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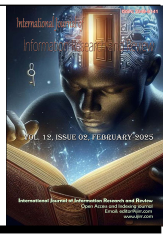

RESEARCH ARTICLE

USING STATE ESTIMATION MODEL TO IMPROVE FLOW METER PERFORMANCE

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ABSTRACT

This study presents a state estimation model designed to identify and minimize errors in flowmeter measurements, ensuring greater accuracy in measurement data. These errors can stem from various sources, including equipment malfunctions, human errors, instrument rigidity, vibrations, and flow medium-related factors. While several methods exist to analyze these inaccuracies, state estimation proves highly effective in detecting and reducing them, achieving nearly zero percent error and a 95% improvement in flow meter performance assessment. Implemented in Python, the model leverages the Kalman filter to generate estimated values, which are then compared with actual meter readings to assess meter reliability and performance. The performance results offer a comprehensive assessment history, aiding in meter calibration and proving through numerical simulations. To achieve the study's objectives, calibration data—whether individual readings or sequential datasets—are analyzed and benchmarked against performance criteria established by international or local regulatory bodies. The results are further validated using the state estimation model, ensuring that measurement series remain accurate, consistent, and reliable.

INTRODUCTION

Accurate measurement is crucial as it provides empirical evidence of proximity to true values. Uncertainty in measurement can stem from faulty equipment, inadequate data processing, or human negligence (Dong, 2023 andZhou *et al*., 2023). Precision refers to the degree of proximity between multiple measurements of a given entity (JCGM, 2012). Several factors influence the efficacy of measuring systems, including proper instrument installation, calibration, and characterization of fluid properties (Everett, 2023). State estimation enables a broader examination of measurement difficulties and facilitates rapid determination of performance history. Measurement accuracy can be influenced by application-specific factors, such as contamination, mechanical wear, and challenging operating environments (Simona *et al*., 2022). Characterizing measurement system accuracy is crucial for ensuring performance in process control, monitoring, and safety applications. This research employs a state estimation model to identify and mitigate errors, enhancing measurement authentication. The approach improves acceptance or rejection criteria for flowmeter operations by providing qualitative and quantitative insights into instrument performance. Traceability is essential for ensuring measurement accuracy, and calibration involves comparing measurements against internationally recognized standards (Mladen *et al*., 2019). Regular calibration optimizes measurement accuracy, mitigates uncertainties, and maximizes revenue. This study aims to measure flow volume, temperature, flow rate, and pressure parameters using physical instruments. A state estimation model implemented in Python, utilizing the Kalman filter, is employed to analyze the filtered results and assess data reliability. The study's findings are significant for the oil and gas, production, and drilling and exploration industries, where accurate measurement instruments are crucial for determining product quality and quantity. Recent studies have focused on enhancing the accuracy and reliability of flowmeters. (Mao *et al*. 2022) developed a novel design for gas ultrasonic flowmeters using contraction flow, achieving higher accuracy than conventional single-channel gas ultrasonic flowmeters. (Lee *et al*. 2021) evaluated the performance of flowmeters in measuring fuel consumption in fishing vessels, confirming that ultrasonic flowmeter measurement errors remained constant under identical flow rate and speed conditions.Woong *et al*. (2022) studied the calibration method for Coriolis mass flowmeters in hydrogen refueling stations, focusing on Density- and Pressure-Matching approaches. (Wang *et al*. 2022) investigated the performance optimization of a gas turbine flowmeter using numerical simulation and experimental measurement, introducing a structural optimization technique for the front rectifier and rear deflector. All this research is geared towards addressing the sources of measurement uncertainty, this research seeks to elevate the accuracy and confidence of flow measurements, driving improvements in process control and decision-making.

