Available *online* at : http://jnte.ft.unand.ac.id/

Jurnal Nasional Teknik Elektro

| ISSN (Print) 2302-2949 | ISSN (Online) 2407-7267 |

Fault Detection In Storage Tank System Using Luenbeger Observer (LO): Simulation-Based Validation.

Dian Mursyitah [1], Ahmad Faizal[1], Hilman Zharory[1], Sitri Permata Sari[1]

[1] Univeristas Islam Negeri Sultan Syarif Kasim Riau, HR. Soebrantas KM 155, 28294, Indonesia

ARTICLE INFORMATION

Received: April 28, 2025
Revised: November 28, 2025
Accepted: November 30, 2025
Available online: December 1, 2025

KEYWORDS

Luenberger Observer, Fault Detection, Storage Tank System, State Estimation, Residual Analysis, System Monitoring

CORRESPONDENCE

Phone: +62 8117671887

E-mail: dmursyitah@uin-suska.ac.id

A B S T R A C T

This study presents a comprehensive, simulation-based validation of a Luenberger Observer (LO) specifically designed for fault detection in storage tank systems. It commences with the development of a nonlinear storage tank model, which is subsequently linearized to streamline the observer design process. The LO estimates critical system states and produces residual signals that enable reliable fault detection. The observer gain is meticulously chosen using pole placement techniques to ensure rapid convergence of estimates and overall stability. To evaluate the effectiveness of this approach, three distinct fault scenarios—ramp, square pulse, and inverted ramp signals—are introduced to simulate various types of abnormal conditions that could occur in real-world operations. Simulation results demonstrate that the LO accurately estimates the liquid level states with a mean absolute error of approximately 0.02 meters, equivalent to about 2.6%. Furthermore, the observer detects faults with an average delay between 5 and 9 seconds following fault injection, indicating its prompt response capability. Notably, even with sensor noise levels reaching 6%, the observer maintains stable tracking performance, demonstrating strong robustness against disturbances. Across all tested scenarios, the residual signals show rapid increases during fault conditions and swiftly return near zero once the system reverts to normal operation, with no false alarms observed. Collectively, these results suggest that the Luenberger Observer provides an accurate, rapid, and disturbance-tolerant method for fault detection in storage tank systems. Such an approach offers a practical alternative to data-driven fault detection methodologies, as it relies less on extensive training datasets and can be more readily implemented for real-time industrial monitoring applications.

INTRODUCTION

Storage tanks are critical units in process engineering, widely used in both small-scale operations and large-scale industrial applications. Their usage is prevalent in the chemical sector, including oil and gas, petrochemicals, and polymers. A storage tank serves as a container for storing various types of liquids or chemicals according to industrial requirements [1]. Due to their extensive use, storage tanks are susceptible to various problems. One major issue is structural damage caused by corrosion on the tank walls, which can lead to leaks or even catastrophic failure. Corrosion is triggered by both internal factors, such as direct contact between the liquid and the tank walls, and external factors, including the surrounding environment. Such damage increases the risk of fire or explosion, which can endanger both workers and the surrounding environment [2, 3].

Although structural degradation, such as corrosion, represents a major source of safety risk, improper liquid-level regulation can also trigger hazardous events in storage tank operations. In practice, undetected flow inconsistencies or sensor faults may lead to overfilling or dry-run conditions, which accelerate structural fatigue, cause pressure imbalance, and increase the likelihood of leakage, fire, or tank rupture. Therefore, maintaining accurate level monitoring and reliable fault detection in the tank dynamics is not only a control problem but also a critical safety measure for preventing industrial accidents.

A notable example occurred at ITC Deer Park in 2019, where a pump failure led to a chemical release and a massive fire, destroying 15 tanks and contaminating the Houston Ship Channel. This disrupted local ecosystems and economic activities, while also risking human health due to hazardous exposure [4]. To manage fluid levels, industries rely on automated systems for filling and draining tanks. Accurate level control is essential in chemical processes, as even slight deviations can impact product quality. However, monitoring levels in closed tanks can be challenging. Inflow-outflow imbalances may lead to overflows or dry runs, both of which can damage equipment and interrupt operations [5, 6]. These systems utilize sensors to monitor fluid levels, but these sensors can fail or produce incorrect data due to issues such as valve damage or aging. This underlines the importance of fault detection, which helps identify and isolate problems early [7, 8]. This highlights the need for fault detection mechanisms, which aim to identify and isolate faults in the system.

https://doi.org/10.25077/jnte.v14n3.1332.2025

Several techniques have been developed for fault detection in tank systems, such as Principal Component Analysis (PCA), Moving Window Principal Component Analysis (MWPCA), Change Finder, Support Vector Machine (SVM), and Moving Window Independent Component Analysis with Adaptive Threshold (MWAT-ICA). These have been used to detect faults in sensors, leaks, and valve blockages [9-13]. While these methods demonstrate good performance, challenges remain, including dependence on training data [10, 11], vulnerability to false positives, and delayed detection under nonlinear dynamics [9]. Therefore, there remains a need for a method that can accurately and quickly detect faults without requiring large historical datasets.

