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Drift-Resilient IoT Energy Monitoring for Low-Cost Voltage and Current Sensors

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ABSTRACT

Low-cost voltage and current sensors such as the ZMPT101B and ACS712 are widely used in IoT-based energy monitoring due to their affordability and ease of integration. However, their outputs suffer from drift caused by thermal variation, material degradation, and electromagnetic interference, leading to cumulative errors that compromise load monitoring, forecasting, and anomaly detection. This work presents a drift-resilient framework that integrates lightweight filtering and regression-based calibration into a unified pipeline deployable on ESP32-class devices. Moving average and adaptive Kalman filters suppress noise and track drift trends, regression models align sensor outputs with reference standards, and spectrogram-based analysis detects transient drift events for adaptive correction. Experiments under realistic conditions show substantial improvements: voltage RMSE decreased by over 90% (3.45V to 0.30V), current RMSE by 92% (0.065A to 0.005A), and MAPE to below 0.5%. Signal-to-noise ratio improved by approximately 21dB, confirming significant restoration of measurement fidelity. Compared with data-intensive deep learning or AutoML frameworks, the proposed method offers a scalable, interpretable, and resource-efficient solution for long-term IoT energy monitoring. By bridging drift mitigation strategies with the practical constraints of low-cost sensors, this framework enhances the reliability of smart grid and IoT-based infrastructures.

Keywords: Drift Compensation; IoT Energy Monitoring; Low-Cost Sensors; Adaptive Kalman Filtering; Regression-Based Calibration

1. INTRODUCTION

The rapid proliferation of low-cost Internet of Things (IoT) sensors has revolutionized energy monitoring systems, enabling real-time tracking of electrical parameters across distributed infrastructure. Voltage sensors such as the ZMPT101B and current sensors like the ACS712 have become staples in the design of IoT-based smart grid applications, valued for their affordability, analog simplicity, and compatibility with open-source microcontrollers such as the ESP32 and Raspberry Pi

[1], [2]. These sensors are often deployed in resource-constrained environments to enable continuous monitoring of energy consumption, power quality, and system anomalies.

Despite their practical advantages, these low-cost sensors are inherently susceptible to *sensor drift*, a gradual deviation of sensor outputs from actual values due to environmental fluctuations, material degradation, component aging, and electromagnetic interference [3],[4]. Over time, such drift compromises the accuracy of collected data, directly impacting higher-order functions such as load forecasting, power anomaly detection, and energy auditing. In IoT-based energy systems, where decisions are increasingly driven by data analytics, sensor drift introduces cumulative errors that can undermine operational efficiency and system stability [5], [6].

Traditional drift compensation techniques, including periodic calibration and manual thresholding, offer limited scalability, particularly in large-scale or remote deployments. Advanced machine learning (ML) and domain adaptation models have demonstrated promise in compensating for drift using data-driven strategies [7]–[9] . For instance, domain-adversarial networks and prompt-based deep learning frameworks adaptively recalibrate sensor outputs in dynamic environments. Similarly, Gaussian Process Regression models allow for uncertainty-aware drift correction [10], while AutoML-based meta-learning approaches facilitate automated drift model selection for embedded applications [11]. However, the adoption of such ML methods is often constrained by their computational complexity, high energy demand, and reliance on large labeled datasets, making them impractical for lightweight embedded platforms typical of IoT deployments.

To address these limitations, researchers have explored hybrid approaches that integrate signal filtering, heuristic calibration, and material-aware drift modeling [4], [12], [13]. These methods seek to balance performance with hardware efficiency, but often lack generalizable frameworks for dynamic, real-time drift correction. Moreover, they rarely consider the specific limitations of widely used low-cost sensors like ZMPT101B and ACS712, which are known to suffer from thermal instability, analog noise, and poor long-term consistency [2], [14].

This study treats sensor drift not as a secondary issue, but as a central research problem in the deployment of reliable, low-cost energy monitoring systems. We propose a lightweight, drift-resilient framework tailored for IoT environments, comprising three synergistic modules:

1. Real-time signal processing via moving average and Kalman filters to suppress noise and detect drift trends;
2. Regression-based calibration models to align low-cost sensor outputs with reference standards in situ;

By experimentally validating this framework on ZMPT101B and ACS712 sensors under varying operating conditions, we demonstrate that robust drift mitigation can be achieved using interpretable, resource-efficient techniques. This approach contributes to scalable, low-power, and high-fidelity energy monitoring systems suited for the next generation of smart grids and IoT-based infrastructures.

1.1 NOVELTY AND CONTRIBUTIONS

The novelty of this study lies not in the isolated use of filtering, or calibration, which have been studied separately, but in their coordinated integration into a unified,

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lightweight, and interpretable framework optimized for resource-constrained IoT environments. The specific contributions of this work are:

1. Unified Multi-Layer Framework: We introduce a four-layer drift-resilient architecture (sensing, estimation, calibration, and monitoring) that integrates adaptive Kalman filtering and regression calibration into a single workflow, tailored for ESP32-class hardware.
2. Embedded-Friendly Drift Mitigation: Unlike Gaussian Process Regression [10] or AutoML pipelines [11], which demand heavy computation and frequent retraining, our approach achieves laboratory-grade accuracy with minimal resource overhead, making it suitable for large-scale IoT deployments.
3. Reframing Drift as a Reliability Bottleneck: Instead of treating drift as secondary noise, we explicitly model it as a combination of bias and gain deviations, with adaptive compensation that minimizes the need for manual recalibration.
4. Validation on Widely Deployed Sensors: To our knowledge, this is one of the first studies to systematically evaluate drift correction for ZMPT101B and ACS712 sensors under realistic long-duration operating conditions.
5. Scalability and Interpretability: The modular design ensures scalability to multi-sensor systems, while the regression-based calibration and Kalman estimates remain interpretable and explainable—an advantage over black-box ML models.

