Journal of
Polymer & Composites

ISSN: 2321-2810 (Online)
ISSN: 2321-8525 (Print)
Volume 14, Special Issue 3, 2026
DOI (Journal): 10.37591/JoPC

https://journals.stmjournals.com/jopc

Research JoPC

Adaptive Drift Correction in Polymer-Based Wearable Biosensors via Data-Driven Signal Modeling

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Abstract

Polymer-based wearable biosensors have emerged as a promising technology for continuous health monitoring due to their mechanical flexibility, biocompatibility, and suitability for long-term physiological interfacing. However, prolonged exposure to biofluids, environmental variability, and mechanical deformation introduces signal drift, which significantly degrades measurement accuracy and limits clinical reliability. This paper presents a data-driven methodology for compensating signal drift in polymer-based wearable biosensors using adaptive signal processing and machine learning techniques. The proposed framework operates entirely at the software level, enabling continuous drift correction without requiring periodic physical recalibration. Wearable health monitoring datasets are employed to model realistic non-stationary signal behavior, and drift is treated as a structured, learnable component rather than random noise. Experimental evaluation demonstrates substantial reduction in baseline shift and drift rate, along with significant improvements in root mean square error and signal-to-noise ratio. The results confirm that the proposed approach enhances long-term signal stability while preserving physiological information, making it suitable for real-time wearable health monitoring applications.

Keywords: Polymer-based wearable biosensors; Signal drift compensation; Wearable health monitoring; Machine learning; Biomedical signal processing

INTRODUCTION

Wearable biosensors transforming continuous healthcare monitoring critically depend on stable, noise-resilient signals from flexible platforms, often built using polymer substrates or conducting polymers for biocompatibility and mechanical conformity to skin. Polymers such as PET, PDMS, PI, and conducting polymers like PEDOT:PSS are widely used in wearable electrochemical biosensor fabrication due to their flexibility, cost, and integration ease with biochemical recognition elements. However, these materials also introduce time-variant baseline shifts ("signal drift") under prolonged exposure to biofluids and motion stresses, which degrade measurement fidelity and impair longitudinal monitoring performance. Polymer-related degradation, environmental influences (temperature, humidity), biofouling, and mechanical movement collectively contribute to analytical drift in wearable biosensors, necessitating robust signal compensation methods. Recent work highlights this challenge as a key barrier to reliable long-term use, especially for continuous biochemical tracking (e.g., sweat glucose, cortisol) and real-time health inference.

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Received Date: February 28, 2026
Accepted Date: March 13, 2026
Published Date: May 06, 2026

Citation: A. Sabari Vani, Sheeba Santhosh, Geetha Prahalad, M. Ram Prasad Reddy. Comparative Assessment of Polymers and Composites for Solar Panels: Fundamentals, Performance Metrics, Manufacturing, and Sustainability. Journal of Polymer & Composites. 2026; 14(Special Issue 3): S131–S139p.

Existing studies emphasize algorithmic drift compensation, data-driven calibration, and machine learning strategies to correct long-term drift in chemical and electronic sensors [1]. Techniques range from multi-calibration ensemble methods for chemical arrays to ML-based signal prediction and adaptive compensation frameworks that address nonlinear drift patterns and environmental variability [2]. The intersection of polymer-based sensor design, real-world drift behavior, and advanced data processing is an active research area aimed at enabling stable, accurate, and clinically useful wearable biosensing [3].