The LO offers a promising solution for fault detection due to its ability to accurately estimate system states and generate residual signals that are useful in identifying faults [14, 15]. This method is designed to estimate the internal states of a system that may not be directly measurable. In addition, the LO is beneficial for control, system identification, and overall performance enhancement [16]. By applying this observer, system linearization can be achieved, making complex nonlinear systems more manageable. Its strengths lie in its simple mathematical formulation, reliable stability, and robustness against disturbances. However, selecting the appropriate observer gain is crucial to ensure accurate state estimation and fast error reduction. Previous studies have demonstrated the effectiveness of the Luenberger Observer in fault detection across various systems, including BLDC motors [17], railway systems [18], DC-DC converters [19], vehicle suspensions [20], and dual-tank systems [21]. However, limited studies have specifically investigated LO-based fault detection for single storage tank systems validated under multiple realistic fault scenarios.

Motivated by this gap, this study proposes the design and simulation-based validation of an LO for fault detection in a storage tank system. The main contributions of this work are: (i) designing an LO adapted to the dynamics of a storage tank model, (ii) evaluating its performance under three different types of faults: ramp, square pulse, and inverted ramp signals, and (iii) assessing its accuracy and robustness in terms of estimation error, fault detection time, and noise tolerance. In contrast to generic LO formulations, the observer designed in this study incorporates three tailoring mechanisms that make it suitable for storage tank dynamics: (i) the observer gain is determined through pole placement adapted to the slow–fast settling characteristics of liquid-level dynamics, ensuring faster convergence than the tank's natural response; (ii) linearization is performed around an operating point that reflects the industrial steady-state balance between inlet and outlet flows, enabling accurate state reconstruction during transient and near-steady regimes; and (iii) the residual evaluation employs thresholds derived from nominal operating behavior rather than fixed limits, allowing reliable detection of gradually developing and leak-type disturbances without false alarms. These technical elements distinguish the proposed LO from conventional observer implementations used in previous studies. The remaining sections of this paper are organized as follows: Section 2 presents the mathematical model and observer design, Section 3 discusses the simulation results, and Section 4 concludes the study and outlines future work.

METHODS

This study consists of three main components: (i) the mathematical modeling of the storage tank system, (ii) the design of the Luenberger Observer, and (iii) the specification of fault scenarios used for evaluation. The simulation results and validation of the proposed method are presented separately in the next section. The overall methodological workflow is illustrated in Figure 6, which outlines the complete fault detection procedure from model development to residual analysis.

Mathematical model of Storage Tank system

The mathematical model of the storage tank system is derived using the volume balance law, which relates the change in liquid volume to the inflow and outflow rates as seen in Figure 1.

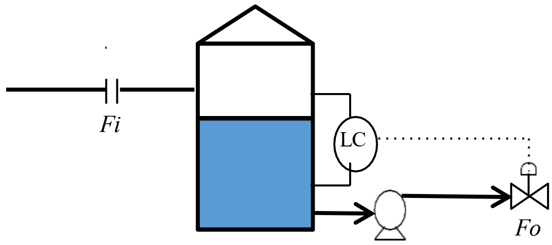


Figure 1. Storage tank system

In this system, liquid enters the tank through a Flow Indicator (F_i). Inside the tank, a Level Controller (LC) is used to regulate and monitor the liquid level, ensuring that the volume remains within the desired limits to prevent overflow or underflow conditions. The stored liquid is then discharged through a flow outlet (F_o) to the next stage of the process, with the outflow regulated by a control valve. According to the principle of volume balance, the change in liquid volume inside the tank is determined by the difference between the inflow and outflow rates. The differential equation representing this system can be expressed as follows:

$$\frac{dV(t)}{dt} = F_i(t) - F_o(t) \tag{1}$$

where the parameters of the tank are shown in Table 1.

Table 1. Parameters of the storage tank system

Parameters	Unit and Symbol
Diameter	d (1 m)
Level	h (0.75 m)
Cross-section area	A ($\pi 4d^2\ m^2$)
Flow input	F_i
Constant	c (0.02 SI)

Since the tank is assumed to have a cylindrical or fixed shape, the liquid volume can be written as $V(t) = Ah(t)$, hence:

$$\frac{dV(t)}{dt} = A\frac{dh(t)}{dt} \tag{2}$$

Then, by substituting equation (2) into equation (1), the following is obtained:

$$\frac{dh(t)}{dt} = \frac{1}{A}F_i(t) - \frac{1}{A}F_o(t) \tag{3}$$

The outflow rate F_o is given by the equation:

https://doi.org/10.25077/jnte.v14n3.1332.2025

$$c\sqrt{h(t)} \tag{4}$$

where h is level and c is a constant that encapsulates the characteristics of the tank's outflow system, such as the pipe diameter, flow resistance, and gravitational factors, and it is typically given by:

$$c = \sqrt{\frac{2gA}{\rho}} \tag{5}$$

with g is gravitation, A is the cross-sectional area, and ρ is fluid density. Therefore, from (3) is obtained:

$$\frac{dh(t)}{dt} = \frac{1}{A}F_i(t) - \frac{c\sqrt{h}(t)}{A} \tag{6}$$

Based on the equation (6), the mathematical model of the storage tank system is nonlinear, requiring a linearization process to simplify the analysis. Using a Taylor series expansion, the linearized model of the storage tank in the form of a state-space equation is presented in (7)

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + v(t) + F(t) \end{aligned} \tag{7}$$

with

$$A = \left[-\frac{c}{2A\sqrt{h}} \right]; B\left[\frac{1}{A} \right]; C = [1] \tag{8}$$

and $x(t) = [h(t)]$ as a state variable, $y(t) = [h(t)]$ is a measurement variable, and $u(t) = [F_i(t)]$ is an input system. Vector v represents Gaussian measurement noise, and the fault is modeled as an additive signal F applied to the measurement. This formulation serves as the foundation for designing the LO for the storage tank system.