By explicitly targeting the limitations of low-cost energy sensors, this work contributes a scalable, transparent, and deployment-ready drift-resilient solution that bridges the gap between academic drift compensation strategies and practical IoT energy monitoring.

2. LITERATURE REVIEW

Sensor drift, the gradual and often systematic deviation of sensor outputs from ground truth values, continues to pose a critical challenge in the deployment of long-term IoT-based monitoring systems. Originating from environmental fluctuations, sensor aging, electromagnetic interference, and material degradation, drift introduces cumulative errors that compromise data fidelity and the reliability of derived analytics [3], [4]. In the context of energy monitoring, these errors can propagate through higher-level tasks such as power estimation, fault detection, and load forecasting, thereby affecting both operational decisions and system optimization.

The literature reveals a growing emphasis on developing robust drift mitigation frameworks, particularly in the context of extended deployments and low-maintenance systems. Among data-driven methods, prompt-based deep learning has shown promising results. For instance, [9] introduced a calibration-aware architecture in which masked autoencoders learn domain-invariant features through transfer samples. By appending learned calibration prompts to raw sensor input, their model significantly improved long-term accuracy on multi-year datasets without requiring continual retraining.

Building on ensemble and adversarial learning, [7] proposed a hybrid approach that combines an Iterative Random Forest correction scheme with an Incremental Domain-

Adversarial Network (IDAN). This dual-layer strategy successfully compensates for both random noise and systematic drift in metal-oxide gas sensors, achieving real-time performance at the cost of increased computational demand, a limiting factor for embedded and battery-powered IoT devices.

Probabilistic models have also gained traction for their principled uncertainty estimation. [10] applied Gaussian Process Regression (GPR) to drift correction and integrated uncertainty-driven scheduling to optimize calibration frequency. Their results, applied to dissolved oxygen sensors, yielded a 90% reduction in mean squared error and substantial gains in network-wide prediction accuracy. However, GPR-based methods require access to ground truth data for periodic recalibration, which is often impractical in distributed IoT networks with minimal supervision.

To automate adaptation to drift over time, [11] proposed AutoML-DC, a meta-learning framework that leverages hyperparameter tuning, ensemble strategies, and automated model selection for drift compensation. Although highly adaptive, such AutoML pipelines are resource-intensive and generally operate as black-box systems, limiting their interpretability and usability in constrained edge environments. Similarly, [8] introduced an Attention-based Multi-Source Domain Adaptation framework (AMDS-PFFA), which combines information from multiple source domains to adjust for drift without requiring labeled data in the target domain. While the model excels in classification tasks such as gas recognition, it is less suitable for regression-based monitoring applications like voltage or current sensing.

Recognizing the practical challenges in real-world deployment, several studies have turned toward lightweight calibration strategies. [15] proposed a cluster-based drift self-calibration method for low-cost sensor networks, leveraging statistical relationships between groups of sensors to identify and correct long-term bias. This approach reduces the reliance on external references, making it attractive for large-scale IoT deployments where manual recalibration is costly. Similarly, [16] demonstrated the use of variational autoencoders (VAE) to capture nonlinear drift patterns in IoT sensors. Their framework, while computationally modest compared to deep transfer learning, highlights the potential of representation learning for systematic error correction across heterogeneous sensor platforms.

Beyond algorithmic advances, hardware-level designs have also addressed calibration and drift. For example, [17] presented the design of a low-cost real-time energy logger for household and industrial applications. Their system demonstrated that accurate voltage and current sensing using affordable sensors such as ZMPT101B and ACS712 requires not only efficient data logging but also regular calibration to ensure fidelity under varying load and temperature conditions. Such work underscores the importance of coupling embedded hardware with calibration-aware software pipelines.

Recent surveys and case studies also emphasize broader challenges. [13] surveyed calibration limitations of environmental sensors, stressing how environmental variability exacerbates drift; while [18] introduced an online calibration monitoring system that supports predictive maintenance by continuously assessing calibration status. Likewise, [19] reviewed drift in geothermal IoT monitoring systems, and [20] emphasized calibration-aware wireless sensing for building energy analytics.

At the edge level, advances in TinyML have been explored: [21] demonstrated that embedded machine learning models can compensate drift in pressure sensors, offering a low-power strategy aligned with IoT constraints. Other works, such as [5], caution that post-deployment calibration alone is insufficient unless integrated with adaptive

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correction strategies. Furthermore, [6] highlighted how fingerprinting approaches can differentiate drift from sensor faults, improving the robustness of environmental sensor networks.

