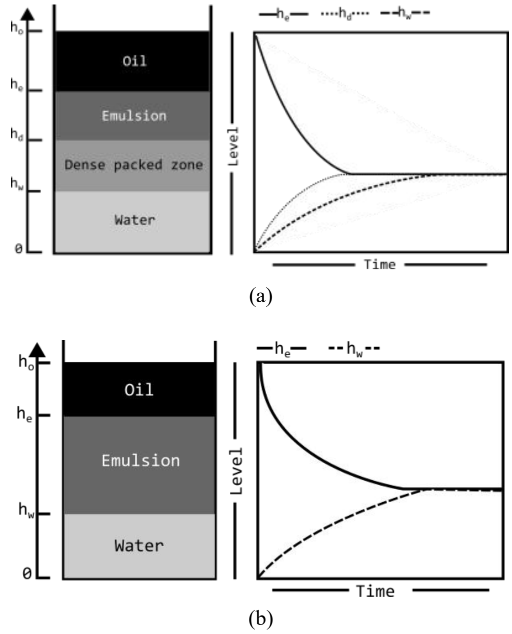

Figure 3. (a) Hartland's Batch Separation Model (b) Proposed Simplified Separation Model

equation simplified by separator constant ($\propto$), as shown in Equation 2:

$$\frac{dh_e}{dt} = -\propto h_e \tag{2}$$

A similar approach is used for water level (h_w) and oil level (h_o) in meter (m). Both variables are affected by the separator constant proportional to their concentration ($\emptyset$) set yield shown in Equation 3:

$$\begin{bmatrix} dh_e \\ dh_o \\ dh_w \end{bmatrix} = \begin{bmatrix} -\propto & 0 & 0 \\ \emptyset.\propto & 0 & 0 \\ (1-\emptyset).\propto & 0 & 0 \end{bmatrix} \begin{bmatrix} h_e \\ h_o \\ h_w \end{bmatrix} \tag{3}$$

A system identification procedure was assisted in determining the separation constant and the oil fraction. The method for identification analysis is presented in the next section. Equation 3 served as a basis for building the continuous separation system model. The difference between continuous and batch systems is the existence of inlet and oil-water outlet flows, as illustrated in Figure 2. The inlet flow material consisted of oil, water, and emulsion. These components flow slowly toward the outlet and gradually separate. At the outlet side, oil and water were assumed to be separated. Respectively, the outlet flows to send the oil and water into the atmosphere. The inlet mass flowrate was described in Equation 4:

$$\begin{aligned} \dot{m}_{in} &= \rho_{input}.Q_{in} \\ &= ((\emptyset - 1).Q_{in}.\rho_w) + ((\emptyset).Q_{in}.\rho_o) \end{aligned} \tag{4}$$

where $\dot{m}_{in}$ is the inlet mass flow rate (kg/s) derived from inlet density and inlet volume flowrate $Q_{in}(m^3/s)$. The inlet density is a combination of water ρ_w and oil density ρ_o (kg/m^3) that varies with oil concentration ($\emptyset$) in percent (%). Equation 5 represents the oil volume flowrate (Q_o) through the first outlet as follows:

$$Q_o = \frac{a_1}{A}\sqrt{2.g.((h_o + h_e + h_w) - h_1)} \tag{5}$$

where a_1 is the oil outlet cross-section area in m^2, and A is the separator medium cross-section area in m^2. The output flow rate is influenced by constant gravity g $(kg.m/s^3)$ and the outlet height h_1 in m. On the other hand, the water volume flow rate is a function of the total height of liquids and their relative densities, as shown in Equation 6:

$$Q_w = \frac{a_2}{A}.\sqrt{\frac{2.g}{\rho_w}.(\rho_o h_o + \rho_e h_e + \rho_w h_w)} \tag{6}$$

Combining Equations (3), (4), (5), and (6), the continuous separation nonlinear model was obtained in Equation 7:

$$\begin{bmatrix} dh_e \\ dh_o \\ dh_w \end{bmatrix} = \begin{bmatrix} -\propto .h_e + \frac{1}{A}.Q_{in} \\ \emptyset.\alpha.h_e - \frac{a_1.2.g}{A}.\sqrt{((h_o + h_e + h_w) - h_1)} \\ (1-\emptyset).\alpha.h_e - \frac{a_2.2.g}{\rho_w A}.\sqrt{\rho_o h_o + \rho_e h_e + \rho_w h_w} \end{bmatrix} \tag{7}$$

