

A Multi-frequency Bioelectrical Impedance Sensing System with Polynomial Modeling

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Electrocardiogram-related physiological activity and blood oxygen concentration (SpO₂) are critical indicators for monitoring cardiovascular status. In this study, we integrate pulse rate and SpO₂ signals with a multi-frequency bioelectrical impedance sensing distribution analysis (MF-BISA) framework to determine the optimal timing for hemodialysis termination. These sensing modalities provide complementary physiological information for evaluating hemodynamic response and fluid status. In water-retentive patients, body impedance changes dynamically with fluid redistribution, tissue hydration, and electrolyte balance during hemodialysis. Therefore, continuous bioelectrical impedance sensing enables the non-invasive monitoring of physiological fluid variations. The proposed MF-BISA framework applies multi-frequency electrical currents and analyzes voltage responses to characterize tissue-dependent impedance behavior during dialysis. A numerical signal analysis framework processes multi-site impedance data from sensor patches at the cardiac output (chest) and peripheral (calf) regions. Impedance distribution curves over a 4 h session are constructed for both locations. Physiological equilibrium is reached when body fluid volume, tissue hydration, and electrolyte concentration converge, reflected by the intersection of the two curves. Experimental results show a crossover point at approximately 1.94 h, indicating the optimal dialysis termination time. In this work, we developed a sensor-driven multi-modal monitoring framework integrating bioelectrical impedance sensing with pulse oximetry to provide a quantitative, real-time solution for fluid status assessment and dialysis optimization.

1. Introduction

The continuous monitoring of physiological signals is important for evaluating patient conditions during hemodialysis. Among these signals, pulse rate, blood oxygen saturation (SpO₂), and bioelectrical impedance provide complementary information regarding

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cardiovascular activity, oxygen transport, and body fluid distribution. Integrating these sensing modalities enables the real-time assessment of physiological variations and supports reliable dialysis monitoring.

(1) Pulse rate and SpO₂ physiological signal monitoring: Heart rate (pulse rate) and SpO₂ are fundamental physiological parameters widely used in health monitoring. Heart rate reflects cardiac activity and circulatory function, typically ranging from 60 to 100 beats/min in adults, while SpO₂ reflects respiratory efficiency and oxygen transport capability, with values above 95% generally considered normal. Variations in heart rate are associated with physical condition, stress level, and metabolic demand. These signals are commonly acquired through pulse oximeters and wearable systems, enabling continuous and non-invasive monitoring. In hemodialysis applications, water-retentive patients often experience cardiovascular and respiratory stress due to fluid imbalance and electrolyte disturbances. The continuous monitoring of pulse rate and SpO₂ therefore provides important information for assessing cardiovascular load and oxygenation status. Abnormal variations in these signals may indicate hemodynamic instability or impaired lung function, supporting timely clinical intervention. Consequently, these sensing modalities play an important role in real-time physiological assessment and treatment safety during dialysis.

(2) Multi-frequency bioelectrical impedance sensing distribution analysis (MF-BISA): Bioelectrical impedance analysis (BIA) is a non-invasive sensing technique for evaluating body composition by applying a small alternating current and measuring the resulting impedance. The measured impedance, including resistance (R) and reactance (X_c), varies with tissue composition and water distribution. In water-retentive patients, impedance values are strongly affected by fluid status, tissue hydration, and electrolyte concentration, making BIA useful for monitoring dialysis-related changes. During hemodialysis, impedance variations reflect fluid redistribution between intracellular and extracellular compartments. Multi-frequency BIA extends this capability by applying currents at different frequencies, where low-frequency currents mainly pass through extracellular water (ECW), while high-frequency currents penetrate cell membranes and capture both ECW and intracellular water (ICW). This frequency-dependent sensing mechanism enables the more detailed characterization of tissue properties and fluid balance. BIA-based monitoring supports the assessment of fluid status, tissue condition, and dialysis effectiveness. Impedance changes can indicate variations in total body water, muscle mass, and cellular integrity. However, measurement accuracy may be affected by body geometry, electrolyte distribution, and external conditions, requiring consistent measurement protocols. Segmental and systemic BIA approaches have been widely used to estimate ECW, ICW, and total body water (TBW), while ratios such as ECW/ICW and ECW/TBW have been applied to predict dry weight in dialysis patients. Commercial BIA systems, such as the InBody and seca body composition analyzers, have been widely applied for body-composition and fluid-status assessment using multi-frequency or segmental impedance measurements. These commercially available systems demonstrate the practical feasibility of BIA-based physiological assessment, while the present study further focuses on time-dependent multi-site impedance sensing and its integration with physiological signals for hemodialysis

monitoring. Prior studies have demonstrated that impedance-based indicators can effectively reflect fluid removal trends and provide a quantitative basis for determining dialysis endpoints.^(1–9)