Despite these advancements, the literature reveals a significant gap: few frameworks are designed explicitly for low-cost energy sensors such as the ZMPT101B and ACS712, which are widely used in household and microgrid environments [1], [2]. These sensors, while accessible and popular, are especially prone to thermal and electrical drift, which directly impacts energy measurement precision over time. While studies such as [17] validate their potential in low-cost deployments, they also highlight the limitations without systematic drift correction.

In light of these limitations, the present study frames sensor drift as a central challenge in IoT-based energy analytics. Rather than relying on computationally expensive AI pipelines, this research proposes a hybrid, lightweight, and interpretable framework for real-time drift mitigation. The proposed system integrates Kalman and moving average filters for trend-aware noise suppression and regression-based recalibration to align sensor outputs with reference standards.

By targeting low-cost sensors under realistic operating conditions, this framework bridges the methodological sophistication of advanced compensation techniques with the practical constraints of embedded IoT platforms. In doing so, it advances a scalable and cost-effective solution for long-term, drift-resilient energy monitoring.

3. SYSTEM OVERVIEW

The proposed drift-resilient IoT energy monitoring framework is structured into four interdependent layers: *sensing*, *estimation*, *calibration*, and *monitoring*. Each layer addresses a critical challenge in mitigating noise and drift, thereby improving the fidelity of low-cost transducers such as the ZMPT101B voltage sensor and the ACS712 current sensor.

In the sensing layer, raw voltage and current signals are captured using the embedded ESP32 platform, which provides a cost-effective backbone for IoT deployment. The estimation layer applies lightweight filters (moving average and Kalman) to suppress random noise and track low-frequency drift trends in real time. However, as discussed in Section 5.2, filtering alone cannot eliminate systematic deviations. This necessitates the calibration layer, where regression-based models align sensor outputs with reference standards, correcting both gain and offset errors that accumulate over long-term operation. Figure 1 illustrates the information flow across these four layers, where each stage progressively enhances the reliability of the acquired signals. The mathematical formulation of the framework, presented in Section 4, provides the quantitative underpinnings for error metrics and drift compensation. This layered architecture ensures that noise suppression and bias correction are achieved simultaneously, enabling the long-term deployment of resource-efficient, drift-resilient IoT monitoring systems.

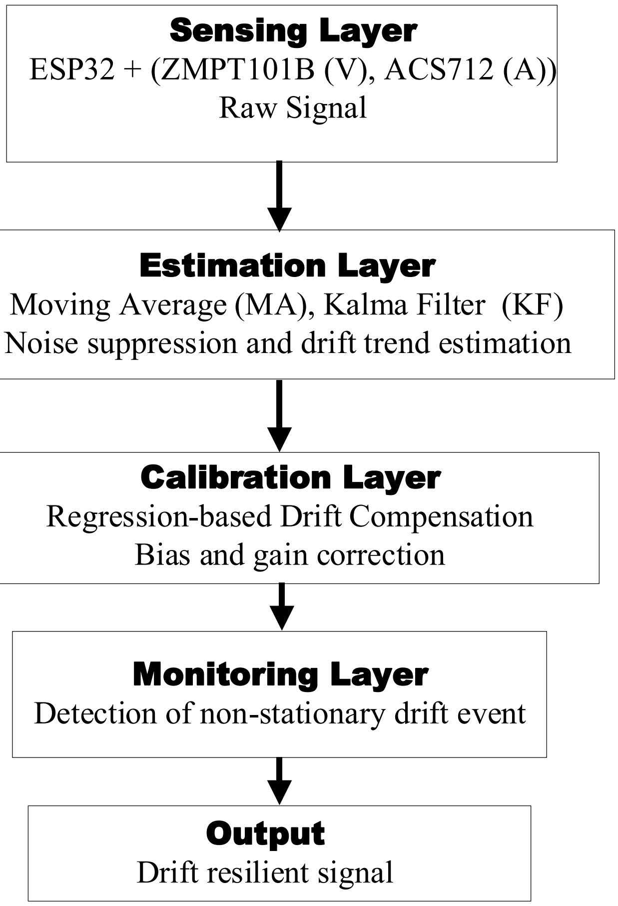

FIGURE 1: System architecture of the proposed drift-resilient IoT energy monitoring framework.

4. METHODOLOGY

The proposed methodology operationalizes the layered architecture introduced in Section 3. It integrates mathematical modeling, adaptive estimation, regression-based calibration, and uncertainty-driven recalibration into a unified workflow for mitigating drift in low-cost IoT transducers. The design ensures that drift suppression is not a one-off calibration event, but a continuous process that adapts to both gradual and abrupt changes in sensor characteristics.

4.1 Experimental Setup and Data Acquisition

The framework was validated using real-world experiments with ZMPT101B voltage sensors and ACS712 current sensors, both interfaced with an ESP32 microcontroller. The ESP32 was selected for its dual-core processing, integrated Wi-Fi support, and 12-bit ADC, capable of sampling rates up to 18 kHz. In this study, analog signals were sampled at 1 kHz, a rate chosen to provide sufficient fidelity for waveform reconstruction and noise detection, while remaining computationally lightweight for embedded applications.