Using the Taylor series method, the linearized version of Equation 8 was obtained as follows:

$$\begin{bmatrix} d\tilde{h}_e \\ d\tilde{h}_o \\ d\tilde{h}_w \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}.\begin{bmatrix} \tilde{h}_e \\ \tilde{h}_o \\ \tilde{h}_w \end{bmatrix} + \begin{bmatrix} \frac{1}{A} \\ 0 \\ 0 \end{bmatrix}\tilde{Q}_{in} \tag{8}$$

where:

$$a_{11} = -\propto \tag{9}$$

$$a_{12} = a_{13} = 0 \tag{10}$$

$$a_{21} = \emptyset.\alpha - \frac{2ga_1}{A\sqrt{2.g.(h_o+h_e+h_w)-h_1}} \tag{11}$$

$$a_{22} = a_{23} = -\frac{2ga_1}{A\sqrt{2.g.(h_o+h_e+h_w)-h_1}} \tag{12}$$

$$a_{31} = (1-\emptyset).\alpha - \frac{2ga_2\rho_e}{\rho_w A\sqrt{\frac{2.g}{\rho_w}.((\rho_o h_o+\rho_e h_e+\rho_w h_w))}} \tag{13}$$

$$a_{32} = a_{33} = -\frac{2ga_2\rho_o}{\rho_w.A.\sqrt{\frac{2.g}{\rho_w}.((\rho_o h_o+\rho_e h_e+\rho_w h_w))}} \tag{14}$$

This linear model is specified by the point where all state variables are linearized at the linear point height h_{eqi} where $\tilde{h}_i = h_i - h_{eqi}$, that used to linearize the model is at 50% separator overall height. Those values were determined by the standard design practice of 50% nominal operation design in mind.

For the measurement model, pressure and level instruments were used. Level measurement was utilized to determine the total fluid height in the tank, which reflects the fluid volume in the tank, and was paired with total pressure measurement, which may indirectly indicate fluid weight. Another pressure measurement was installed to measure the oil's way pressure because this approach may reflect the height of the oil phase. The level measurement model can be described as the total of all state heights with Equation 15:

$$y_1 = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}\begin{bmatrix} h_e \\ h_o \\ h_w \end{bmatrix} \tag{15}$$

Meanwhile, the pressure at the water outlet is the total mass of each height state, as shown in Equation 16:

$$y_2 = \begin{bmatrix} \rho_e.g & \rho_o.g & \rho_w.g \end{bmatrix}\begin{bmatrix} h_e \\ h_o \\ h_w \end{bmatrix} \tag{16}$$

Last, oil outlet pressure is described as mass at the oil phase's height, as expressed in Equation 17:

$$y_3 = \begin{bmatrix} 0 & \rho_o.g & 0 \end{bmatrix}\begin{bmatrix} h_e \\ h_o \\ h_w \end{bmatrix} \tag{17}$$

B. Kalman Filter and Hypothesis Testing Algorithm

The estimation procedure utilized a combined Kalman filter and hypothesis testing algorithms to determine the closest operating point and adjust system parameters accordingly. The Kalman filter algorithm was well developed [22], and the extended Kalman filter methods were available for highly nonlinear systems such as separation systems [26]. However, the computational complexity of the known nonlinear Kalman filter limited its realization in microcontroller-based instruments [27], [28]. Therefore, this research employed the linear Kalman filter algorithm on the multiple-linearized separator models to accommodate both the separator system's nonlinearity and the microcontroller's computational capability.

Figure 4 illustrates the proposed state estimation method using the Kalman filter and a hypothesis testing algorithm. The actual process simulation was represented by its nonlinear model in a discrete state space, derived using Runge-Kutta with fourth-order methods (A_k, B_k, C_k, D_k). Suppose the general statement of the linear model is described in Equations 18 and 19, The state estimation $\hat{x}_{k|k}$ is determined by predicted

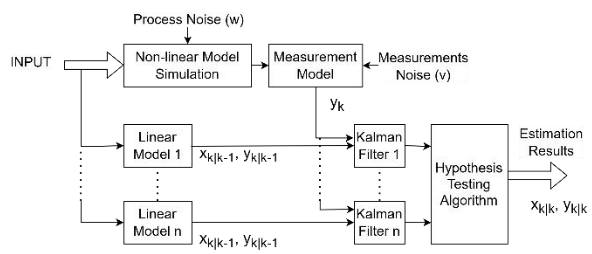

Figure 4. Kalman Filter Reinforced with Hypothesis Testing Selection Algorithm

state $\hat{x}_{k|k-1}$ and $\hat{y}_{k|k-1}$ from a linear model corrected by y_k in the measurement simulation as describe in Equation 20.