Design of Luenberger Observer

The LO estimates the internal states of the tank system using the linearized state-space model. The observer structure is expressed as:

$$\begin{aligned} \dot{\hat{x}}(t) &= A\hat{x}(t) + Bu(t) + K\left(y(t) - \hat{y}(t)\right) \\ \hat{y}(t) &= C\hat{x}(t) \end{aligned} \tag{9}$$

where $\hat{x}(t) \in \mathbb{R}^1$ is the estimated state vector and, $y(t) \in \mathbb{R}^1$ is a vector measurement, and $u \in \mathbb{R}^1$ continuous input vector, $A \in \mathbb{R}^{3\times3}, B \in \mathbb{R}^{3\times2}$, and $C \in \mathbb{R}^{2\times3}$ are known matrix. Vector v represents Gaussian measurement noise. To obtain the linearized model required for observer design, the nonlinear tank dynamics were expanded around the operating point using a first-order Taylor series approximation. The equilibrium liquid height h^* was computed by enforcing the steady-state condition $\dot{h} = 0$, such that inflow and outflow rates are balanced. The Jacobian matrices $\frac{\partial f}{\partial h}$ and $\frac{\partial f}{\partial u}$ were evaluated at (h^*, u^*) to form the state and input matrices A and B, while the output C is the same as (8). This procedure ensures that the resulting linear model captures the local behaviour of the tank around nominal operation and provides a suitable representation for the LO design.

The linearization was performed at the steady-state liquid level of 0.75 m, which represents the nominal operating height used throughout the simulation study. The equilibrium point $(h_0, F_{i,0}, F_{0,0})$ was obtained by enforcing the condition $\dot{h} = 0$, resulting in $F_{i,0} = F_{0,0}$. To express deviations from the equilibrium, the perturbed variables were defined as $\Delta h = h - h_0$ $\Delta F_i = F_i - F_{i,0}$, and $\Delta F_o = F_o - F_{o,0}$. Substituting these definitions into the nonlinear model and neglecting higher-order terms yields the linearized state-space model used for observer design.

The LO gain K is computed using pole placement for the linear time-invariant model to ensure fast convergence and estimation stability [22]. Since the system matrices are constant, the resulting observer gain is also constant and does not vary with time. The poles are selected such that the eigenvalues of $(A - KC)$ yield a settling time faster than the open-loop system [23]. A closed-loop block diagram representing the interaction between the storage tank system and the LO is presented in Figure 2. The LO was implemented following a prediction–correction structure at every sampling instant. First, the system input $u(t)$ was used to predict the next state based on the linearized model. The innovation term $K(y(t) - \hat{y}(t))$ was then applied to correct the prediction using the difference between the measured and estimated outputs.

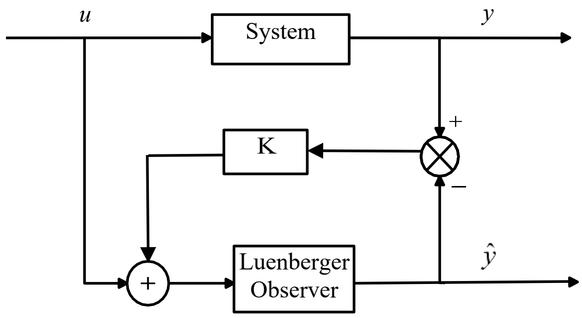


Figure 2. Block diagram of the storage tank system with Luenberger Observer for fault detection.

The diagram highlights the residual generation mechanism:

$$r(t) = y(t) - \hat{y}(t) \tag{10}$$

The residual signal serves as the fault indicator, significant deviations from zero indicate abnormal behavior. To avoid false alarms, the fault-detection threshold r_{th} is defined as a multiple of the noise level, namely:

$$r_{th} = \mu_r + k\sigma_r \tag{11}$$

where $k > 1$ is a design parameter (analogous to a k-sigma rule) chosen such that noise-induced residual fluctuations remain below the threshold. A fault is declared when the absolute value of the residual exceeds this threshold, i.e. when $|r(t)| > r_{th}$. The fault detection delay is defined as:

$$t_d = t_{\det} - t_f \tag{12}$$

where t_f is the fault injection time and t_{det} is the first time instant at which $|r(t)|$ crosses the threshold.

Scenario of faults

To evaluate the fault detection capability of the Luenberger Observer, three representative fault scenarios are designed and injected into the system output during simulation.

Ramp Fault Signal

A ramp fault represents a gradually developing abnormal condition in the storage tank system. The signal increases linearly over time with a constant slope, starting from zero and rising toward its maximum value. In industrial practice, this type of progressive valve degradation, where the measurement error increases gradually rather than abruptly.

