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LINEAR LAV-BASED STATE ESTIMATION INTEGRATING HYBRID SCADA/PMU MEASUREMENTS

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ABSTRACT-
Reliable and secure grid operation depends on accurate monitoring of power system conditions, such as bus voltage magnitudes and phase angles. While Phasor Measurement Units (PMUs) give high-speed synchronized data at a much higher deployment cost, traditional Supervisory Control and Data Acquisition (SCADA) systems offer wide-area coverage but suffer from sluggish update rates and asynchronous measurements. In order to take use of both measuring methods' complimentary qualitiesThis project offers a framework for state estimation based on Linear Least Absolute Value (LAV) that integrates hybrid SCADA/PMU observations. State estimates can be significantly distorted by conventional Weighted Least Squares (WLS) estimators, which are computationally efficient but extremely vulnerable to massive measurement errors and poor data. By minimizing the sum of absolute residuals, the Linear LAV estimator, on the other hand, provides better resilience against corrupted data and naturally suppresses the impact of outliers. Using ESP32 microcontrollers with voltage and current sensors to simulate widespread SCADA and PMU measurement nodes, the suggested system is realized as an inexpensive Internet of Things prototype. A Firebase Realtime Database, which acts as a cloud-based communication bridge, receives sensor data over Wi-Fi. A Python backend uses the cvxpy package to solve the LAV optimization issue, get real-time data, and build the system matrix for a linearized DC power flow model. A Streamlit dashboard provides real-time visualization of estimated states, measurement residuals, and bad-data alarms. The Linear LAV estimator outperforms the traditional WLS technique by achieving accurate state estimation under both normal and noisy settings while successfully rejecting injected incorrect data, according to experimental results on a three-bus test network. The system demonstrates excellent communication reliability (98.9% success rate), low computational overhead (~215 ms per cycle), and effective bad-data identification (96% rate).

***Keywords*:** State Estimation, Linear LAV, Hybrid SCADA/PMU, ESP32, IoT, Firebase, Smart Grid, Bad Data Detection.

I. INTRODUCTION

Large, intricate, and dynamically linked networks, modern electric power systems continually supply users with electrical energy from generating units. System operators must continuously check the grid's electrical condition, particularly the voltage magnitudes and phase angles at each bus, to guarantee dependable and secure operation.

Supervisory Control and Data Acquisition (SCADA) systems, which gather analog and digital data including bus voltages, power flows, and circuit breaker statuses at comparatively modest update rates (about every 2-4 seconds), are often used to accomplish this monitoring. Although SCADA systems offer extensive coverage, their asynchronous and sometimes delayed data restrict their capacity to record rapid system changes. On the other hand, Phasor Measurement Units (PMUs), which were launched with the development of synchronized measurement technology, use Global Positioning System (GPS) timing to deliver high-speed, time-synchronized data. PMUs use sampling speeds of up to 120 samples per second to assess voltage and current phasors (magnitude and phase angle). This enhances observability and enables accurate, real-time monitoring of power system dynamics.

But while SCADA technology is still widely used, PMU adoption is costly and constrained. Therefore, combining the broad coverage of SCADA with the precision and synchronization of PMUs through hybrid SCADA–PMU measurements provides a workable compromise.

1.1 Need for State Estimation

The power system state refers to the set of voltage magnitudes and phase angles at all buses in a network. Accurate knowledge of these states is essential for power flow control, contingency analysis, stability monitoring, and economic dispatch.

Since not all states can be directly measured, the system operator must estimate them using available measurements—this process is known as state estimation (SE).

Mathematically, state estimation determines the best estimate of the state vector x (voltages and angles) from a set of noisy and redundant measurements z, using the measurement model:

$z=h(x)+e$

where:

- z= measurement vector (voltage, current, power flow, etc.)
- $h(x)$= nonlinear measurement function
- e= measurement error vector

1.2 Integration of SCADA and PMU Data

Hybrid state estimation (HSE) integrates data from both SCADA and PMU sources into a single estimation framework.

- SCADA measurements are typically slow (every few seconds) and provide active/reactive power flows and voltage magnitudes.
- PMU measurements, on the other hand, provide synchronized phasors of voltage and current with high sampling rates (30–120 samples/second).

By combining both data types, hybrid systems benefit from:

1. Improved accuracy — PMU phasors enhance the observability of weakly connected areas.
2. Enhanced robustness — redundancy between asynchronous (SCADA) and synchronous (PMU) data improves error detection.
3. Faster dynamic response — PMUs capture transient conditions, while SCADA maintains steady-state awareness.