$$\hat{x}_{k|k-1} = A_k\hat{x}_{k-1|k-1} + B_k u_{k-1} \quad (18)$$

$$\hat{y}_{k|k-1} = C_k\hat{x}_{k|k-1} + D_k u_{k-1} \quad (19)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(y_k - \hat{y}_{k|k-1}\right) \quad (20)$$

where $\hat{x}_{k|k-1}$ is the calculated state variable from state space in Equation 8 and $\hat{y}_{k|k-1}$ is the measurement model calculation described in Equation 15 – 16. K_k as Kalman gain is derived from the noise covariance mentioned in Equation 19:

$$K_k = P_{k|k-1}C_k^T\left(C_k P_{k|k-1} C_k^T + R_k\right)^{-1} \quad (21)$$

where $P_{k|k-1}$ is the process noise covariance, and R_k is the measurement noise covariance. The process noise covariance is not identified by this research. However, it was determined by the difference between the oil concentration and the parameter used in Kalman filter (KF) algorithm. The measurement noise is given in the simulation using Gaussian white noise in the simulated plant and selected by 1% covariance in the KF design.

Linear estimation for a nonlinear system is limited by its operation range. In other words, its accuracy will be reduced if it is used to estimate state variables far from the respective linearization points. Several linearization's were used at various points along the height of the tank to widen the estimation range. Since this research used multiple-linearized models simultaneously to estimate the process, a hypothesis test was required to select the most accurate estimator. This method was widely used, especially to identify anomalies within the boundary of expected variables, such as in work by Ranganathan et al. [29] in the biomedical research area and Perkins et al.[30] in the chemical hazard research area. Since the anomaly in each separator is calculated, the most accurate estimator can be decided.

The hypothesis testing algorithm to select the most accurate estimator is shown in Figure 5. The selection was based on a null hypothesis that examined the innovation covariance of the process measurement, and the estimator should be minimum as follows in Equation 22:

$$X = e_k^T E_k^{-1} e_k \quad (22)$$

where e_k is the prediction error, and E_k^{-1} is the error covariance. Then, by using Equation 23:

$$Cov[e_k] = E_k = C_k P_{k|k-1} C_k^T + R \quad (23)$$

where $Cov[e_k]$ is the covariance of the process model, and R is the covariance of measurement noise representing measurement accuracy.

As illustrated in Figure 5, only one estimate should be produced through this process. Every testing iteration uses 10 data points to calculate innovation covariance. If one iteration did not produce exactly one correct estimator, the iteration was repeated up to five times. If the fifth iteration still produced two or more estimators, the one with the minimum cumulative error variance was selected as the correct one.

C. Experiment and Simulation Setup

As described in the previous section, the performance of this algorithm is tested using MATLAB simulation. A nonlinear model is used to simulate a natural separator system. The separation constant ($\propto$) should be identified through an experiment to obtain an accurate model parameter of a continuous atmospheric tank. The experiment batch separation is used to obtain time-constant parameters used in the simulation is similar to Das and Biswas's research [31], which was conducted by mixing oil and water at a predetermined ratio and a certain height, as illustrated in Figure 6. The mixture is allowed to separate naturally. The emulsion height is measured every 10 seconds until it has entirely separated. This way, a dynamic response of oil-water separation can be obtained. This procedure is repeated at different concentrations. If the response of the oil-water separation complies with Jeelani et al. model [32], the rate of separation can be described as a first-order dynamic system using Equation 24:

$$h_e(t) = e^{\propto t} \quad (24)$$

The minimum sum of squared error using Equation 25 between the experiment data and the approximate curve is used to obtain the optimal time constant parameter.