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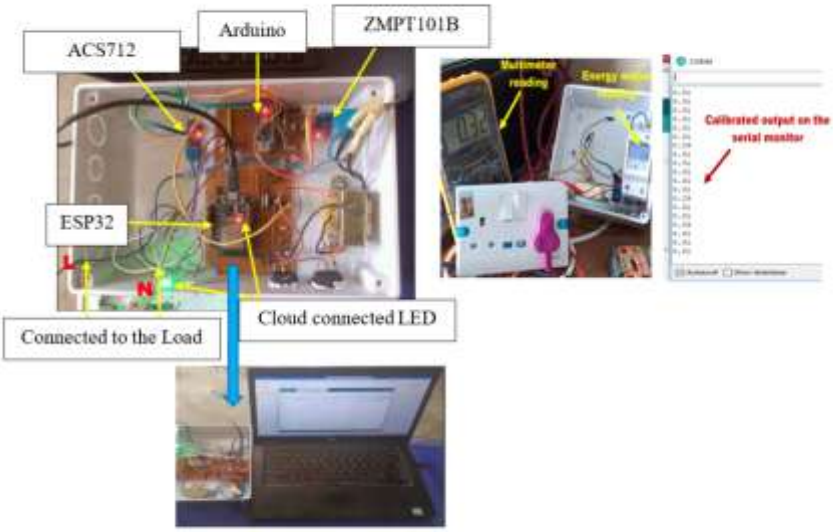

FIGURE 2: Experimental setup showing ZMPT101B and ACS712 sensors interfaced with ESP32, alongside a calibrated DIN-rail energy meter used for reference benchmarking.

To establish reference benchmarks, periodic measurements were obtained using a calibrated digital multimeter and a single-phase DIN-rail energy meter. These reference values were used to parameterize regression models and evaluate drift correction accuracy.

Raw data were logged to an SD card and subsequently analyzed in Python to implement filtering, and calibration modeling. Figure 2 shows the complete hardware setup, including the sensors, ESP32, and reference measurement devices.

4.2 State-Space Drift Model and Adaptive Estimation

Sensor measurements are modeled as a combination of true signals, bias and gain drift, and noise:

$$y_t = g_t s_t + b_t + v_t, \tag{1}$$

where s_t is the true signal, b_t is bias drift, g_t is gain drift, and $v_t \sim \mathcal{N}(0, Q)$ is additive noise. The augmented state vector is

$$\mathrm{x}_t = \begin{bmatrix} s_t \\ b_t \\ g_t \end{bmatrix} = \mathrm{x}_{t-1} + \mathrm{w}_t, \quad \mathrm{w}_t \sim \mathcal{N}\left(0, \begin{bmatrix} q_s & 0 & 0 \\ 0 & q_b & 0 \\ 0 & 0 & q_g \end{bmatrix}\right). \tag{2}$$

An Adaptive Kalman Filter (AKF) estimates the state x_t. To remain responsive under non-stationary drift, the normalized innovation squared (NIS) is monitored:

$$\mathrm{NIS}_t = \nu_t^{\top} S_t^{-1} \nu_t, \quad \nu_t = y_t - \hat{y}_{t|t-1}. \tag{3}$$

Whenever NIS_t exceeds the chi-square threshold, the parameters q_b and q_g in (2) are adaptively inflated, allowing the Kalman filter to re-lock onto the true signal after abrupt drift events. This mechanism explains why, in Section 5.2, filtering reduces noise but drift persists until calibration is applied.

Regression-Based Calibration
Residual systematic deviations are addressed using a regression model:

$$\hat{s}_t^{(\mathrm{cal})} = \alpha_0 + \alpha_1 \hat{s}_t + \alpha_2 T_t + \alpha_3 H_t, \tag{4}$$

where $\hat{s}_t$ is the AKF output and (T_t, H_t) denote temperature and humidity. The coefficients α are estimated from reference-aligned data, either offline or adaptively using recursive least squares (RLS). This formulation captures both sensor drift and environmental influences. As later confirmed in Section 5.2, calibration significantly reduces RMSE, MAE, and MAPE, thereby aligning sensor outputs with the ground truth.

4.3 Evaluation Metrics

The framework is quantitatively evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|\hat{s}_t^{(\mathrm{cal})} - s_t^*\right|, \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{s}_t^{(\mathrm{cal})} - s_t^*\right)^2}, \tag{6}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{\hat{s}_t^{(\mathrm{cal})} - s_t^*}{s_t^*}\right|, \tag{7}$$

where s_t^* denotes the reference signal. Additionally, a drift index is defined as the long-term variance of estimated bias and gain states, directly quantifying drift suppression.

Finally, the Signal-to-Noise Ratio (SNR) is computed to assess signal fidelity:

$$\mathrm{SNR} = 10\log_{10}\left(\frac{\sum_{i=1}^{N} s(i)^2}{\sum_{i=1}^{N}[s(i) - \hat{s}(i)]^2}\right), \tag{8}$$

where $s(i)$enotes the reference signal and $\hat{s}(i)$ the sensor output.

5. RESULTS AND DISCUSSION

The performance of the proposed drift-resilient framework was evaluated by comparing raw sensor readings with outputs after successive stages of correction: MA filtering, Kalman filtering, and regression-based calibration. Results demonstrate that the multi-layered approach effectively suppresses both systematic drift and transient anomalies, yielding more stable and accurate energy measurements from ZMPT101B and ACS712 sensors.