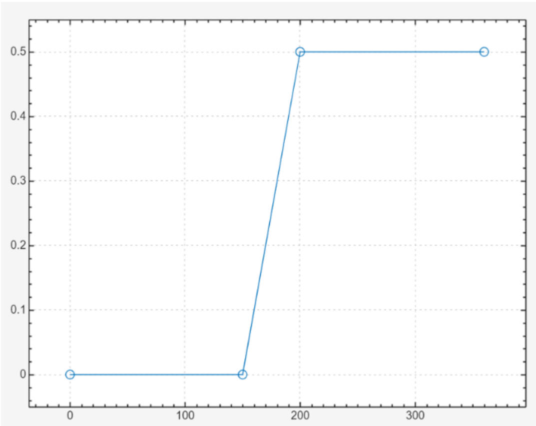


Figure 3. Ramp Fault Signal

In the system simulation, the ramp fault is used to model a slowly developing abnormal condition. This type of disturbance represents situations where deviations accumulate progressively over time rather than appearing suddenly. In the context of the storage tank, a ramp signal corresponds to an undetected increase in inlet flow or gradual deterioration of a level sensor that causes the measured liquid level to drift upward. In this study, the ramp fault is injected during the time interval of 150–200 seconds with a magnitude of 0.5 m, as presented in Figure 3. This scenario enables the evaluation of the observer's sensitivity to faults that evolve gradually and are typically challenging to identify in their early stages.

Square Pulse Fault Signal

A square pulse signal is characterized by abrupt alternation between two levels, switching rapidly between high and low values. In system simulation, this type of disturbance is commonly used to represent faults that occur suddenly and intermittently. In the context of the storage tank system, a square pulse fault corresponds to a transient disturbance in the level sensor or abrupt changes in the outlet valve position, resulting in short-duration fluctuations in the measured liquid level.

In this study, the square pulse fault is introduced during the time interval of 160–230 seconds with a magnitude of 0.3 m, as shown in Figure 4. This scenario is used to evaluate the ability of the LO to detect abrupt and short-duration faults by examining how rapidly and accurately the residual signal responds to sudden deviations from normal operating conditions.

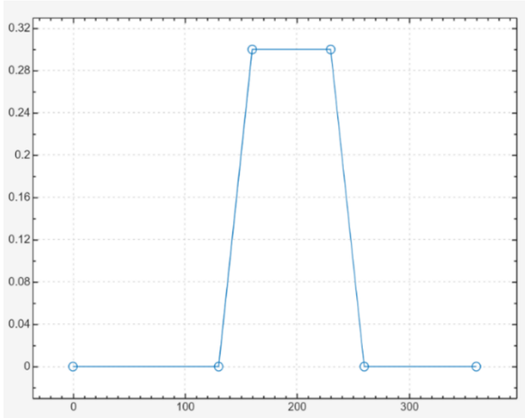


Figure 4. Square Pulse Fault Signal

Inverted Ramp Fault Signal

An inverted ramp signal is characterized by a linearly decreasing profile over time. In system simulation, this fault type represents a gradually developing disturbance that leads to a continuous reduction in the measured process variable. In the context of the storage tank system, an inverted ramp fault corresponds to an undetected leak or persistent loss of outflow control, resulting in a gradual decline in the liquid level.

In this study, the inverted ramp fault is applied during the time interval of 100–200 seconds with a magnitude of 0.5 m, as shown in Figure 5. This scenario enables assessment of the observer's ability to detect fault conditions that develop slowly and reduce the measured level rather than increasing it. Since such faults may initially appear as normal variations, this case is used to evaluate the observer's robustness and early detection capability under progressive downward disturbances.

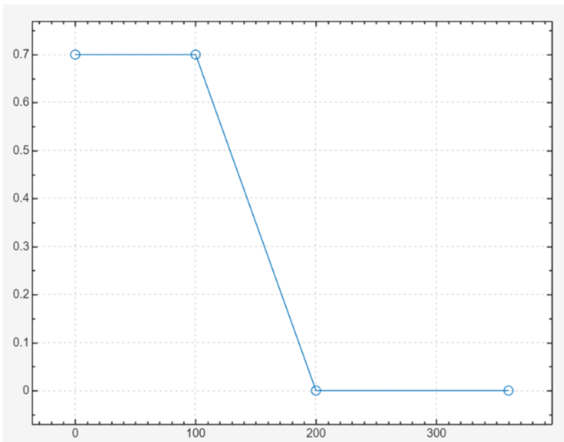


Figure 5. Inverted Ramp Fault Signal

The fault magnitudes used in the simulation were intentionally selected to represent severe but safety-critical deviations from the nominal operating level of 0.75 m. In particular, the ramp and inverted-ramp faults with an amplitude of 0.5 m correspond to large level excursions that would be associated with serious overfilling or leak-type events, while the 0.3 m square disturbance represents an abrupt, high-impact anomaly in the measurement or flow. These magnitudes were chosen to emulate worst-case

https://doi.org/10.25077/jnte.v14n3.1332.2025

scenarios that are of primary concern in industrial practice, where late detection of such large deviations can lead to equipment damage or safety hazards. A detailed sensitivity analysis for smaller and more subtle faults is beyond the scope of this study and is considered a direction for future work. The fault scenarios have defined, the fault detection evaluation of the storage tank system using the LO can be conducted by analyzing the residual response generated under each disturbance as shown in Figure 6.