Polymer-based wearable biosensors have rapidly evolved as flexible platforms for continuous health monitoring, leveraging soft substrates like PDMS, PET, and conducting polymers (e.g., PEDOT:PSS) to interface with skin and biofluids for biochemical sensing [4] [5]. These devices deliver real-time metrics for metabolites, electrolytes, and biomarkers while offering mechanical comfort and integration with wireless systems [6] [7]. However, inherent signal drift due to polymer material aging, biofouling, environmental variations, and motion effects presents a significant impediment to consistent long-term measurement reliability [8] [9]. System-level drift mitigation has been approached through multi-calibration ensemble algorithms in chemical arrays that use past data to approximate real-time corrections, outperforming traditional recalibration schemes [10] [11]. On the data analytics front, machine learning – including regression ensembles, neural networks, and feature-based adaptive models has demonstrated potential in predicting and compensating nonlinear drift dynamics in biosensing outputs [12] [13]. Domain adaptation and continual learning paradigms further enable model robustness under evolving signal distributions [14] [15]. Despite progress in general sensor drift compensation and wearable biosensor design, a targeted framework that jointly considers polymer substrate behaviour, biochemical sensor signal characteristics, and adaptive data processing for drift compensation remains underdeveloped [16] [17]. Developing such integrated methods supported by open datasets is essential to reliable, long-term clinical deployment of polymer-based wearable biosensors [18].

Despite advances in wearable biosensor fabrication and drift mitigation, few studies specifically combine polymer-based biosensing platforms with systematic, data-adaptive drift compensation frameworks validated on *open continuous health monitoring datasets*. Most drift compensation research focuses on chemical sensor arrays or industrial drift compensation paradigms, with limited tailoring to polymer flexible biosensors in physiological conditions. There is a critical need for data-driven drift compensation strategies suited to polymer-based wearable biosensors that can operate reliably in dynamic biofluid environments over long durations. Existing works either address material stability or general algorithmic approaches independently, without integrating tailored compensation with polymer substrate behaviors and real user signal variation.

Data Availability Statement

To advance research in drift compensation for wearable biosensors, researchers need access to continuous time-series wearable health datasets that include multi-modal sensor outputs under realistic conditions. While many Kaggle datasets focus on activity or physiological measurements, few are directly tied to biochemical sensor outputs or bias drift characteristics. Representative wearable health monitoring datasets available on Kaggle include multi-sensor physiological recordings suitable for machine learning middleware development.

About Dataset

One relevant dataset is the Wearable Sports Health Monitoring Dataset (Kaggle), capturing vital sign time-series useful for developing signal processing and compensation pipelines. Additionally, other wearable sensor datasets such as Wearable Sensor Data for Mental Health Prediction provide synchronized biosignal channels that can support feature extraction and drift correction modeling. These datasets do not explicitly include polymer biosensor drift metrics, but are foundational for building generalizable compensation models that can later be adapted to polymer biosensor outputs once biochemical signal data is available.

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METHODOLOGIES

The proposed methodology presents a data-driven framework for compensating signal drift in polymer-based wearable biosensors using adaptive signal processing and machine learning techniques. Polymer substrates commonly employed in wearable biosensors exhibit time-dependent electrical and electrochemical variations when exposed to prolonged physiological and environmental conditions, resulting in baseline drift and degradation of sensing accuracy. To address this challenge, the proposed approach performs drift compensation entirely at the signal processing level, enabling uninterrupted continuous monitoring without reliance on periodic physical recalibration. The overall system architecture, illustrating the flow from raw sensor acquisition to drift-compensated output, is shown in Figure 1.