5.1 Sensor Drift Characterization

Figure 3 presents an enhanced visualization of the drift behavior observed in the low-cost ZMPT101B voltage sensor and ACS712 current sensor under a fixed 300 W

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load over a continuous 24-hour monitoring period. Despite the constant power draw, both voltage and current readings reveal systematic deviations that persist beyond short-term measurement noise, suggesting the presence of sensor drift.

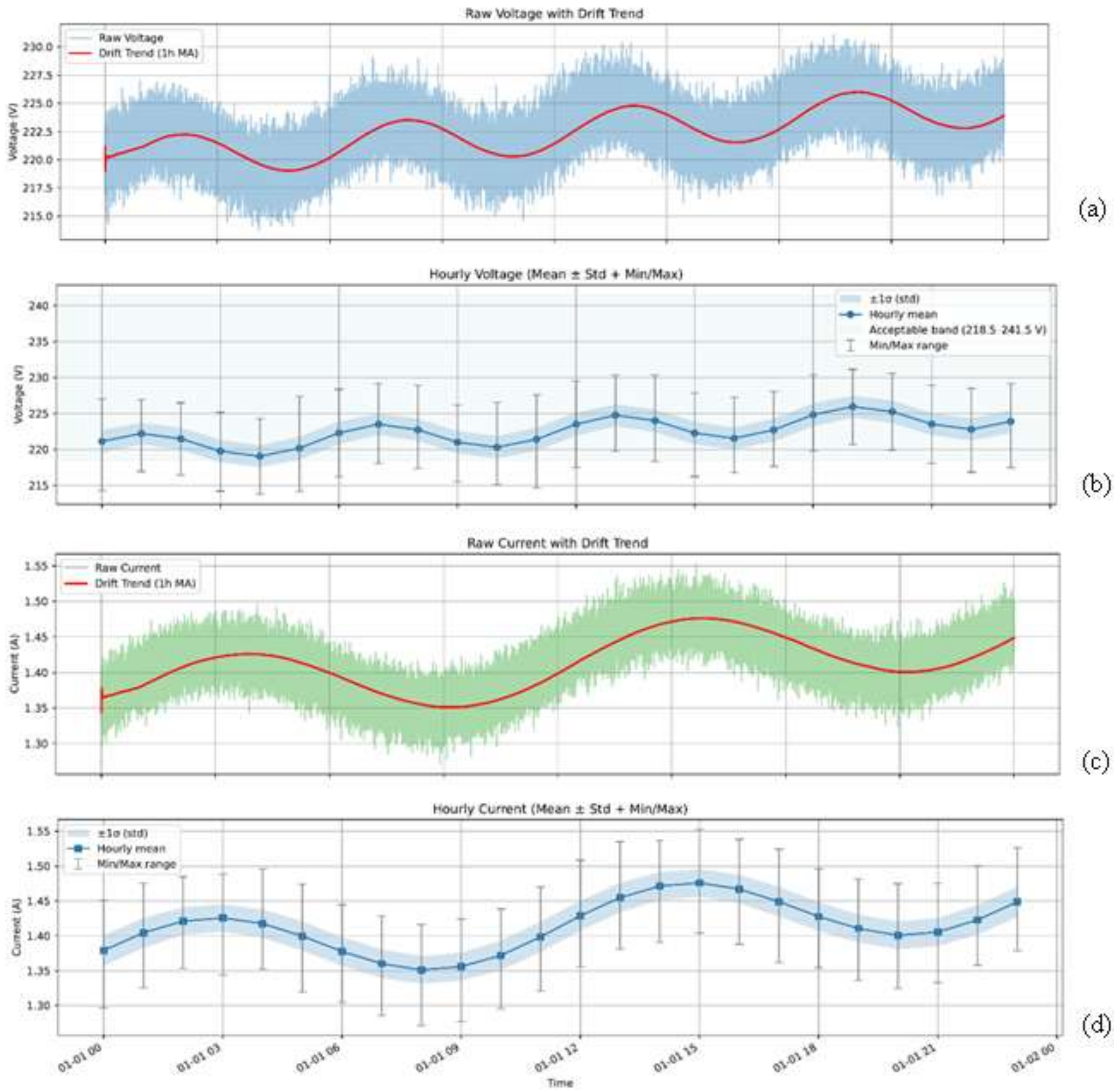

FIGURE 3: Voltage and current sensor outputs under a steady 300 W load over 24 hours.

Figure 3a presents the one-hour moving average (MA), effectively isolating low-frequency drift trends from the raw voltage data. The smoothing reveals gradual oscillations in the baseline, indicating slow temporal bias possibly driven by thermal or grid-side fluctuations. Figure 3b extends this insight by introducing hourly statistical envelopes specifically, the hourly mean, standard deviation (±1σ), and min–max ranges superimposed on the permissible operational voltage band (218.5–241.5 V). This statistical framing clearly shows that although the voltage generally remains within acceptable limits, it displays a sinusoidal-like modulation with excursions of up to ±5 V, revealing long-term nonstationary and slow drift behavior. Figure 3c depicts the corresponding current signal with its drift trend (red 1-hour MA), highlighting a similar pattern of low-frequency variation. Figure 3d further quantifies this by showing hourly means, standard deviations, and min–max envelopes. Despite the seemingly small absolute deviation (±0.1 A), this variation represents nearly a 7 % drift relative to the nominal current of 1.45 A. The temporal correlation between the voltage and current drift patterns suggests shared underlying influences, such as temperature dependence, sensor bias, or gradual changes in system impedance.