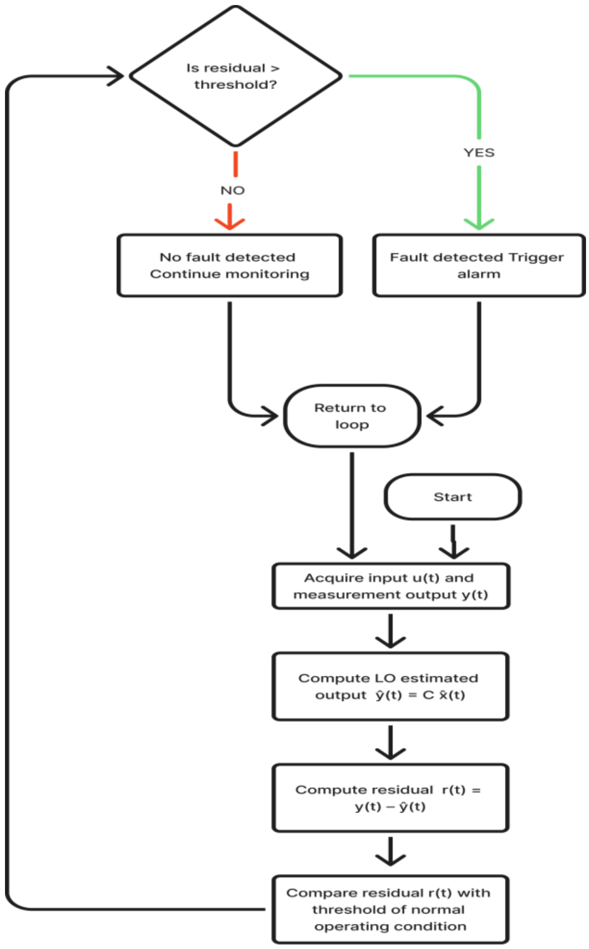


Figure 6. Flowchart of the LO fault detection algorithm using residual evaluation.

RESULTS AND DISCUSSION

Behaviour of the storage tank system

The simulation was carried out for 360 seconds with a sampling time of 1 second. The initial liquid level was set to $h(0) = 0,6m$, representing a partially filled tank. The inflow $F_i(t)$ was set as a constant value of $5\times10^{-4} m^3/s$ during the interval $0 \le t \le 90$ s, and increased to $6,11\times10^{-4} m^3/s$ for $t \ge 90$ to evaluate sensitivity under different operating conditions. The outflow was defined by the nonlinear discharge model, and no disturbances or faults were introduced in the open-loop simulation. Under these inputs, the liquid level converged to a steady-state value of approximately 0.75 m, consistent with the derived equilibrium operating condition, as shown in Figure 7.

At the beginning of the simulation, the liquid level increases rapidly due to a higher inflow rate compared to the outflow rate. After approximately 200 seconds, the system approaches equilibrium and reaches a steady-state value of around 0.75 m, as indicated by the nearly constant curve.

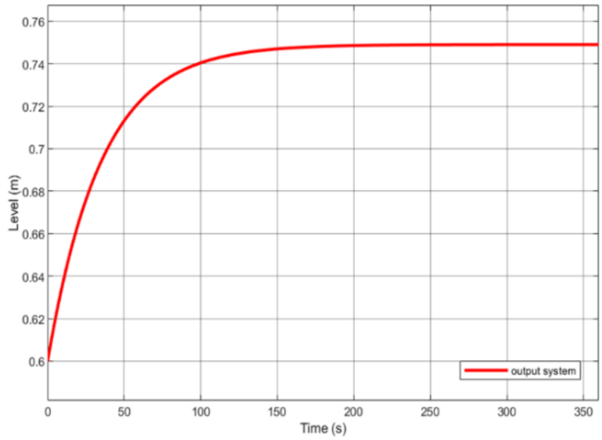


Figure 7. Output respons for open loop storage tank system

This behaviour is consistent with the nonlinear hydraulic characteristics of storage tanks, where the liquid-level response increases rapidly before gradually stabilising once the inlet and outlet flows become balanced. Establishing this baseline condition is important because it provides a reference for distinguishing normal operation from abnormal behaviour in later subsections. Any deviation from this steady-state pattern during fault scenarios will be reflected in the residual signal generated by the LO.

State estimation performance

Before proceeding with fault detection, it is essential to ensure that the observer provides accurate state estimation. The observer's performance is evaluated using two indicators: sensitivity and robustness. Sensitivity refers to the ability of the observer to track state changes when the input varies, while robustness evaluates its performance in the presence of measurement noise. To assess sensitivity, two different input profiles were applied: the first during 0–90 seconds and the second during 90–360 seconds. The corresponding estimated and actual outputs are presented in Figure 8.

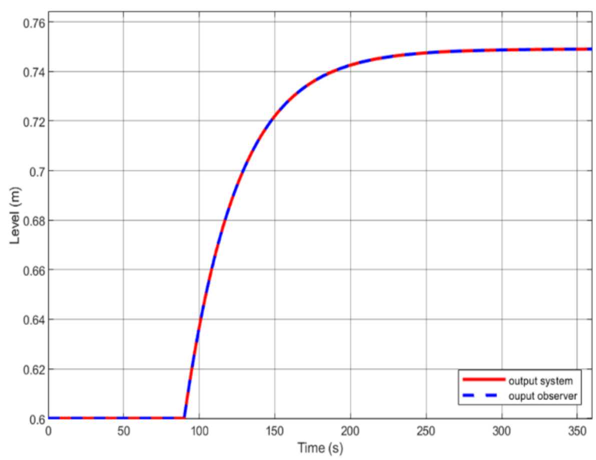


Figure 8. LO Output under Input Variation.

As shown in the Figure 8, the estimated output closely follows the actual system output, indicating strong state-tracking performance. A slight deviation appears during the initial transition phase before steady-state is reached, which is expected as the observer adjusts to the input change. When the input variation is introduced at 90 seconds, the observer continues to track the resulting level change and stabilises at approximately 0.75 m, demonstrating good sensitivity to input variations and rapid convergence. For the robustness analysis, measurement noise is introduced into the simulation, modeled as $v \sim \mathcal{N}(0, R)$ where the value of $R = [0.0020]$. The state estimation is shown in Figure 9.