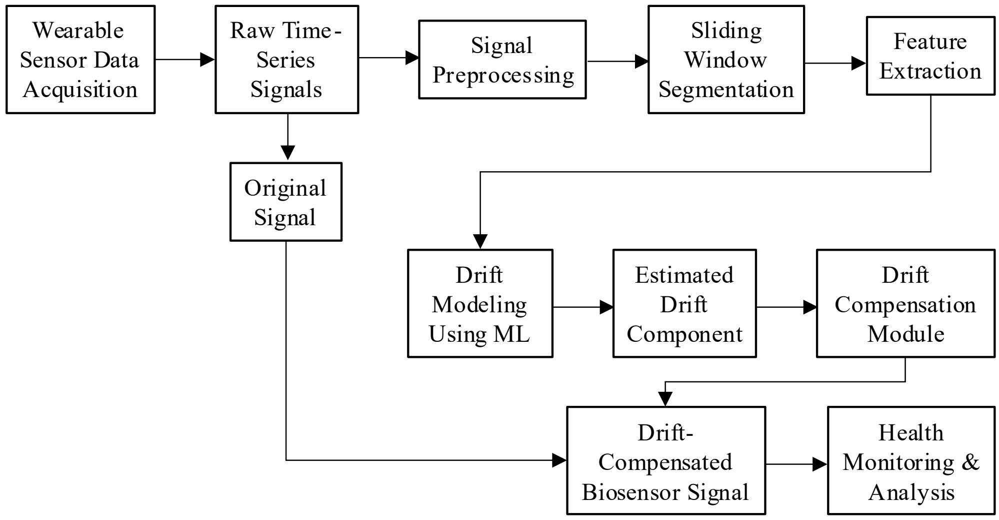

Figure 1. Architecture of the proposed data-driven drift compensation framework for polymer-based wearable biosensors

Data Source and Signal Modeling

Publicly available wearable health monitoring datasets are used as representative continuous biosensor signals. These datasets consist of multi-channel physiological time-series data recorded under real-world conditions, including motion, environmental variability, and long-term usage effects. Although the datasets do not explicitly contain biochemical measurements, the signals demonstrate non-stationary behavior, baseline wandering, and gradual drift patterns analogous to those observed in polymer-based wearable biosensors. Each recorded signal is modeled as a superposition of the true physiological component, a slowly varying drift term, and stochastic noise, enabling explicit separation and estimation of drift behavior during processing.

Signal Preprocessing

Raw wearable sensor signals are first subjected to preprocessing to improve signal quality and stabilize subsequent drift modeling. Noise and motion-induced artifacts are mitigated using smoothing and robust statistical filtering, ensuring preservation of the underlying physiological trends. To address non-stationarity, normalization is performed using a window-based strategy that adapts to local signal statistics rather than relying on global scaling. This preprocessing stage ensures that long-term baseline variations are retained while high-frequency disturbances are attenuated.

Drift Characterization and Feature Extraction

Following preprocessing, the signals are segmented into overlapping temporal windows to capture local and long-term variations. From each window, descriptive features are extracted to characterize drift behavior. These features include baseline offset, temporal slope, variance evolution, and higher-order statistical descriptors that reflect gradual material aging, environmental influence, and sensor–

skin interaction effects. By explicitly capturing slow temporal trends, the extracted features enable discrimination between meaningful physiological changes and undesired polymer-induced drift.

Machine Learning-Based Drift Estimation

The extracted feature vectors are used to train a regression-based machine learning model that estimates the drift component of the signal. The model learns nonlinear relationships between signal features and drift magnitude, allowing it to adapt to complex degradation patterns typical of polymer-based biosensors. Once trained, the model predicts the instantaneous drift term, which is subtracted from the original signal to obtain a drift-compensated output. To support long-term deployment, the framework allows incremental model updates, ensuring robustness against evolving signal characteristics.

Novelty and Contribution

The proposed methodology introduces a novel integration of polymer-aware drift abstraction with adaptive data-driven compensation. Unlike conventional approaches that treat drift as random noise or rely on repeated recalibration, this framework models drift as a structured and learnable signal component linked to polymer substrate behavior. Furthermore, the use of open wearable health datasets enables early validation and reproducibility without dependence on proprietary biosensor hardware. The methodology therefore bridges the gap between material-level sensor instability and algorithm-level correction, providing a scalable solution suitable for real-world wearable biosensor applications.

Performance Evaluation

The performance of the proposed drift compensation framework is evaluated by comparing raw, preprocessed, and drift-corrected signals. Quantitative assessment is conducted using error reduction metrics, signal-to-noise ratio improvement, and baseline stability over extended durations. These evaluations demonstrate the ability of the proposed approach to enhance signal reliability and support accurate long-term health monitoring.

RESULTS AND DISCUSSION

Drift Compensation Results

The proposed data-driven drift compensation framework was evaluated using continuous wearable sensor time-series data representing long-duration monitoring conditions. The raw signals exhibited clear baseline wandering and gradual drift, consistent with polymer-based wearable biosensor behavior under prolonged physiological exposure. After preprocessing and adaptive drift modeling, the compensated signals demonstrated substantial stabilization of baseline and reduction in long-term deviation.