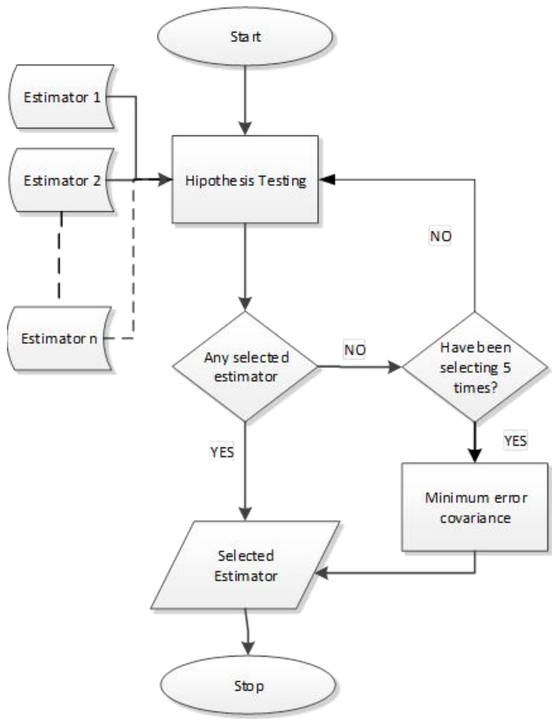

Figure 5. Flow Diagram of the Hypothesis Testing

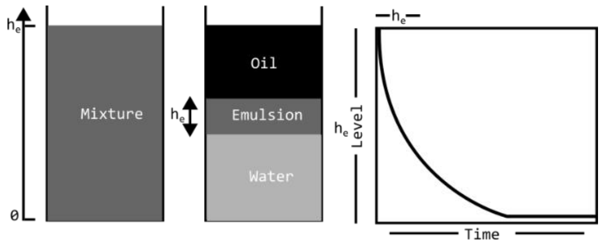

Figure 6. Batch Separation Experiments Illustration

$$min\, f(h_e, t) = \sum_0^t h_{e,t} - e^{\propto t} \tag{25}$$

Accurate models and parameter values were required to achieve reliable simulation accuracy. Those characteristics were the separator tank's nominal design. Resident time is the primary concern in separator tank design. Odiette et al. [33] established a relationship between residence duration and inlet flow rate since a quicker mixture requires more area (A). As established by the batch separation experiment, the cross-section area should be sufficient for the resident time required for the mixture to separate. Cross-section tank area (A), emulsion level (h_e), and total liquid level (h_1), as shown in Figure 7, must all be determined at a given concentration. This parameter is used in the state estimator's simulation.

The separation parameters obtained were used for the estimator model. The difference is that those models and parameters are linearized into several operating conditions. The estimation result is then compared to the nonlinear model simulation. The hypothesis testing method selects the most accurate estimation in every simulation condition. This study primarily uses simulation with parameters acquired from a batch separation experiment utilizing a diesel fuel and water combination. This experiment should yield reliable results, assuming the diesel fuel and water are not polluted. The initial nonlinear model that employs that parameter is anticipated to approximate the natural system.

The performance of this method is evaluated by measuring the estimation accuracy in several conditions. The first condition is the design operating condition of the separation process with a 10% flow rate variation, as it becomes the basis of Q covariance matrices for the KF design. The enhancement algorithm is compared to the Kalman filter to show the benefit of the hypothesis testing enhancement. Second is the estimator's capability to estimate state variables with inlet disturbance in the form of oil-water concentration. Last, the estimator's capability to determine that process conditions are already out of bounds. These three scenarios were tested during the simulation.

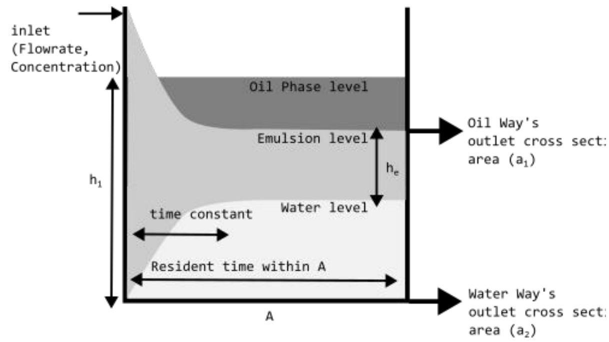

Figure 7. Continuous Separator Tank Model

III. Results and Discussion

As mentioned in the previous section, several simulation scenarios are conducted to evaluate the proposed algorithm's performance, and the simulation parameter is provided from batch separation experiments.

A. Batch Separation Experiment Result

The batch separation experiment results in Figure 8 indicate that changes in the interface level between oil and emulsion comply with Jeelani et al. batch separator model [32] after the liquid has filled the tank. Five separate concentration studies were carried out, and all of them consistently showed that the change interface level approximated the first-order response. As a result, the first system general equation indicated in Equation 22 may be utilized to find the separation constant ($\propto$).

This method gives a $\propto$ = 0.0286 in 50% oil concentration mixture. The result is an approximate curve shown in Figure 8, and the average error for the data was 5.4%. This curve gives the approximate residence time required to complete the oil separation from the rest of the mixture. Combining the residence time with the inlet flow rate would determine the size of the continuous atmospheric tank.

Table 1 shows the model parameters illustrated in Figure 6 for a cross-section tank area (A) of 1000 mm and an emulsion height of 80 mm at steady conditions.