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MATERIAL AND METHODS

Material

This study utilized the following primary materials

- Positive Displacement (PD) meter
- Prover tank

Additional instruments used to measure physical quantities essential for meter performance evaluation included:

- Thermometer
- Hydrometer
- Stopwatch
- Pressure pump
- Computer
- Pressure gauge

A standard reference acceptance criterion by API MPMS guideline suggests that meter factors should not exceed ±0.2% deviation for reliable performance was employed to benchmark meter errors for acceptance. The acceptance criteria varied depending on the intended purpose of the meter, ensuring accurate evaluation and reliable results.

Method

This study utilizes a state estimation model to analyze and investigate data measured using physical measurement instruments and equipment. The primary objective is to ensure flow meter reliability and improved performance while minimizing errors. The accuracy of the meter factor for liquid petroleum and petroleum products under dynamic conditions was measured and validated. The validation process of Table 1followed the relevant steps and procedures outlined by (Das 2018) in computing state estimation, and (Kamon 2024) for obtaining meter factor computation while ensuring adherence to established standards.

Table 1. Calibration Test values of a meter – Measured

(V1) Metered Corrected Volume (BBLS)	(T1) Temp ˚F	(P1) Press Psi		(V2) Prover Corrected Volume (BBLS)	(T2) Average Temp (˚F)	(P2) Average Pressure (Psi)	(FR) Flow Rate (LPM)
1	2	3		4	5	6	7
METER UNDER TEST(M1)				PROVER (M2)			
V1	T1	P1		V2	T2	P2	FR(LPM)
100.23	119.00	22.5		101.27	99.70	25.0	549.20
100.16	119.00	22.5		101.27	99.50	25.0	540.19
100.18	119.00	22.5		101.25	99.30	25.0	538.90
100.21	119.50	22.5		101.28	99.00	25.0	548.23
100.12	119.00	22.5		101.30	99.00	25.0	547.72

The calibration values presented in Table 1 will serve as input for state estimation, enabling the determination of actual meter performance through the application of the Kalman filter algorithm in Python. “The procedure allows:

Given Data: The data set provided consists of the following variables:

Meter under test (M1)

- **V1**: Initial volume
- **T1**: Initial temperature
- **P1**: Initial pressure

Prover (M2)

- **V2**: Final volume
- **T2**: Final temperature
- **P2**: Final pressure
- **FR(LPM)**: Flow rate in liters per minute

The goal is to apply the Kalman filter to refine these values, reducing measurement uncertainty and improving accuracy. The Kalman Filter Model

The Kalman filter is a recursive state estimation algorithm consisting of two main steps:

- **Prediction Step:** Uses the system model to predict the next state.
- **Update Step:** Uses actual measurements to correct the predicted state.

State-Space Representation

We define the state vector **X** as: X=[V1T1P1V2T2P2FR]TX = \begin{bmatrix} V1 & T1 & P1 & V2 & T2 & P2 & FR \end{bmatrix}^TX=[V1T1P1V2T2P2FR]T

The state transition equation: Xk=FXk−1+wkX_k = F X_{k-1} + w_kXk=FXk−1+wk
where:

- **F** is the state transition matrix (assumed identity since variables are measured independently)
- **w_k** is processing noise (assumed Gaussian)

Measurement equation:

Zk=HXk+vkZ_k = H X_k + v_kZk=HXk+vk

where:

- **Z_k** is the measurement vector
- **H** is the observation matrix
- **v_k** is measurement noise (assumed Gaussian)

Implementing the Kalman Filter in Python

We use the filterpy.kalman library to apply the Kalman filter applying the following:

Step 1: Import Required Libraries

```
importnumpy as np
from filterpy.kalman import KalmanFilter
```

Step 2: Initialize the Kalman Filter

```
kf = KalmanFilter(dim_x=7, dim_z=7)  # 7 state variables (V1, T1, P1, V2, T2, P2, FR)
```