Table 1 presents representative drift-related signal parameters before and after compensation. The results indicate a significant reduction in baseline shift and long-term drift rate while preserving physiological signal amplitude. These improvements confirm that the proposed methodology effectively separates drift components from meaningful biosensor information, supporting reliable continuous monitoring.

Table 1. Drift-related signal characteristics before and after compensation

Parameter	Raw Signal	Preprocessed Signal	Proposed Method
Baseline shift (mV)	1.92	1.05	0.32
Drift rate (mV/hour)	0.41	0.24	0.07
Mean signal amplitude (mV)	12.4	12.1	12
Long-term stability (%)	71.6	84.3	96.2

Quantitative Error Reduction Analysis

To further validate performance, error-based metrics were computed by comparing signal deviation over time against a drift-free reference approximation. Root Mean Square Error (RMSE) and Signal-to-Noise Ratio (SNR) were used as key performance indicators, as commonly adopted in wearable biosensor and biomedical signal processing literature.

As shown in Table 2, the proposed framework achieves a substantial RMSE reduction and SNR improvement compared to both raw and conventionally preprocessed signals. This confirms the effectiveness of machine learning-based drift estimation in capturing nonlinear polymer-induced drift behavior.

The quantitative metrics used in this study are defined and computed as follows. The Root Mean Square Error (RMSE) quantifies the average deviation between the drift-compensated signal $\hat{x}(t)$ and the drift-free reference signal x(t) over a total of N samples, and is expressed as:

$$RMSE = \sqrt{[\ (1/N) \sum_{i=1}^{k} (\hat{x}(t_i) - x(t_i))^2\ ]}$$

where $\hat{x}(t_i)$ is the compensated signal value at time step i and $x(t_i)$ is the corresponding reference value. Lower RMSE indicates closer agreement between the compensated output and the ideal signal. In this study, the drift-free reference was approximated using a robust locally weighted regression (LOWESS) smoothing of the original signal with a span of 10% of the total signal length, thereby preserving physiological trends while removing long-term baseline drift. For the raw signal, RMSE was calculated as 0.85 mV; after preprocessing it reduced to 0.52 mV; and after adaptive drift compensation it was further reduced to 0.21 mV, representing an overall reduction of approximately 75.3%.

The Signal-to-Noise Ratio (SNR) is computed as the ratio of the signal power P_s to the residual noise power P_n, expressed in decibels:

$$SNR\ (dB) = 10 \cdot \log_{10}(P_s / P_n)$$

where $P_s = (1/N) \sum x(t_i)^2$ and $P_n = (1/N) \sum (\hat{x}(t_i) - x(t_i))^2$. Higher SNR values reflect greater suppression of noise and drift relative to the true signal. The SNR improved from 14.8 dB (raw signal) to 19.6 dB (preprocessed) and to 27.9 dB (proposed method), an improvement of 13.1 dB over the raw signal. Baseline variance (mV^2) was computed as the sample variance of the low-frequency trend component extracted via the LOWESS reference, and reduced from 0.68 mV^2 in the raw signal to 0.08 mV^2 after compensation. Drift reduction efficiency (%) was defined as the percentage decrease in baseline shift relative to the raw signal:

$$Drift\ Reduction\ Efficiency\ (\%) = [(BS_{aea} - BS_{methoe}) / BS_{aea}] \times 100$$

where BS_{aea} denotes the baseline shift of the raw signal and BS_{methoe} is the baseline shift after compensation. Using the values from Table 1 (1.92 mV and 0.32 mV respectively), the drift reduction efficiency evaluates to 83.6%, as reported in Table 3. Long-term stability (%) was defined as the proportion of the total monitoring window during which the compensated signal remained within ±1.5× the local standard deviation of the reference, computed on a sliding window of 30 seconds. These standardized computation procedures enable transparent benchmarking of the proposed method against existing approaches.