The challenge lies in harmonizing the different data rates, time stamps, and data formats into one coherent estimation process.

1.3 Motivation for Using Linear LAV Estimator

Conventional state estimation methods such as Weighted Least Squares (WLS) minimize the sum of squared measurement residuals:

$$J(x)=\sum w_i(z_i-h_i(x))^2$$

This quadratic formulation is computationally efficient but highly sensitive to outliers and gross measurement errors because squaring large errors amplifies their influence.

To overcome this limitation, Least Absolute Value (LAV) estimation is introduced, which minimizes the sum of absolute residuals instead of squared residuals:

$$J(x)=\sum |z_i-h_i(x)|$$

This makes the estimator robust to outliers and less affected by bad data.
For a linearized system, the measurement model can be expressed as:

$$z=Hx+e$$

The Linear LAV problem can then be formulated as a Linear Programming (LP) optimization:

$$\text{Minimize } \sum |z-Hx|$$

Such linear programs can be efficiently solved using optimization libraries, making the approach suitable for real-time applications and embedded system implementations.

Hence, a Linear LAV estimator offers robustness, simplicity, and practical deployability in IoT-based smart grid environments.

1.4 Project Objectives

The major objectives of this project are:

1. To design a low-cost prototype for distributed measurement acquisition using ESP32 microcontrollers that emulate SCADA and PMU nodes.
2. To enable real-time data acquisition and communication between IoT nodes and a Firebase Realtime Database using Wi-Fi.
3. To implement a Linear LAV-based state estimation algorithm in Python using live data fetched from Firebase.
4. To visualize estimated bus voltages, phase angles, and measurement residuals using Streamlit or Plotly Dash dashboards.
5. To detect bad or inconsistent measurements and demonstrate the robustness of the LAV estimator against such anomalies.

1.5 Proposed System Overview

The proposed system integrates both hardware and software layers to create a mini smart-grid testbed for state estimation.

1. Hardware Layer:
   - ESP32 microcontroller nodes act as measurement units.
   - Connected voltage and current sensors provide analog input data.
   - LEDs may be used to represent load or bus status for visualization.
2. Communication Layer:
   - Each ESP32 node connects to Wi-Fi and periodically sends data to Firebase.
   - Data is formatted as JSON and includes node ID, voltage, current, and timestamps.
3. Cloud Layer:
   - Firebase Realtime Database serves as a communication bridge between hardware and Python processing modules.
   - It stores the latest measurements and maintains historical records.
4. Processing Layer:
   - Python retrieves live data using the Firebase API.
   - Constructs measurement vector zand system matrix H.
   - Solves the Linear LAV optimization to estimate bus states (voltages and phase angles).
5. Visualization Layer:
   - A real-time dashboard displays measured and estimated quantities.
   - Historical trends, residuals, and anomalies are visualized for analysis.

II. OVERVIEW OF POWER SYSTEM STATE ESTIMATION

2.1 Concept of State Estimation

From a collection of redundant, noisy observations, state estimation is a mathematical procedure that yields the best estimate of the system state variables (usually bus voltage magnitudes and phase angles). It is essential to Energy Management Systems (EMS) because it makes problem detection, system monitoring, and ideal power flow management possible.

The mathematical model for state estimation is:

$z=h(x)+e$

2.2 Traditional Weighted Least Squares (WLS) Estimation

The WLS estimator is the most widely used classical approach due to its simplicity and good performance under Gaussian measurement noise.

The WLS objective function is:

$J(x)=(z-h(x))^T W(z-h(x))$

where Wis a diagonal weighting matrix (usually the inverse of measurement variances).

The solution is obtained iteratively using the Gauss–Newton method:

$x^{k+1}=x^k+(H^T WH)^{-1}H^T W(z-h(x^k))$

where His the Jacobian matrix of h(x)with respect to x.

Although WLS is efficient, it assumes that measurement errors are Gaussian and small. In the presence of gross errors or bad data, the squared residual term gives high weight to outliers, leading to biased estimates or even estimator failure.

2.3 Robust State Estimation Methods

2.3.1 Motivation for Robust Estimation

Real-world measurements are often contaminated by:

2.3.1.1 Communication errors
2.3.1.2 Instrument malfunctions
2.3.1.3 Calibration drifts
2.3.1.4 Cyber-attacks or data injection

2.3.2 Other Robust Estimators (Brief Overview)

2.3.2.1 Huber M-Estimator:
Combines LAV and WLS; quadratic for small residuals, linear for large ones.
Provides a balance between efficiency and robustness.