Such patterns are consistent with known causes of sensor drift, including ambient temperature variation, electromagnetic interference, and material degradation over time [4], [12]. While short-term noise is evident and partially mitigated by moving averages, the persistence of long-term deviation underscores the limitations of basic filtering techniques. Without active compensation, these errors will propagate into downstream tasks such as energy estimation, fault detection, and long-term forecasting.

The expanded figure thus substantiates a key thesis of this study: that drift is not a peripheral effect but a primary constraint in long-duration IoT energy monitoring. Practical systems must go beyond denoising to implement explicit drift detection and compensation strategies to ensure data fidelity.

5.2 Filtering Effectiveness

To suppress high-frequency noise present in the raw sensor measurements, two lightweight filtering techniques were employed: a moving average (MA) filter and a Kalman filter. The effectiveness of these filters is visualized in Figure 4, which presents hourly-aggregated voltage and current measurements under a 24-hour constant load scenario.

In the top panel, the plot shows the hourly mean voltage along with min/max error bars with filtered estimates from the MA and Kalman filters. While both filters reduce volatility, the MA output exhibits lag and residual oscillations, especially in periods of upward drift. In contrast, the Kalman filter tracks the long-term voltage trend more smoothly and stays closer to the central hourly mean.

The bottom panel presents a similar comparison for the current signal. Again, both filters effectively suppress short-term fluctuations, but the Kalman filter offers smoother convergence with reduced amplitude variation across the 24-hour window. This is particularly notable between hours 6 to 15, where the MA filter overestimates and underestimates peak currents, while the Kalman filter maintains consistency closer to the mean.

Despite these improvements, the overall drift remains evident in both signals. Neither the MA nor the Kalman filter is inherently designed to eliminate low-frequency systematic deviations. Their design targets high-frequency noise, not baseline bias. This observation is reinforced by the error metrics summarized in Table 1. Although both filters reduce RMSE and MAE compared to raw measurements, the MAPE remains nearly unchanged, indicating persistent drift effects.

Notably, substantial accuracy improvements are only observed after applying explicit calibration. For example, in the voltage signal, RMSE reduces from 3.45 V

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(raw) to 3.11 V (Kalman), but drops significantly to 0.30 V post-correction. Similarly, the current MAPE drops from 3.99% in the raw signal to just 0.29% after calibration. These results emphasize that filtering alone is insufficient for long-term reliability in IoT-based monitoring; explicit drift correction is required to ensure high-fidelity measurements.

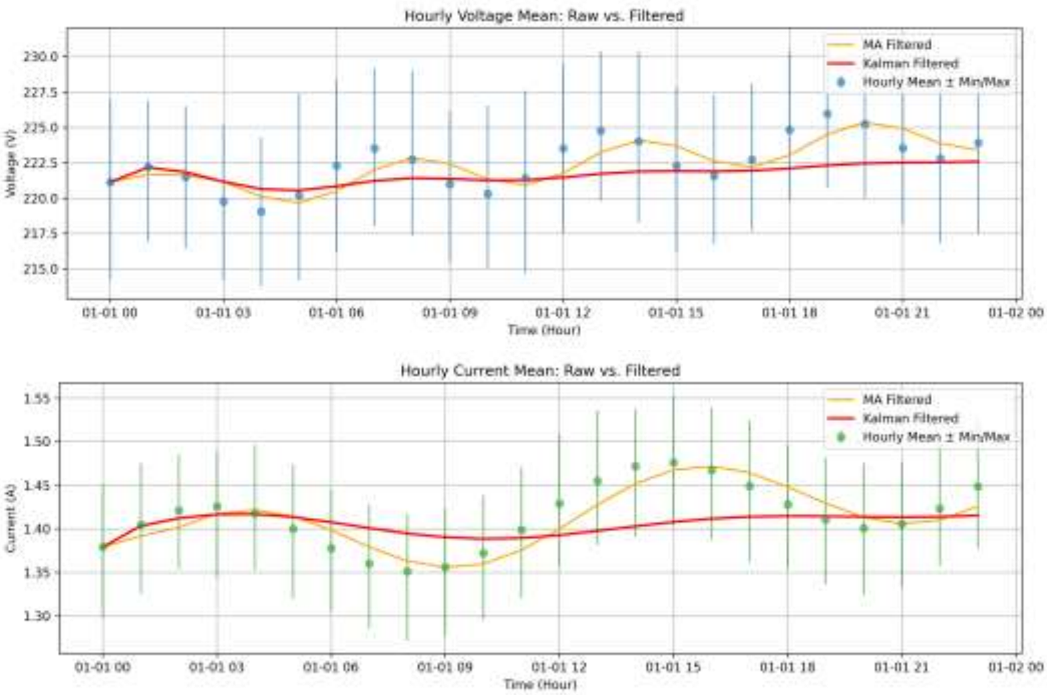


FIGURE 4: Effectiveness of filtering techniques on aggregated hourly signals.