Step 3: Define Matrices

```
# Initial state vector (from first row of data)

x_init = np.array([100.23, 119.00, 22.5, 101.27, 99.70, 25, 549.20])

# State transition matrix (Identity matrix, assuming direct measurement updates)
kf.F = np.eye(7)

# Measurement matrix (Identity matrix, assuming direct measurement updates)
kf.H = np.eye(7)

# Initial covariance matrix (Assume small uncertainty)

kf.P = np.eye(7) * 0.01

# Process noise (Assumed small)

kf.Q = np.eye(7) * 0.001

# Measurement noise (Estimated from sensor accuracy)

kf.R = np.eye(7) * 0.05

# Initialize state

kf.x = x_init
```

Step 4: Run the Kalman Filter for Each Measurement

```
# Measurement data (from given table)
```

```
measurements = np.array([
    [100.23, 119.00, 22.5, 101.27, 99.70, 25, 549.20],
    [100.16, 119.00, 22.5, 101.27, 99.50, 25, 540.19],
    [100.18, 119.00, 22.5, 101.25, 99.30, 25, 538.90],
    [100.21, 119.50, 22.5, 101.28, 99.00, 25, 548.23],
    [100.12, 119.00, 22.5, 101.30, 99.00, 25, 547.72]
 ])

# Store estimated states

estimated states = []

for i in range(len(measurements)):

kf.predict()  # Predict next state

kf.update(measurements[i])  # Update state using measurement

estimated_states.append(kf.x)  # Store estimated state

# Convert results to a readable format
estimated_states = np.array(estimated_states)

# Print results
for i, est in enumerate(estimated_states):
print(f"Estimated State {i+1}: {est}")
```

RESULTS

The estimated values after applying the Kalman filter:

V1	T1	P1	V2	T2	P2	FR(LPM)
100.23	119.01	22.5	101.27	99.66	25	548.81
100.19	119.00	22.5	101.27	99.58	25	544.48
100.19	119.00	22.5	101.26	99.48	25	542.38
100.19	119.16	22.5	101.27	99.32	25	544.27
100.17	119.11	22.5	101.28	99.23	25	545.29

Table 2. Extracted Result of Estimated Measured value

(V1) Metered Corrected Volume (BBLS)	(T1) Temp ˚F	(P1) Press Psi		(V2) Prover Corrected Volume BBLS)	(T2) Average Temp (˚F)	(P2) Average Pressure (Psi)	(FR) Flow Rate (LPM)
1	2	3		4	5	6	7
METER UNDER TEST(M1)				PROVER(M2)			
V1	T1	P1		V2	T2	P2	FR (LPM)
100.23	119.00	22.5		101.27	99.66	25.0	548.81
100.19	119.00	22.5		101.27	99.58	25.0	544.48
100.19	119.00	22.5		101.26	99.48	25.0	542.38
100.19	119.16	22.5		101.27	99.32	25.0	544.27

Meter Performance Evaluation: Table 1 presents the calibrated meter measurement values and Table 2 the estimated values, which can be further analyzed to determine the meter factor (MF) and the meter factor percentage deviation using Table 3 and Table 4, a modified Table of 1 and 2. The purpose of this is aimed at evaluating meter performance. To obtain the meter factor (MF) of measured and estimated, this study adopts the standardized method for calculating the meter factor (MF) outlined in the American Petroleum Institute (API) Manual of Petroleum Measurement Standards (MPMS) procedure guide 2018. Specifically, the methodology follows the guidelines set by the Nigerian Midstream and Downstream Petroleum Regulatory Authority (NMDPRA) 2024, which adopted the API standards and the defunct Department of Petroleum Resources (2019) procedure guide. The method involves the following steps:

Calculate the meter factor (MF)of each series or runs in the measured and estimated value which is:

MF = (Vp / Vm) × (ρm / ρm) = (Vp x pm) / (Vmx ρm)

Where:

- MF = Meter factor
- Vp = Prover volume
- Vm = Metered volume
- ρm = Density of the liquid at metering conditions
- ρp = Density of the liquid at prover conditions
- (Vp x pm) = V2 = Prover corrected volume
- (Vmx ρm)= V1 = Metered corrected volume