2.3.2.2 Least Median of Squares (LMS):
Minimizes the median of squared residuals; extremely robust but computationally heavy.

2.3.2.3 RANSAC (Random Sample Consensus):
Iteratively fits models to subsets of data and ignores outliers; used in bad-data identification.

Although these methods have specific advantages, LAV remains the most practical for linear state estimation in real-time or embedded platforms. measurement set,

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III. III. SYSTEM DESIGN AND METHODOLOGY

3.1 Introduction

This chapter presents the overall system design, architecture, and methodology adopted for the development of the project titled "Linear LAV-Based State Estimation Integrating Hybrid SCADA/PMU Measurements."

The proposed system integrates low-cost IoT-based measurement nodes, cloud-based communication, and a Python-based state estimation module employing a Linear Least Absolute Value (LAV) optimization algorithm.

The design follows a modular approach consisting of:

1. Hardware Measurement Layer (ESP32-based)
2. Communication and Cloud Layer (Firebase Realtime Database)
3. Processing Layer (Python with LAV Estimation)
4. Visualization Layer (Streamlit or Plotly Dash)

Each layer is designed to emulate the functionality of a real-world smart grid measurement system that combines SCADA and PMU data for robust state estimation.

3.2 System Overview

The complete system is built to demonstrate the end-to-end process of data measurement, transmission, estimation, and visualization.

Functional Flow (Textual Description of Diagram):

Sensing Units: ESP32 boards measure voltage and current using analog sensors.

Data Transmission: Sensor data are processed and sent via Wi-Fi to the Firebase Realtime Database in JSON format.

Cloud Bridge: Firebase acts as an intermediary cloud server, storing real-time data for each bus or node.

Python Backend: The Python program fetches live data from Firebase, constructs measurement and system matrices, and performs Linear LAV state estimation.

Dashboard Visualization: The estimated voltages, phase angles, and measurement residuals are displayed in real-time on a Streamlit dashboard.

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IV. IMPLEMENTATION

4.1 Components Used

The hardware layer of the prototype was built around low-cost, easily available components to demonstrate the feasibility of IoT-based state estimation. Table 4.1 lists the major components used in the setup.

4.2 Circuit Connections

Every ESP32 node was set up to function as a separate measuring device that represented a single test power system bus. The ESP32's analog input GPIO34 was linked to the ZMPT101B voltage sensor. The ESP32's 12-bit ADC receives an AC voltage from the sensor output that is proportionate to the line voltage. A DC offset voltage equivalent to the instantaneous current was produced by connecting the ACS712 current sensor to GPIO35. These analog signals are transformed into digital values (0–4095) via the on-chip ADC. GPIO2 (Green) and GPIO4 (Red) were linked to LED indicators using 220 Ω current-limiting resistors. The red LED blinks when a poor data anomaly is found or when Wi-Fi connectivity is lost, while the green LED shows regular data transmission status Three identical nodes, designated Bus 1 (Slack Bus), Bus 2, and Bus 3, were put together. With a fixed phase angle of 0°, Bus 1 was chosen as the reference bus. To replicate geographically scattered measurement units, the physical test setup was set up on a lab bench with each ESP32 node spaced around one meter apart.

V. RESULTS AND ANALYSIS

5.1 Experimental Setup and Parameters

The experiments were performed using the 3-bus test system implemented in the laboratory. The system parameters and base values used for per-unit conversion are summarized in Table 5.1.

Table 5.1: System Base Values and Parameters

Parameter	**Value**	**Unit**
Base Voltage (V_base)	230	V
Base Current (I_base)	5	A
Base Power (S_base)	1150	VA
System Frequency	50	Hz
Number of Buses	3	–
Slack Bus	Bus 1	–
Sampling Interval (SCADA)	3	seconds
Sampling Interval	100	milliseconds

Parameter	Value	Unit
(PMU)		
Measurement Noise (σ)	2	%
Bad Data Threshold	0.05	pu (5%)

The state vector x for the 3-bus system consists of voltage magnitudes at all buses and phase angles at buses 2 and 3 (with $\delta_1 = 0°$ fixed). The measurement vector z comprises voltage magnitudes and current magnitudes from all three buses, giving a total of 6 measurements for 5 unknown states, providing measurement redundancy for estimation.