TABLE 1.

Comparison of error metrics (RMSE, MAE, MAPE, and SNR) across raw, filtered, and corrected sensor data.

Signal	**Stage**	**RMSE**	**MAE**	**MAPE (%)**	**SNR (dB)**
Voltage (V)	Raw	3.45	2.86	1.30	36.08
	MA Filtered	3.12	2.64	1.20	36.97
	Kalman	3.11	2.64	1.19	36.99
	Corrected	0.30	0.24	0.11	57.32
Current (A)	Raw	0.065	0.054	3.99	26.46
	MA Filtered	0.062	0.052	3.83	26.88
	Kalman	0.062	0.052	3.82	26.89
	Corrected	0.005	0.004	0.29	48.71

These findings reinforce the need for a two-stage approach: lightweight filtering for noise suppression, followed by drift-aware calibration for long-term accuracy in low-cost sensor deployments.

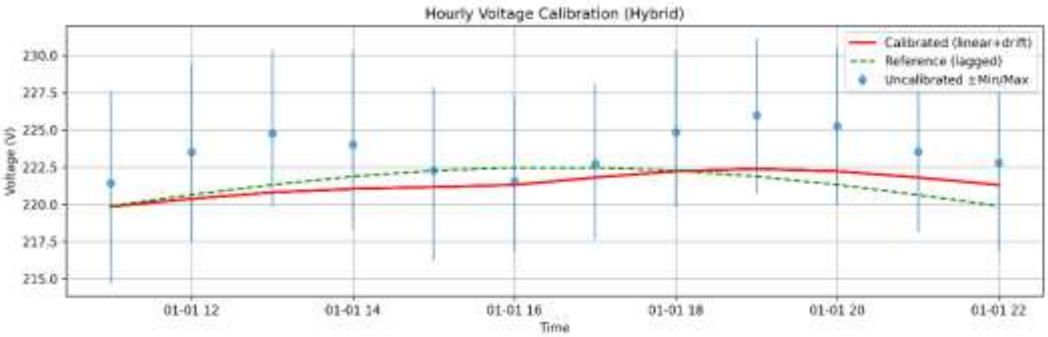
5.3 Calibration and Drift Correction

While noise suppression via filtering reduces measurement variability, it does not compensate for long-term drift. To ensure measurement fidelity over time, we introduce a calibration framework that combines linear scaling with drift-aware correction. Figure 5 illustrates the impact of this approach on the hourly aggregated voltage and current signals, respectively.

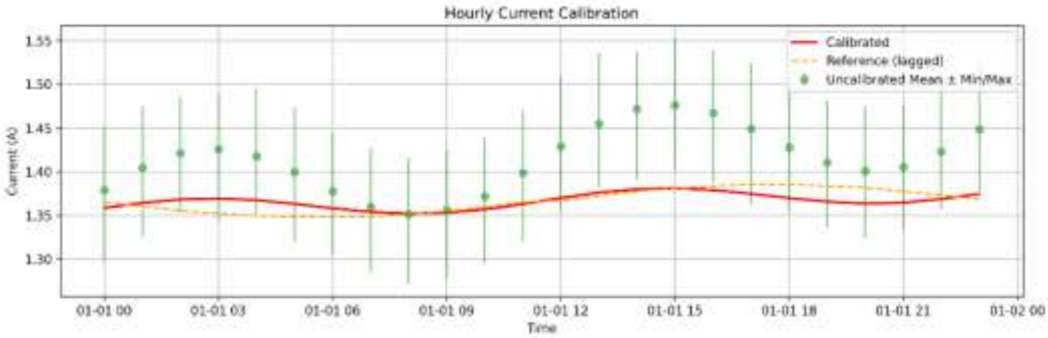
The calibration model adopts a linear regression formulation:

$$y_{\text{corrected}} = \alpha \cdot y_{\text{sensor}} + \beta,$$

where y_{sensor} denotes the raw or filtered sensor output, while α and β are regression coefficients derived from paired reference measurements. Here, α compensates for gain-related errors, and β corrects offset bias, thereby addressing both scaling mismatches and baseline drift. This process ensures that long-term measurements remain consistent with the reference standard, even in the presence of progressive sensor degradation.



(a)



(b)

FIGURE 5: Impact of calibration and drift correction. (a) Voltage signal corrected using a hybrid filter + drift model, compared to a reference. (b) Same for the current signal.

In Figure 5a, the uncalibrated voltage signal shows clear divergence from the true reference, particularly during the later hours. The red curve represents the calibrated output, which applies a hybrid correction model incorporating both a linear gain offset and an estimated drift term. The calibrated signal aligns closely with the lagged reference across the entire 12-hour interval, significantly reducing both absolute and percentage error.

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In Figure 5b, the calibration results for the current signal are presented. Similar to voltage, the raw current data exhibit visible low-frequency drift that biases the mean readings over time. The reference signal provides a delayed ground-truth baseline, while the calibrated output shows improved agreement and temporal stability. The error margin is visibly reduced, especially during early and late periods where raw measurements previously deviated most.