Calculate the meter factor deviation (ΔMF) of the measured and the estimated using:

- ΔMF = MF_measured - MF_ref
- ΔMF = Difference between the measured
- MF measured = Measured metered factor
- MF_ref = Reference meter factors

Calculating Meter Factor Deviation Percentage using the following formula:

ΔMF% = (ΔMF / MF_ref) × 100

By following the procedure outlined in steps (i) to (iii), the resulting meter factor percentage deviations (ΔMF) for both measured and estimated values will be obtained, as presented in columns 8 of modified Tables 3 and 4, respectively. MF Deviation = ΔMF = MF_measured - MF_ref = 1.011786 – 1.010376 = 0.00141

Table 3. Measured Meter Factor Modified Table MF Percentage Deviation Result

(V1) Metered Corrected Volume (BBLS)	(T1) Temp ˚F	(P1) Press Psi		(V2) Prover Corrected Volume (BBLS)	(T2) Average Temp (˚F)	(P2) Average Pressure (Psi)	(FR) Flow Rate (LPM)	(MF) METER FACTOR
1	2	3		4	5	6	7	8
METER UNDER TEST(M1)				PROVER (M2)				V2/V1
V1	T1	P1		V2	T2	P2	FR (LPM)	MF
100.23	119.00	22.5		101.27	99.70	25.0	549.20	1.010376
100.16	119.00	22.5		101.27	99.50	25.0	540.19	1.011082
100.18	119.00	22.5		101.25	99.30	25.0	538.90	1.010681
100.21	119.50	22.5		101.28	99.00	25.0	548.23	1.010678
100.12	119.00	22.5		101.30	99.00	25.0	547.72	1.011786

MF Deviation = ΔMF = MF_measured - MF_ref = 1.011786 – 1.010376 = 0.00141
MF percentage Deviation ΔMF% = (ΔMF / MF_ref) × 100
= (0.00141/1.010376) x 100 = 0.14

Table 4. Estimated Meter Factor Modified Table with MF Percentage Deviation Result

(V1) Metered Corrected Volume (BBLS)	(T1) Temp ˚F	(P1) Press Psi		(V2) Prover Corrected Volume (BBLS)	(T2) Average Temp (˚F)		(FR) Flow Rate (LPM)	(MF) METER FACTOR
1	2	3		4	5	6	7	8
METER UNDER TEST(M1)				PROVER(M2)				V2/V1
V1	T1	P1		V2	T2	P2	FR (LPM)	MF
100.23	119.00	22.5		101.27	99.66	25.0	548.81	1.0103761
100.19	119.00	22.5		101.27	99.58	25.0	544.48	1.0107795
100.19	119.00	22.5		101.26	99.48	25.0	542.38	1.0106797
100.19	119.16	22.5		101.27	99.32	25.0	544.27	1.0107795
100.17	119.11	22.5		101.28	99.23	25.0	545.29	1.0110812

MF Deviation = ΔMF = MF_measured - MF_ref = 1.0110812 – 1.0103761 = 0.0007051
MF percentage Deviation ΔMF% = (ΔMF / MF_ref) × 100
= (0.000751/1.0103761) x 100 = 0.07

RESULTS AND DISCUSSION

The results indicate that both the measured and estimated MF percentage deviations are within the acceptable limit of 0.2% as specified in API Chapter 5. However, there is a noticeable difference between the measured (0.14%) and estimated values (0.07%).

Measured MF Percentage Deviation (0.14): The measured MF percentage deviation of 0.14% suggests that the meter's actual performance is slightly deviating from the expected value. This deviation may be attributed to various factors such as human error, instrument calibration, environmental conditions, or fluid properties.