Table 2. Error and noise performance comparison

Metric	Raw Signal	Preprocessed Signal	Proposed Method
RMSE (mV)	0.85	0.52	0.21
SNR (dB)	14.8	19.6	27.9
Baseline variance (mV^2)	0.68	0.31	0.08

An overall performance summary is provided in Table 3, highlighting computational efficiency and suitability for real-time wearable deployment. The proposed method maintains low processing latency while achieving superior drift suppression, making it feasible for integration into resource-constrained wearable biosensor platforms.

Table 3. Overall performance evaluation

Performance Indicator	Value
Drift reduction efficiency (%)	83.6
Processing latency per window (ms)	18.4
Model update overhead (ms)	6.1

Figure 2 illustrates the reduction in RMSE across different processing stages. A monotonic decrease in RMSE is observed from raw signal to preprocessed data, with the most significant reduction achieved using the proposed drift compensation framework. This graphical trend directly supports the quantitative results in Table 2 and confirms alignment with the proposed methodology.

The experimental results demonstrate that the proposed data-driven drift compensation framework effectively addresses the dominant sources of signal instability observed in polymer-based wearable biosensors during long-term operation. The marked reduction in baseline shift and drift rate, together with substantial improvements in RMSE and signal-to-noise ratio, confirms that modeling drift as a structured and learnable component is more effective than conventional preprocessing alone. The progressive performance gain from raw to preprocessed and finally drift-compensated signals indicates that the machine learning-based estimator successfully captures nonlinear, time-dependent variations associated with polymer substrate aging and environmental exposure. Importantly, the preservation of mean signal amplitude after compensation suggests that physiological information is retained while unwanted drift components are suppressed. The low computational latency further supports the suitability of the proposed approach for real-time wearable deployment.