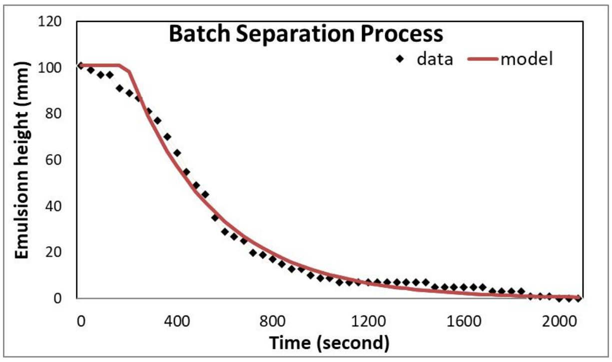

Figure 8. Simulation and Data Comparison in one of the Experiments

TABLE 1
SEPARATOR TANK SIMULATION DESIGN PARAMETER

Parameter	Value	Unit
Inlet Flowrate (Q_{in})	1.94	lt/min
Total Height (h_1)	320	mm
Emulsion layer Height (h_e)	80	mm
Cross section area of oil way (a_1)	6.99	mm^2
The cross-section area of the waterway (a_2)	3.55	mm^2
Oil density (ρ_o)	850	Kg/m^3
Water density (ρ_w)	1000	Kg/m^3

Inlet flowrate at given tank parameter Q_{in} is obtained by Equation 8 at $\Delta h_e = 0$ while $\propto$ is the separation constant obtained by the experiment.

B. Estimator Simulation Result

The first scenario is a simulation within desired design operating conditions, which is within 50-70% feed flow rates, and three estimators in 50%, 60%, and 70% linearization points are used to estimate all three states, which is emulsion layer height, oil layer height, and water layer height. It is shown in Figure 9 that most estimators cannot withstand process changes outside their design parameters; even the covariance of Q matrices is determined by the difference in the parameter. That is a common weakness for the Kalman filter when facing a nonlinearity problem [34], and the process parameter differences due to the linearity cannot be considered as process noise with normal distribution.

The hypothesis testing algorithm is used on all estimators to select the most accurate estimator on each condition. Figure 10 shows the selected estimation in each condition. From the selection results, most of the selections match each condition. However, a transient area between each condition cannot decide the accuracy of the selected estimator [35].

Figure 11 shows that the proposed method can accurately estimate each state variable using the hypothesis algorithm by selecting the estimator with minimum covariance. The algorithm provides accurate estimation in most conditions. The inaccuracies occur in transient conditions, which are not within any estimator parameter constraint. The root means square (RMS) calculation provides that the inaccuracies during transient conditions are no more than 3.3%. The oil layer estimation provides the most accurate state estimation since a pressure measurement in that layer can directly correct the oil layer estimation using Equation 17.

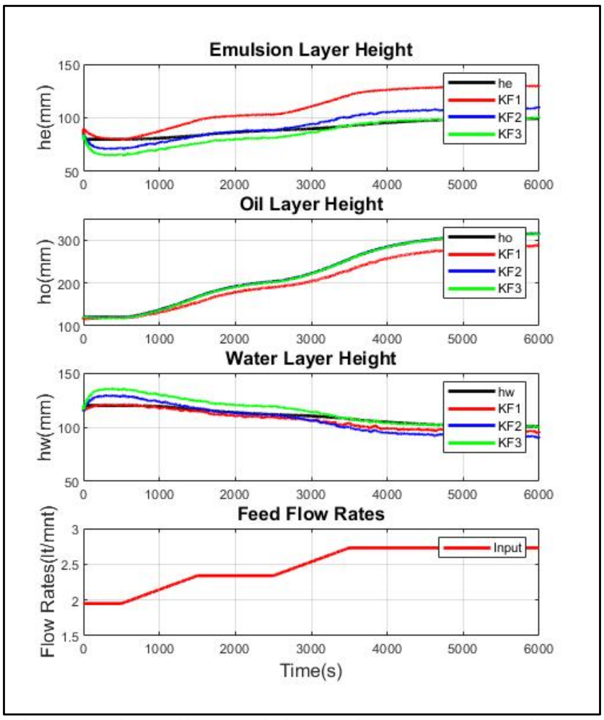

Figure 9. Kalman Filter Simulation on Three Operating Conditions with Three Estimators on each Condition