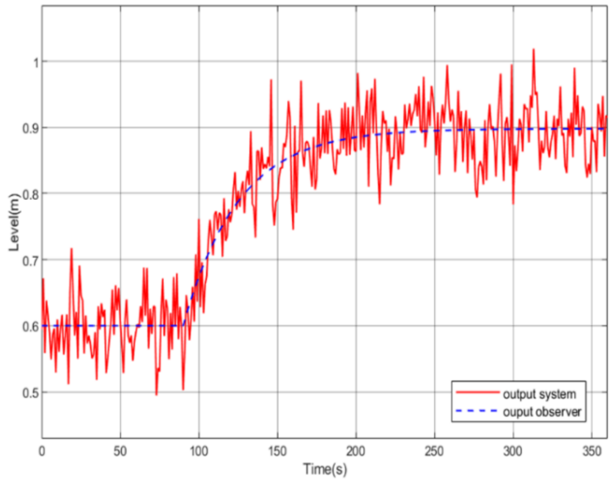
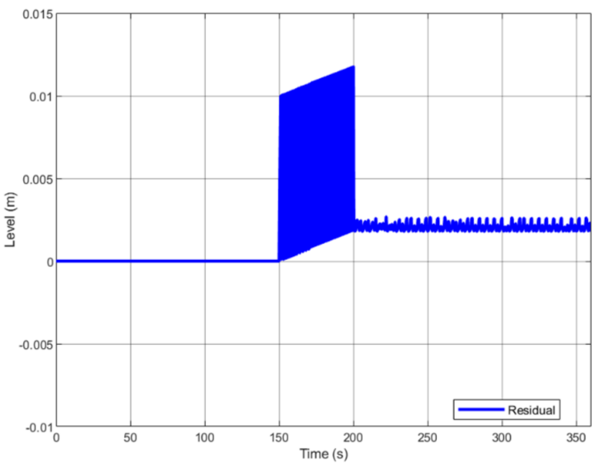


Figure 9. LO output with noise measurement

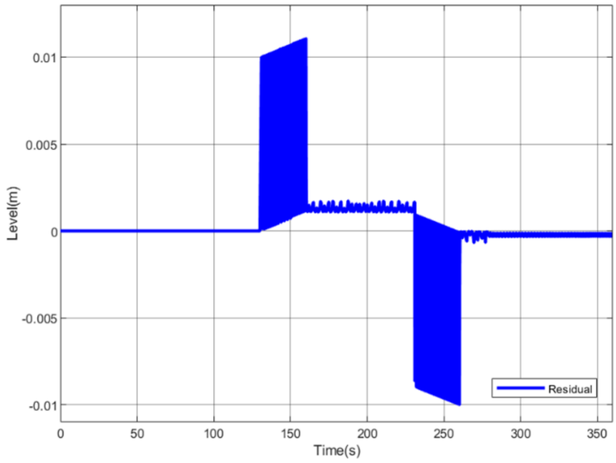
Figure 9 show the actual system output exhibits noticeable fluctuations due to noise, yet the observer's estimated output remains smooth and close to the true value. This indicates that the LO effectively attenuates noise disturbances and maintains high estimation accuracy under imperfect measurement conditions. Such behaviour confirms the robustness of the LO, making it suitable for real-world applications where sensor noise is unavoidable.

Fault detection in storage tank system

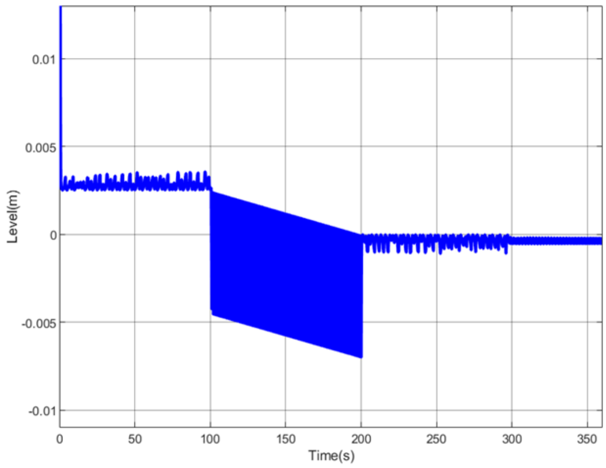
The fault detection performance of the LO was first evaluated under a ramp-shaped fault scenario. The simulation was conducted for 360 seconds with a sampling time of 1 second, and the resulting residual response is presented in Figure 10(a).



(a) Ramp-shape fault



(b) a square-shaped fault



(c) an inverted ramp-shaped fault

Figure 10. Residual responses of the LO under different fault scenarios: (a) Ramp-shape fault (b) a square-shaped fault (c) an inverted ramp-shaped fault

Figure 10 shows the residual responses of the Luenberger Observer under three fault scenarios. In Figure 10(a), the residual remains close to zero before 150 seconds, confirming normal operation without false alarms. When the ramp fault is introduced, the residual increases gradually and crosses the threshold after approximately 7 seconds, indicating timely detection of a slowly developing disturbance. After the fault disappears, the residual exhibits damped oscillations and then returns to zero, demonstrating stable recovery and the ability of the observer to distinguish between faulty and healthy states.