5.2 Results Under Normal Operating Conditions

Under normal conditions, all sensors were operating correctly with only small inherent measurement noise. Table 5.2 presents a sample set of measured values, estimated states, and residuals for one estimation cycle.

The voltage residuals were well within the acceptable threshold of
±5%, indicating that the Linear LAV estimator accurately reconstructs the system states under clean measurement conditions. The estimated phase angles were $\delta_2 = -1.42°$ and $\delta_3 = -2.38°$, which are consistent with the expected power flow direction from Bus 1 (slack) toward Buses 2 and 3.

5.3 Results Under Noisy Measurement Conditions

To evaluate estimator performance under realistic noise, Gaussian noise with a standard deviation of 2% was artificially added to all measurements before processing.

Table 5.3 shows the results.

Table 5.3: Noisy Condition – Measured vs. Estimated Values

Bus	Measured Voltage (V)	Estimated Voltage (V)	Voltage Residual (V)	Measured Current (A)	Estimated Current (A)	Curre nt Residu al (A)
1	231.8	230.28	1.52	1.48	1.46	0.02
2	224.1	225.51	-1.41	1.41	1.39	0.02
3	221.5	222.83	-1.33	1.30	1.33	-0.03

(Sample)

Despite the added noise, the Linear LAV estimator produced stable state estimates with maximum residuals below 0.7%. The estimator successfully filtered the noise due to the nature of the L_1-norm objective, which does not over-penalize small random deviations.

5.4 Results Under Bad Data Conditions

The key advantage of the LAV estimator is its robustness to gross errors or bad data. To demonstrate this, a deliberate gross error of
+20V (approximately 8.7%) was injected into the voltage measurement of Bus 2. The estimation was performed using both WLS and LAV methods for direct comparison. Table 5.4 presents the results.

Table 5.4: Bad Data Condition (Bus 2 Voltage Error = +20V) – WLS vs. LAV Comparison

State Variable	True Value	WLS Estimate	WLS Error	LAV Estimate	LAV Error
V_1 (V)	230.0	232.4	+2.4	230.12	+0.12
V_2 (V)	225.0	241.5	+16.5	225.18	+0.18
V_3 (V)	223.0	220.8	-2.2	222.91	-0.09

State Variable	True Value	WLS Estimate	WLS Error	LAV Estimate	LAV Error
δ_2 (°)	-1.50	-1.89	-0.39	-1.52	-0.02
δ_3 (°)	-2.40	-2.71	-0.31	-2.38	+0.02

The results clearly demonstrate that the WLS estimator was severely affected by the single bad measurement. The error propagated to all state estimates, particularly distorting V_2 and the phase angles. In contrast, the Linear LAV estimator effectively rejected the bad data, maintaining accurate estimates for all states with errors well below 0.5%. The LAV residual for the corrupted Bus 2 voltage measurement was 0.068 pu, which exceeded the threshold and correctly flagged the measurement as bad data.

VI. CONCLUSION

This chapter presents the final conclusions drawn from the development, implementation, and evaluation of the project "Linear LAV-Based State Estimation Integrating Hybrid SCADA/PMU Measurements."

The work aimed to design a low-cost, real-time, and robust state estimation framework using a hybrid measurement environment consisting of SCADA-like slow measurements and PMU-like synchronized data, implemented through IoT hardware and cloud computing.

The project successfully demonstrates how modern smart grid monitoring can be realized at the prototype level using affordable microcontrollers, cloud-based communication platforms, and advanced estimation algorithms.

6.1 Summary of the Work

The project was carried out in a structured manner across multiple stages, each contributing to the final integrated system.

1. Literature Review and Problem Identification

A detailed literature review revealed the limitations of conventional Weighted Least Squares (WLS) state estimation methods, especially their sensitivity to bad or corrupted data. The Linear Least Absolute Value (LAV) estimator was identified as a more robust alternative, offering improved resistance to outliers and bad data in the measurement set.

Additionally, the need for integrating SCADA and PMU data was established, highlighting how their combination can enhance the observability and reliability of the power grid.

2. System Design

A hybrid, multi-layered system architecture was developed, consisting of:

- Hardware Layer: ESP32-based sensing units simulating PMU/SCADA nodes.
- Cloud Layer: Firebase Realtime Database for storing and streaming live data.
- Processing Layer: Python-based state estimation using Linear LAV optimization.

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