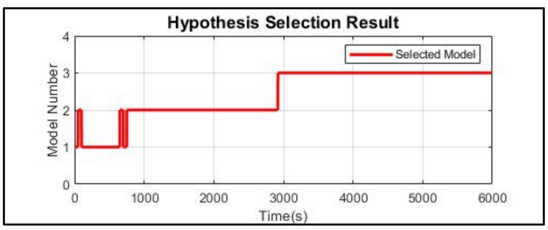

Figure 10. Selected Estimator in each Condition

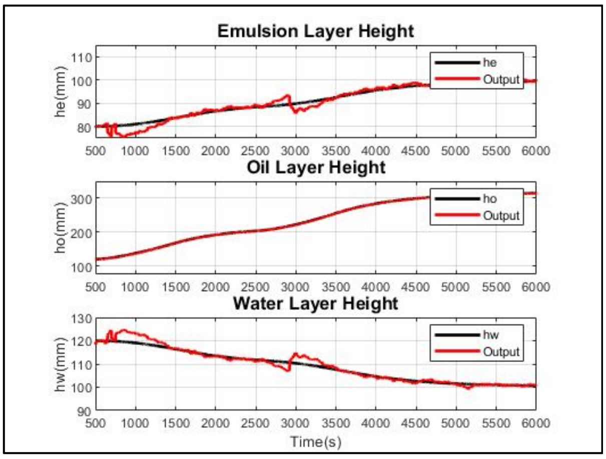

Figure 11. Final Estimation Result for Three State Variables

More simulation is needed to raise confidence in the hypothesis testing algorithm. Table 2 reveals that the higher the confidence, the more likely false alarms exist. The number of iterations and how frequently the minimum algorithm is used while deciding the selected estimator.

Table 3 shows another simulated variable: the influence of measurement noise, which affects the determination of covariance R in the KF algorithm. This testing procedure rejects all estimators by altering their accuracy by more than 1%, even though the estimation

TABLE 2
ESTIMATION COMPARISON IN VARIOUS DEGREES OF CONFIDENCE

Degree of Confidence	Type one fault/false alarm	Type two fault/miss alarm	Minimum Algorithm Used
90%	0.0%	28.7%	28.7%
95%	3.3%	20.7%	24.2%
99%	30.9%	0.00%	30.9%

TABLE 3
ESTIMATION COMPARISON AT VARIOUS MEASUREMENT ACCURACY.

Variable	Manipulated Measurement Error				
	1%	2%	3%	4%	5%
h_e accuracy (mm)	2.8	9.0	7.9	8.1	9.2
h_o accuracy (mm)	0.7	1.4	2.2	2.7	3.4
h_w accuracy (mm)	2.2	7.3	6.2	5.8	7.6
Hypothesis Testing rejection (%)	11.6	97.5	100.0	100.0	100.0

accuracy is reduced slightly. The rejection occurred since the hypothesis testing algorithm already considered the measurement error. If the measurement error exceeds the considered measurement noise, the hypothesis test rejects the result. This characteristic makes this algorithm commonly used in anomaly detection [36].

The second scenario simulates the changes in oil concentration in input. We use a 10% concentration offset in the input parameters. This scenario aims to determine the effects of process change on state estimators since raw material going into the separators never has a constant concentration [37]. Figure 12 shows that state estimation produces more inaccuracies than the previous simulations. However, from the RMS calculation, the estimator's accuracy is at most 5.08%. Those inaccuracy results are sufficient since some market-ready sensors provide a 5% measurement error. The parameter offset brings additional uncertainty, which affects the selection algorithm, as shown in Figure 13.

The estimator selection shown in Figure 13 suggested that the algorithm needed help to pick the estimator confidently. Nonetheless, as shown in Table 3, observation accuracy within 1% of measurement noise yields less than 3% inaccuracy, but the hypothesis testing algorithm cannot confidently detect anomalies in the process. The algorithm confidence is 11.6%, which can still give an alert within the error situation. However, since the purpose of the algorithm focused on estimation accuracy, the algorithm proves that the estimator can withstand 10% process noise deviation.

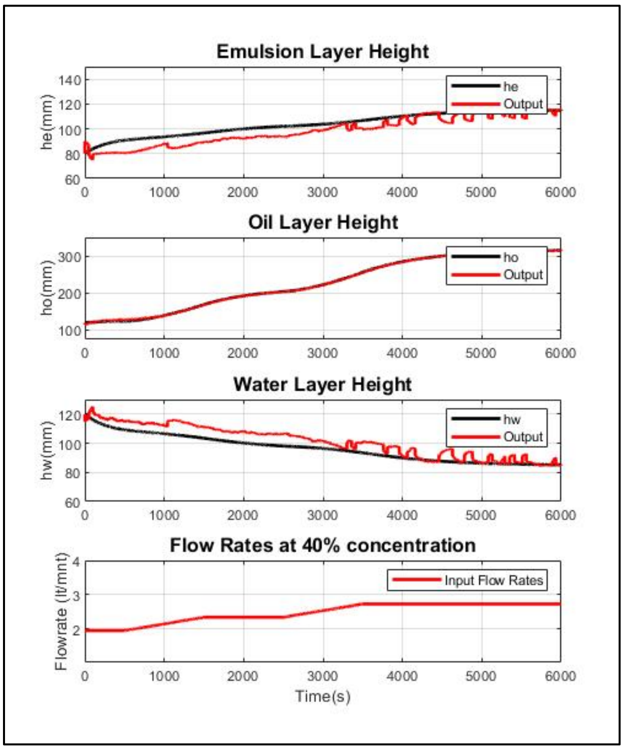

Figure 12. Hypothesis Testing Algorithm's Estimation Result in Concentration Offset