Estimated MF Percentage Deviation (0.07%): The estimated MF percentage deviation of 0.07% indicates that the state estimation model is able to accurately predict the meter's performance, with a deviation that is nearly half of the measured value. This suggests that the model is effective in compensating for some of the errors or uncertainties associated with the measurement process and performance. This improved performance can be sustained by operating the said meter with the estimated flow rate.

Implications for Meter Performance: The results imply that the meter's performance is acceptable according to the API Chapter 5 standard. However, the difference between the measured and the acceptable limit of 0.2% suggests that there may be some room for improvement in the meter's accuracy or calibration. The state estimation model's ability to provide a more accurate estimate of the meter's performance highlights the potential benefits of using advanced modeling techniques to enhance meter performance evaluation.

CONCLUSION

The results of the meter factor percentage deviation analysis indicate that both the measured and estimated values are within the acceptable limit of 0.2% as specified in API Chapter 5. However, the estimated value (0.07%) shows a significant improvement over the measured value (0.14%), demonstrating the effectiveness of the state estimation model in enhancing meter performance evaluation.

The study concludes that:

- The state estimation model is a valuable tool for improving meter performance evaluation.
- The use of advanced modeling techniques can help to identify areas for improvement in meter accuracy and calibration.

Overall, the study highlights the importance of using advanced modeling techniques to enhance meter performance evaluation and ensure accurate measurement results.

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REFERENCES

American Petroleum Institute(API) Manual of Petroleum Measurement Standards, Chapter 5, 2018.

Das, B, Computer Aided Power System Analysis. 2018, Indian Institute of Technology, Roorkee, Retrieved from: https://onlinecourses.nptel.ac.in/noc20_ee88/preview.

Department of Petroleum Resources (DPR), Procedure Guide2019.

Dong Z. Adaptive Approximation-Based Control for Nonlinear Systems: A Unified Solution with Accurate and Inaccurate Measurements, 2023; Journal of Latex Class Files, Vol. XX, No. X, X 2020.

Everett, M. C. Rotary Oil Meters of the Positive-Displacement and Current Types Journal of Fluids Engineering; 2023.

Joint Committee for Guides in Metrology (JCGM). Maintaining and promoting the Guide to the Expression of Uncertainty in Measurement and the International Vocabulary of Metrology, 2012

Kamon, A. Mastering Python, a detailed guide to advanced Python topics, 2024.

Lee, J., Kim, J., and Lee, Y. Evaluation of flowmeters for measuring fuel consumption in fishing vessels2021.

Mao, X-Y, Lin-Song, C and Xie D.-L. Novel design of gas ultrasonic flowmeter using contraction flow 2022.

Mladen Z., Duro, B. and Sergej, B. Precise Determination of Calibration Baseline Distances. (2019), Journal of Surveying Engineering145(4):

Nigerian Midstream and Downstream Petroleum Regulatory Authority NMDPRA), Petroleum Measurement Regulations, 2023.

Simona, D., Maja, A., Viktor, G., and Vasko, C., Uncertainty Estimation in Environmental Road Traffic Noise Measurements using ISO 1996-2:2017, 2022.

Wang, Z., Yan, W., Xiao, Y., Lin, J. and Zhang, S.Study on Performance Optimization of Gas Turbine Flowmeter by Numerical Simulation and Experimental Measurement, 2022. Yi Qi Yi Biao Xue Bao/Chinese Journal of Scientific Instrument.

Woong. K, Jinwoo. S, Byungro .Y, Sunghee .K, Sangsik .Y, Wonguk.H, andUnbong .B, Investigation of a Calibration Method of Coriolis Mass Flowmeters by Density- and Pressure-Matching Approaches for Hydrogen Refueling Stations,.2022 Journals of Applied Sciences12(24):12609

Zhou, Z., JianKui, C., Hua, Y., andZhouping, Y, 2023, Accurate Measurements of Droplet Volume with Coherence Scanning Interferometry IEEE Transactions on Instrumentation and Measurement PP(99):1-1

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