The integration of bioimpedance sensors into hemodialysis monitoring has attracted increasing attention. Hemodialysis aims to maintain physiological equilibrium by removing excess fluid and metabolic waste, traditionally relying on biochemical parameters, ultrafiltration settings, and body weight measurements. However, these approaches provide limited temporal resolution and may not fully capture real-time fluid dynamics. Sensor-based impedance monitoring offers a complementary solution through the continuous and non-invasive assessment of tissue-level changes.^(10–18) In clinical practice, dialysis performance is affected by multiple factors, including treatment duration, ultrafiltration rate, biochemical indicators, and body weight variation. These parameters are typically adjusted on the basis of clinical experience and intermittent measurements, making the determination of the optimal dialysis endpoint complex uncertain. The incorporation of bioimpedance sensing provides a more direct and real-time measurement of fluid redistribution, reducing reliance on indirect indicators. By linking multi-frequency impedance signals with physiological sensing data, a more robust and quantitative framework for dialysis monitoring can be established.^(19–25)

Recent studies have further demonstrated the potential of machine learning (ML) for intelligent hemodialysis monitoring. Zhang *et al.* developed a real-time ML model using clinical and intradialytic data to predict intradialytic hypotension 15–75 min in advance, demonstrating the feasibility of integrating real-time dialysis data with predictive analytics.⁽²⁶⁾ More recently, Yang *et al.* have developed an artificial-intelligence-based prediction system incorporating information from previous and ongoing dialysis sessions, enabling the individualized prediction of intradialytic hypotension and supporting real-time clinical decision making.⁽²⁷⁾ These studies indicate that combining physiological sensing and data-driven analysis may provide an important pathway toward personalized and adaptive dialysis monitoring. Despite these advances, the accurate determination of fluid removal and dry weight remains challenging. Conventional evaluation methods, such as pre- and post-dialysis weight comparison, lack sensitivity to transient physiological changes. Therefore, integrating multi-modal sensing technologies, including bioelectrical impedance and vital signal monitoring, presents a promising direction for improving dialysis safety and effectiveness. In addition, combining multi-modal sensing with numerical signal interpretation provides an opportunity to establish quantitative and data-driven criteria for dialysis termination. Compared with conventional empirical assessment, sensor-based monitoring improves temporal resolution and supports continuous physiological evaluation during treatment. In this study, a multi-modal sensing framework combining pulse rate, SpO₂, and MF-BISA is proposed to investigate physiological variations during hemodialysis. Unlike conventional dialysis monitoring approaches relying mainly on intermittent body weight measurements and clinical experience, the proposed framework continuously analyzes synchronized physiological and impedance signals to identify quantitative indicators associated with fluid redistribution and dialysis equilibrium.

2. Methodology

For clarity and consistency, the major abbreviations used throughout this study are summarized in Table 1, together with their full terms and brief descriptions.

Pulse rate, SpO2, electrocardiogram (ECG), photoplethysmography (PPG), and MF-BISA signals were acquired as time-series physiological data and organized according to their measurement timestamps. The signal-processing procedure consisted of five main stages: signal acquisition, preprocessing, temporal alignment, feature extraction, and multi-modal interpretation. First, the acquired physiological signals were preprocessed to reduce short-term fluctuations and measurement noise. The signals were then temporally aligned according to the corresponding acquisition times to enable the comparison of physiological variations within the same monitoring period. Pulse rate and SpO2 were extracted from the PPG-related measurements, while ECG was used to characterize cardiac electrical activity. For MF-BISA, impedance measurements from the chest and lower leg were organized as regional time-series data and temporally averaged to characterize fluid-related impedance variations. No modality-specific weighting coefficients or mathematical normalization-based fusion were applied in the present framework. Instead, multi-modal integration was performed at the interpretation level by comparing temporally aligned cardiovascular, oxygenation, and impedance trends. This approach enables complementary physiological information from different sensing modalities to be evaluated within a common temporal framework while preserving the original characteristics of each signal. The overall signal-processing pipeline is schematically illustrated in Fig. 1. The processing sequence can be summarized as follows: signal acquisition → preprocessing → timestamp-based temporal alignment → modality-specific feature extraction → time-series comparison → multi-modal physiological interpretation.