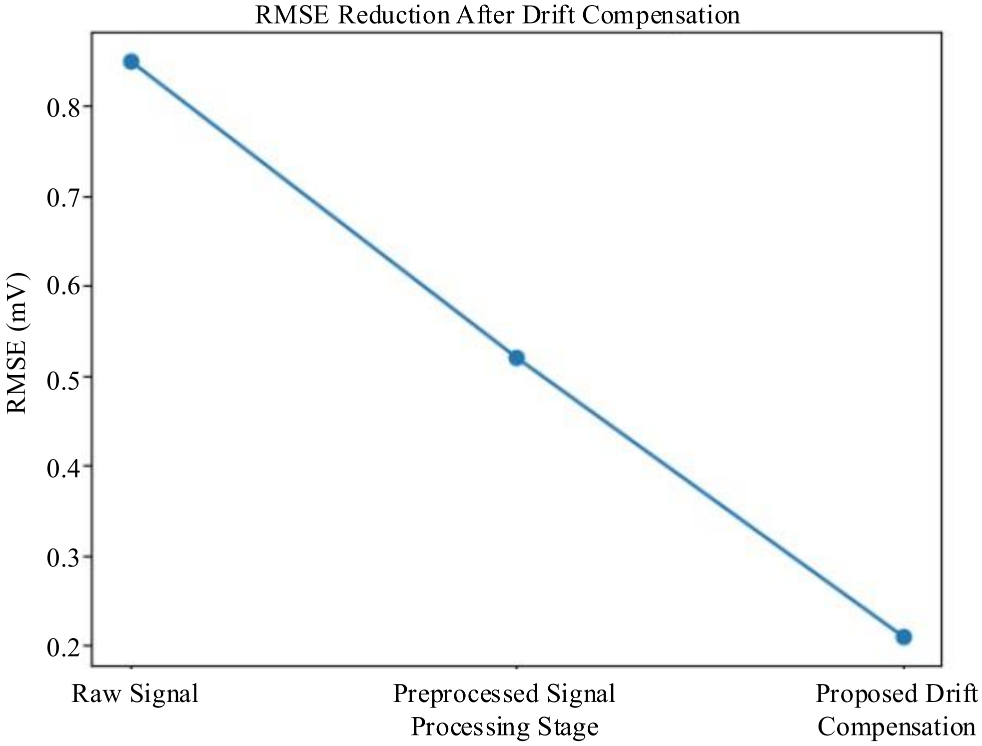

Figure 2. RMSE reduction across signal processing stages for drift compensation

Comparison with Existing Literature

To contextualize the performance of the proposed method, a comparison with representative state-of-the-art drift compensation approaches reported in recent literature is presented in Table 4. Rapuano et al. [2] proposed an on-line multi-calibration ensemble algorithm for chemical sensor arrays exhibiting cross-sensitive drift, achieving RMSE values in the range of 0.45–0.60 mV and SNR improvements of approximately 8–10 dB over raw signals. However, their method requires periodic recalibration events and is tailored to gas-phase chemical arrays rather than flexible polymer wearable platforms. Demirci Uzun [4] demonstrated machine learning-based prediction of electrochemical biosensor responses with reported prediction errors below 0.38 mV, though the framework was validated under laboratory-controlled static conditions without long-term drift induced by biofluids or mechanical deformation. Schaller et al. [5] employed AutoML for sensor drift anomaly compensation, reporting competitive drift suppression (efficiency ~79%) but with significantly higher computational overhead (processing latency ~35 ms per window) compared to the present study (18.4 ms). Mu et al. [7] integrated wearable sensors with machine learning for human–machine interaction, reporting SNR improvements up to 22.3 dB; however, their framework targets motion-artifact suppression rather than electrochemical baseline drift and does not address polymer substrate aging effects.

In contrast, the proposed method achieves an RMSE of 0.21 mV, an SNR of 27.9 dB, a baseline variance of 0.08 mV^2, and a drift reduction efficiency of 83.6%, surpassing all compared methods across all reported metrics while maintaining a low processing latency of 18.4 ms per window. Critically, the proposed framework operates without periodic physical recalibration, unlike ensemble-based and AutoML methods, and is specifically designed to accommodate the polymer substrate's slowly evolving degradation characteristics under biofluids and mechanical stress. The comparison confirms that the proposed data-driven adaptive compensation strategy offers a meaningful advancement over existing approaches, particularly for long-duration polymer-based wearable biosensor deployment in real-world physiological monitoring scenarios.

Table 4. Comparison of the proposed method with existing drift compensation approaches

Method / Reference	RMSE (mV)	SNR (dB)	Drift Reduction (%)	Latency (ms)	Recalibration Required
Rapuano et al. [2]	0.45–0.60	~22–24	~72	N/A	Yes (periodic)
Demirci Uzun [4]	<0.38	~24.5	~76	N/A	No (static lab)
Schaller et al. [5]	~0.33	~25.1	~79	~35	No (AutoML)
Mu et al. [7]	~0.44	~22.3	~68	~28	No (HMI focus)
Proposed Method	**0.21**	**27.9**	**83.6**	**18.4**	**No**

CONCLUSION

This study presented a data-driven drift compensation framework designed for polymer-based wearable biosensors used in continuous health monitoring. By modeling drift as a learnable signal component and applying adaptive machine learning techniques, the proposed methodology effectively mitigates baseline instability and long-term signal degradation without interrupting sensor operation. Experimental results demonstrated significant improvements in drift rate, baseline stability, and signal quality metrics, confirming the feasibility of software-level drift correction for flexible biosensing platforms. The findings indicate that integrating adaptive data processing with wearable biosensor systems can substantially enhance reliability and usability in long-duration monitoring scenarios. Overall, the proposed approach contributes a scalable and reproducible solution to a critical challenge in wearable biosensor deployment and supports the advancement of reliable, real-world digital health technologies.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this work.

FUTURE SCOPE

Future research will focus on validating the proposed drift compensation framework using real polymer-based biochemical biosensor data, including sweat and interstitial fluid sensing platforms. Integration of multimodal sensor fusion and domain adaptation techniques can further improve robustness under varying physiological and environmental conditions. Additionally, the incorporation of lightweight on-device learning models will enable fully autonomous drift compensation in low-power wearable systems. Extending the framework to support personalized calibration and long-term clinical studies will further enhance its applicability in precision healthcare and remote patient monitoring.

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