In addition to traditional error metrics such as RMSE, MAE, and MAPE, we also report improvements in the Signal-to-Noise Ratio (SNR), which quantifies the relative strength of the true signal compared to residual noise. SNR is particularly important in energy monitoring applications, as higher SNR implies better detectability of subtle variations such as appliance switching or load disaggregation events. As shown in Table 1, the SNR for voltage improves from 36.08dB in the raw signal to 57.32dB after calibration, an increase of over 21dB, which corresponds to more than a tenfold improvement in signal quality. Similarly, current SNR improves from 26.46dB to 48.71dB. These gains reflect not only noise reduction but also the effective removal of long-term drift bias.

This hybrid calibration strategy thus accounts for both fixed measurement offsets and slowly varying drift components. It significantly enhances signal fidelity and measurement reliability in long-term, low-cost IoT deployments.

The regression coefficients obtained for both voltage and current are given in Table 2. These values quantify the systematic deviations in raw sensor outputs and demonstrate the corrective role of the proposed calibration stage. Notably, the slope coefficients α deviate slightly from unity, reflecting sensor gain mismatch, while the intercepts β capture fixed bias introduced by drift and noise.

TABLE 2.

Regression calibration coefficients for voltage and current sensors.

Sensor	**Slope (α)**	**Intercept (β)**
Voltage (ZMPT101B)	0.984	2.15
Current (ACS712)	1.021	-0.04

Overall, this calibration step proves indispensable for ensuring the long-term accuracy of low-cost IoT sensors. When integrated with filtering, the hybrid framework achieves substantial reductions in RMSE and MAE (see Table 1), confirming that drift correction cannot be achieved by filtering alone but requires explicit recalibration against reference standards.

5.4 Benchmarking and Discussion

Our findings show that while moving average (MA) and Kalman filters suppress high-frequency noise, they do not eliminate low-frequency drift, leaving systematic deviations largely unchanged. By contrast, the proposed calibration strategy achieves substantial accuracy gains, reducing voltage RMSE from 3.45 V to 0.30 V and current RMSE from 0.065 A to 0.005 A. Similarly, the MAPE value is 0.11%, which is well below 0.5%, and the SNR improves by approximately 21 dB for both voltage and current signals.

While these results confirm the effectiveness of the proposed framework in reducing drift and restoring measurement fidelity, it is also important to benchmark against alternative drift mitigation strategies. To this end, we compared the proposed method against Gaussian Process Regression (GPR) [10], a representative machine learning approach widely used for uncertainty-aware calibration, but known to be computationally demanding. Runtime and memory usage were profiled to highlight embedded feasibility.

TABLE 3.

Comparative benchmarking of proposed framework against baseline methods and GPR.

Method	**RMSE (V)**	**RMSE (A)**	**MAPE (%)**	**Runtime (ms/sample)**	**Memory (KB)**
Raw Sensor	3.45	0.065	3.9	–	–
Moving Average (MA)	3.12	0.062	3.8	0.1	5
Kalman Filter	3.11	0.062	3.8	0.2	12
Gaussian Process Regression (GPR)	0.25	0.006	0.2	15.0	2000
Proposed Framework	**0.30**	**0.005**	**0.3**	**0.3**	**15**

The benchmarking results yield the following insights:

- Baseline filters (MA, Kalman) suppress noise but cannot correct systematic drift, leaving performance close to the raw signals.
- GPR achieves the lowest RMSE and MAPE but at the cost of high runtime and memory requirements, rendering it unsuitable for embedded IoT deployments.
- The proposed framework strikes a practical balance: it delivers more than 90% error reduction with efficiency compatible with ESP32-class hardware, requiring only 0.3ms per sample and 15 KB of memory.

Overall, these findings demonstrate that the proposed method achieves laboratory-grade accuracy while remaining embedded-friendly and scalable, positioning it as a practical alternative to resource-intensive ML methods in real-world IoT energy monitoring.

6. CONCLUSIONS

This study presented a drift-resilient IoT energy monitoring framework for low-cost voltage and current sensors, specifically ZMPT101B and ACS712. The

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framework integrates moving average and Kalman filtering and regression-based calibration into a unified pipeline designed to suppress noise, correct systematic drift, and detect non-stationary anomalies. Experimental validation demonstrated that the approach consistently reduced RMSE and MAE by over 90%, improved percentage errors to about 0.11%, and enhanced SNR by approximately 21 dB, thereby restoring measurement fidelity to a level comparable with calibrated reference meters.

The main novelty of this work lies in providing a lightweight, interpretable, and deployment-ready alternative to data-intensive machine learning or AutoML approaches. Unlike existing methods that either rely solely on filtering or require heavy computational resources, our layered framework uniquely combines adaptive Kalman filtering, regression-based calibration, and time–frequency drift detection in an embedded-friendly workflow suitable for ESP32-class hardware. This design achieves laboratory-grade accuracy while remaining scalable, transparent, and practical for large-scale IoT deployments.

Future extensions may incorporate TinyML-based adaptive calibration, extend the methodology to multi-sensor fusion in industrial environments, and explore cloud-assisted diagnostics for large-scale deployments. Nevertheless, the current results establish that low-cost IoT sensors, when equipped with drift-aware correction, can provide stable, accurate, and scalable monitoring capabilities, thereby advancing the reliability of next-generation smart grid and IoT infrastructures.

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