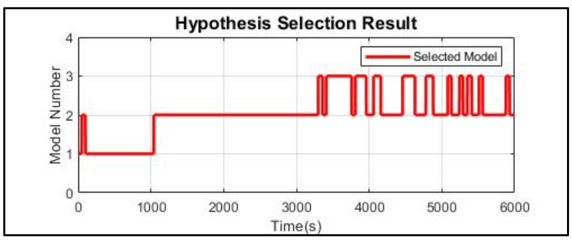

Figure 13. Estimator Selection during Concentration Offset Simulation

The last simulation is to determine the accuracy of the state estimator if the process input is outside its designed operating range. Input flow rates fall from 50% under normal operating conditions to 40% and rise to 70%. Figure 14 depicts the simulation results, which show that no estimator can accurately measure the state variables in the 40% operation range. The error caused by nonlinearity significantly affects the process when feed flow rates fall under its design operation. Mohayesi et al. [38] also confirm an optimum condition for a separation process mathematical model that depends on the separator design. Therefore, the estimation will never be accurate, no matter what the hypothesis algorithm chooses.

The estimator's accuracy relies on the model's accuracy since the hypothesis testing algorithm calculates the probability of fault within the designed constraint and covariance[39]. To prove that the model improvement is the solution for anomaly conditions, a 4th model is added to the hypotheses testing algorithm. Fig 15 shows that the fourth estimator can estimate accurately when the process is outside the design condition.

After the fourth estimator is added to the hypothesis algorithm, the estimation during the last scenario is shown in Figure 16. The selected estimator follows the fourth estimator when the process is inside its respective area. Some errors occurred mainly caused by the transient condition between two estimators close to each other. The estimation RMS accuracy is no more than 2.5%, which proves that the estimation accuracy will be