In Figure 10(b), the residual again remains near zero during the normal operating period. When the square-shaped fault is applied, the residual rises sharply and exceeds the threshold within 5 seconds, showing rapid detection of abrupt and intermittent disturbances. The residual then stays at a high magnitude while the fault persists and returns to zero after 260 seconds, confirming no false alarms during the transition back to normal conditions. Figure 10(c) represents the inverted ramp fault scenario. The residual progressively decreases once the fault occurs and crosses the threshold after approximately 9 seconds, indicating detection of leak-type faults that develop in the negative direction. After the fault is removed, the residual gradually returns to zero without oscillations, confirming stable convergence and robust performance of the observer.

https://doi.org/10.25077/jnte.v14n3.1332.2025

Across all fault conditions, the observer consistently detects both the onset and clearance of faults with detection delays between 5 and 9 seconds, demonstrating fast and reliable fault identification without false alarms. While data-driven methods such as PCA and MWPCA [9], SVM [10], and MWAT-ICA [11] have shown good performance in detecting process and sensor faults, their applicability to storage tank systems is limited by the need for large and representative historical datasets and their tendency to produce delayed detection for slowly developing faults. In contrast, the proposed LO does not require training data and successfully detects ramp-type, square-type, and inverted-ramp disturbances with short detection delays even under 6% measurement noise, highlighting its suitability for storage tank applications characterized by nonlinear slow–fast dynamics and sparse fault datasets.

In order to provide a quantitative evaluation of fault detectability, a threshold-based decision rule was applied. The fault-detection threshold was set to $r_{th} = 0.04m$, which corresponds to approximately three times the maximum residual amplitude observed under nominal conditions with 6% sensor noise. A fault was considered detected when the absolute residual first exceeded this threshold. Based on this criterion, the LO successfully detected the ramp, square, and inverted-ramp disturbances with detection delays of approximately 7 s, 5 s, and 9 s, respectively, measured from the moment each fault was injected until the residual crossed the threshold. Furthermore, in all three scenarios, the peak residual amplitude during the fault was several times larger than the noise-induced residual, demonstrating clear separability between normal and faulty behavior. These results confirm that the LO provides fast and reliable fault detection across multiple disturbance profiles, even in the presence of significant measurement noise.

CONCLUSIONS

Based on the simulation results and analysis, the Luenberger Observer demonstrated effective performance in estimating system states and detecting faults in the storage tank process. Before fault injection, the observer achieved high estimation accuracy with minimal error and remained robust under 6% measurement noise, indicating adequate sensitivity and tolerance to disturbances. When fault scenarios were applied, the observer successfully detected all three fault types, namely ramp, square pulse, and inverted ramp, with detection delays of approximately 7 seconds, 5 seconds, and 9 seconds, and the residual consistently returned to zero after the fault was removed, confirming the absence of false alarms and stable recovery. The main contribution of this work is the demonstration that a model based Luenberger Observer designed through pole placement and supported by an operating point linearization can provide reliable and noise tolerant fault detection in a nonlinear storage tank system. This is achieved by explicitly incorporating the slow and fast liquid level dynamics into the observer structure, resulting in better performance than generic observer designs and data driven methods. Overall, the findings indicate that a physically grounded observer based scheme is a practical and computationally efficient solution for real time monitoring in industrial storage applications, and future research should include experimental validation, assessment under model uncertainties and nonlinear operating conditions, and the development of adaptive or gain scheduled observer structures for improved performance in time varying and multivariable processes.

ACKNOWLEDGMENT

The authors would like to express their gratitude to Universitas Islam Negeri Sultan Syarif Kasim Riau for providing research facilities and academic support throughout the completion of this study. The authors also extend sincere appreciation to the reviewers for their constructive feedback and insightful comments, which significantly improved the quality of this manuscript. In addition, the authors thank the ELINS research team for assistance during simulation validation and technical discussions.

REFERENCES

[1] R. Alida and A. P. Anjastara, "Penentuan Waktu Pemakaian Storage Tank Melalui Analisa Data Hasil Pengukuran Ultrasonic Thickness Pada Tangki Tep-028 Di Stasiun Pengumpul Jemenang Pt Pertamina Ep Asset 2 Field Limau," *Jurnal Teknik Patra Akademika,* vol. 11, no. 02, pp. 26-32, 2020.

[2] H. Hardiyono, P. Pongky, S. Purwanti, K. Rusba, I. Siboro, and H. E. Putri, "Inspeksi Storage Tank Di PT. ABC Pada Proyek PT. XYZ Menggunakan Metode Risk Based Inspection," *Media Bina Ilmiah,* vol. 17, no. 9, pp. 2311-2318, 2023.

[3] H. Alenezi and O. Al-Qabandi, "A review of hazard management in petroleum/chemical facilities–fires and explosions," *NeuroQuantology,* vol. 20, no. 5, pp. 4222-4240, 2022.

[4] A. Phill, "Report: 5 Key Findings from 2019 Tank Farm Explosion, Fire," 24 February 2025 2019, Available: https://www.hazmatnation.com/news/report-5-key-findings-from-2019 tank-farm-explosion-fire/.

[5] F. Jan, N. Min-Allah, S. Saeed, S. Z. Iqbal, and R. Ahmed, "IoT-based solutions to monitor water level, leakage, and motor control for smart water tanks," *Water,* vol. 14, no. 3, p. 309, 2022.

[6] H. R. Gandhi, "An accidental release of flowback water from storage system: a risk assessment study," University of British Columbia, 2017.

[7] P. M. Laso, D. Brosset, and J. Puentes, "Analysis of quality measurements to categorize anomalies in sensor systems," in *2017 Computing Conference*, 2017, pp. 1330-1338: IEEE.