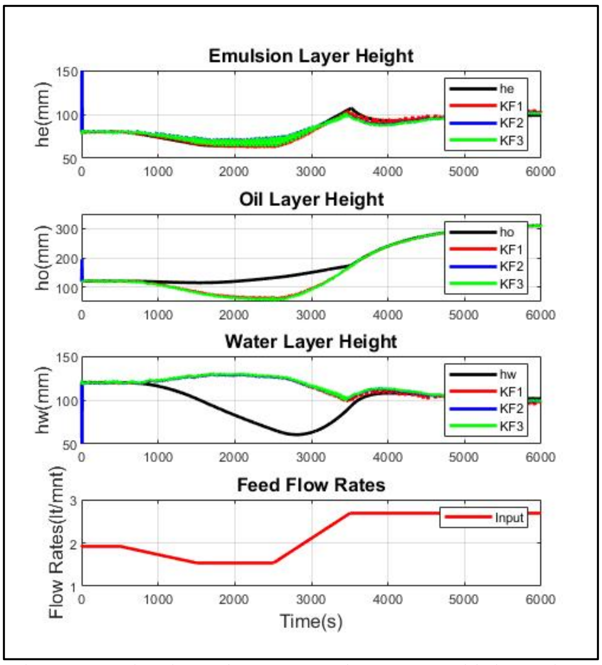

Figure 14. Estimations when Process Flowrates Outside its Design Condition

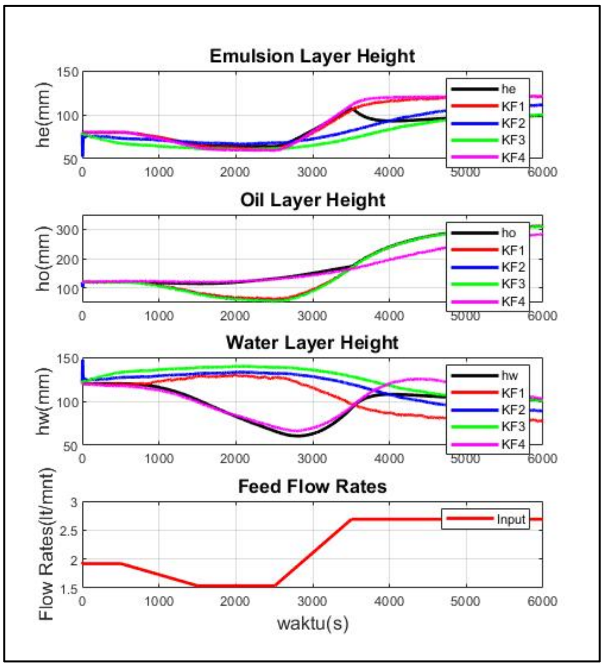

Figure 15. The Fourth Estimator Added to the Algorithm

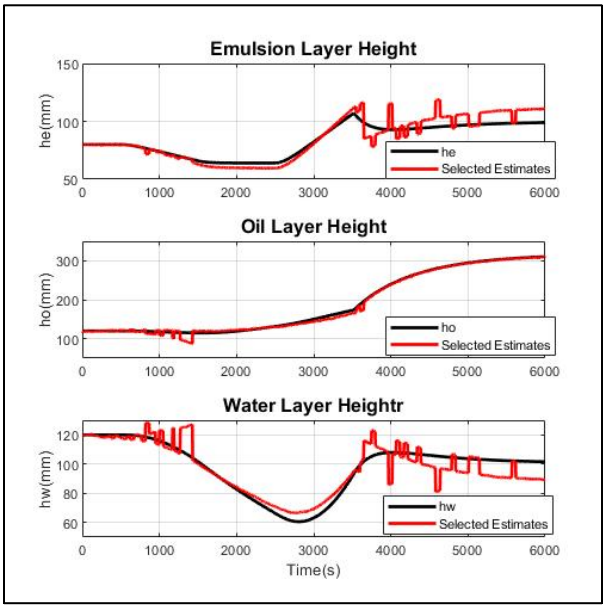

Figure 16. Estimation of Hypothesis Testing Algorithm after the Fourth Estimator Added

improved with more estimators used for the selection algorithm.

IV. Conclusion

State observers enhanced with the hypothesis testing method on continuous oil-water separator has been simulated with nominal operation's oil content liquid that flows at 3.9 L/min at maximum. The proposed method, which was tested on 50-70% operation conditions, can estimate all state variables with less than 3.5% observation error and 3.3% false alarm. Furthermore, this estimator could withstand process noise as input concentration by 10% differences. Another benefit of this method is that it can detect failure from defective measurements.

This study shows that observing all state variables on oil-water separators uses two pressure sensors and one level. However, the linearized model operation range lowered the precision of this method. If hypothesis testing is performed outside of optimal conditions, missed alarms are unavoidable. The improvement using an additional model that increases the hypothesis testing option is one of the methods required. That is why more research related to other measuring methods and additional operation models were required to improve reliability. Another filter-based method, or the usage of the currently emerging Artificial Intelligence technique, can be an additional solution to adhere to the weakness of our methods, especially to increase the accuracy of the unknown parameter of the models [40]–[42].

Nomenclature

h_e	height of emulsion layer (mm)
h_o	height of oil layer (mm)
h_w	height of the water layer (mm)
V_e	emulsion volume (lt)
a_1	Oil outlet's cross-section area (mm^2)
a_2	Water outlet's cross-section area (mm^2)
A	Atmospheric tank cross-section area (mm^2)
g	Gravitational acceleration (m/s^2)
Q_{in}	Inlet Flow rate (lt/s)
y_1	Total liquid height (mm)
y_2	Water outlet pressure (kg.m/s^2)
y_3	Oil outlet pressure (kg.m/s^2)
K_k	Kalman gain (-)
P	Prediction covariance (-)
X	Innovation matrices (-)
$Cov[e_k]$	Error covariance (-)

Greek symbols

β	Separation velocity constant (-)
τ_c	Resident time (s)
$\propto$	The separator time constant (1/s)
$\emptyset$	Oil concentration (-)
ρ_o	Oil density (kg/m^3)
ρ_w	Water density (kg/m^3)
ρ_e	Emulsion density (kg/m^3)

Declarations

Conflict of Interest

The authors have declared that no competing interests exist.

CRediT Authorship Contribution

Zaid Cahya : Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Writing-Original Draft Preparation, Writing-Review and Editing; Parsaulian Siregar : Conceptualization, Methodology, Supervision; Estiyanti Ekawati : Conceptualization, Methodology, Supervision; Irfan Bahiuddin : Writing-Original Draft Preparation, Writing-Review and Editing, Supervision; Dito Eka Cahya : Formal Analysis, Data Curation; Tsani Hendro Nugroho : Data Curation, Writing-Review and Editing; Heru Taufiqurrohman : Resources, Writing-Review and Editing, Visualisation;

Mohamed Boudaoud : Visualisation, Data Curation; Zaid Cahya, Parsaulian Siregar, and Estiyanti Ekawati are the main contributors to this paper; All authors have read and agreed to the published version of the manuscript.

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