[8] M. Farajian, N. Saeed, and W.-H. Kang, "Seismic vulnerability assessment of base isolated liquid storage tanks under near-fault ground motions," in *Structures*, 2022, vol. 43, pp. 1901-1912: Elsevier.

[9] C. Zhou and X. Li, "Fault Detection Method Based on Moving Window Principal Component Analysis for Three-Tank System," in *2017 International Conference on Industrial Informatics-Computing Technology, Intelligent Technology, Industrial Information Integration (ICIICII)*, 2017, pp. 280-285: IEEE.

[10] Y. Furukawa and M. Deng, "Fault detection of tank-system using ChangeFinder and SVM," in *2020 international conference on advanced mechatronic systems (icamechs)*, 2020, pp. 260-265: IEEE.

[11] M. Liu, Y. Liao, and X. Li, "Data-Driven Fault Detection of Three-Tank System Applying MWAT-ICA," *Journal of Shanghai Jiaotong University (Science),* vol. 25, pp. 659-664, 2020.

[12] M. C. Dippenaar, G. van Schoor, K. R. Uren, and W. M. van Niekerk, "Fault Detection and Isolation in Transient Conditions on a Heated Two-Tank System: A Multiway Principal Component Analysis Approach," *Processes,* vol. 12, no. 8, p. 1620, 2024.
[13] Y. Furukawa and M. Deng, "SVM-based fault detection for double layered tank system by considering ChangeFinder's characteristics," *International Journal of Advanced Mechatronic Systems,* vol. 9, no. 4, pp. 185-192, 2022.
[14] J. Cao, M. U. B. Niazi, M. Barreau, and K. H. Johansson, "Sensor Fault Detection and Isolation in Autonomous Nonlinear Systems Using Neural Network-Based Observers," in *2024 European Control Conference (ECC)*, 2024, pp. 7-12: IEEE.
[15] N. Trapani and L. Longo, "Fault detection and diagnosis methods for sensors systems: a scientific literature review," *IFAC-PapersOnLine,* vol. 56, no. 2, pp. 1253-1263, 2023.
[16] D. Mursyitah, D. Delouche, T. Zhang, and F. Kratz, "Leak Detection and Localization in Pipeline System," *2022 10th International Conference on Systems and Control (ICSC),* pp. 385-390, 2022.
[17] Y. Al-Mutayeb, M. Almobaied, and M. Ouda, "Real-time simulation and experimental implementation of luenberger observer-based speed sensor fault detection of bldc motors," *acta mechanica et automatica,* vol. 18, no. 1, 2024.
[18] A. Rawia, T. Hatem, and K. Jilani, "Fault detection using luenberger observer in a railway system," in *2016 4th International Conference on Control Engineering & Information Technology (CEIT)*, 2016, pp. 1-6: IEEE.
[19] J. Li, Z. Zhang, and B. Li, "Sensor fault detection and system reconfiguration for DC-DC boost converter," *Sensors,* vol. 18, no. 5, p. 1375, 2018.
[20] A. Sellami and N. Zanzouri, "Fault diagnosis of a vehicular active suspension system by Luenberger observer using bond graph approach," in *2017 International Conference on Green Energy Conversion Systems (GECS)*, 2017, pp. 1-8: IEEE.
[21] F. Kousar, M. Abid, and A. Q. Khan, "Sensor fault detection in coupled liquid tanks system," in *2012 10th International Conference on Frontiers of Information Technology*, 2012, pp. 318-324: IEEE.
[22] H. L. Kennedy, "On the design of fixed-gain tracking filters by pole placement: Or an introduction to applied signals-and-systems theory for engineers," *arXiv preprint arXiv:2110.00153,* 2021.
[23] D. Mursyitah, P. S. Maria, S. Pebriani, D. Delouche, T. Zhang, and F. Kratz, "Fault Detection in Continuous Stirred Tank Reactor (CSTR) System Using Extended Luenberger Observer," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI),* vol. 10, no. 4, pp. 681-690, 2024.

AUTHOR(S) BIOGRAPHY

Dian Mursyitah

Dian Mursyitah is a lecturer in Electrical Engineering at the State Islamic University of Sultan Syarif Kasim Riau, Indonesia. She specializes in control systems, automation, and fault detection in industrial applications, particularly in systems like storage tanks and pipelines. Dian has published several works on the application of advanced observers, such as the Luenberger Observer and High Gain Observer, for fault detection and estimation in complex systems. Her research focuses on improving the robustness and reliability of control systems under varying conditions

Ahmad Faizal

Ahmad Faizal is a lecturer in Electrical Engineering at the State Islamic University of Sultan Syarif Kasim Riau, Indonesia. He specializes in control systems and instrumentation of control systems. His research interests focus on enhancing the performance and reliability of control systems, particularly in industrial applications.

Hilman Zahrory

Hilman Zahrory is a lecturer in Electrical Engineering at the State Islamic University of Sultan Syarif Kasim Riau, Indonesia. He specializes in control systems and the Internet of Things (IoT). His research interests focus on the integration of control strategies and IoT technologies for enhancing system performance and efficiency in various industrial applications. Hilman has contributed to studies on optimizing control systems through IoT-based solutions.

Sitri Permata Sari

Sitri Permata Sari is a student at the State Islamic University of Sultan Syarif Kasim Riau, Indonesia, studying in the field of Electrical Engineering.

https://doi.org/10.25077/jnte.v14n3.1332.2025