Table 1
Abbreviations, full terms, and brief descriptions of the physiological and bioelectrical impedance parameters used in this study.

Abbreviation	Full term	Brief explanation
SpO2	Peripheral oxygen saturation	Blood oxygen saturation estimated by pulse oximetry
MF-BISA	Multi-frequency bioelectrical impedance sensing distribution analysis	Multi-frequency bioimpedance sensing and analysis framework used to evaluate fluid-related impedance variations
BIA	Bioelectrical impedance analysis	Non-invasive technique for evaluating tissue and body fluid characteristics using electrical impedance
ECG	Electrocardiogram	Electrical signal representing cardiac activity
PPG	Photoplethysmography	Optical measurement of peripheral blood volume variations
RESP	Respiration	Respiratory signal used to characterize breathing-related physiological variation
ICG	Impedance cardiography	Impedance-based measurement reflecting cardiovascular and hemodynamic changes
ECW	Extracellular water	Body water located outside cells
ICW	Intracellular water	Body water located inside cells
TBW	Total body water	Total amount of water in the body
R	Resistance	Resistive component of measured bioelectrical impedance
Xc	Reactance	Reactive component of measured bioelectrical impedance

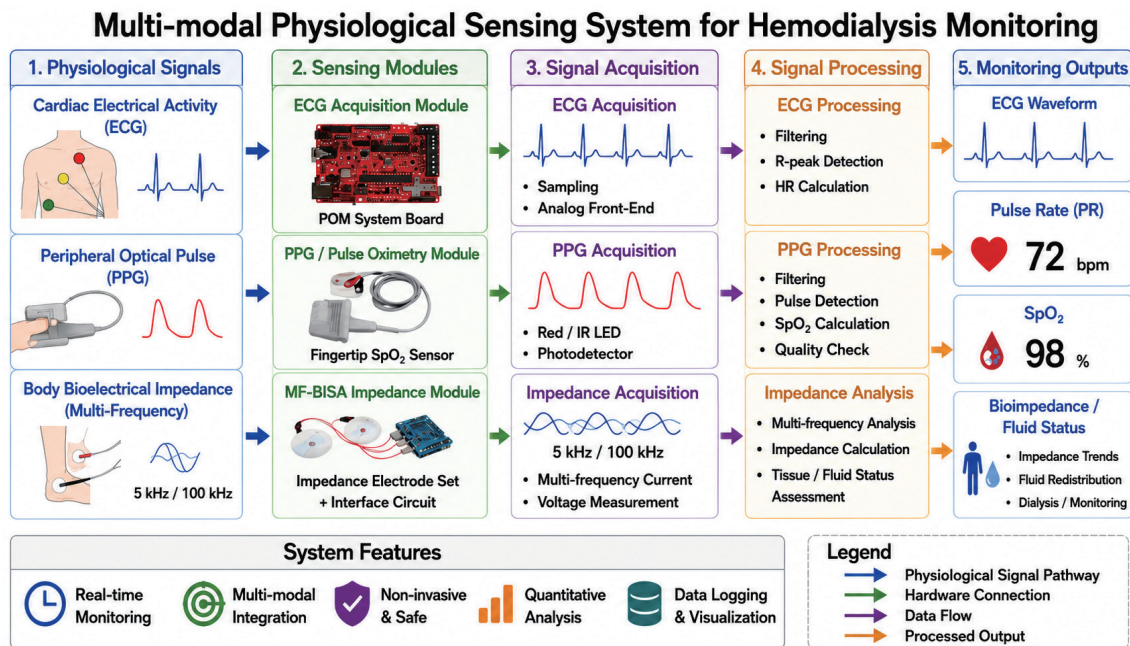


Fig. 1. (Color online) Architecture of the developed multi-modal physiological sensing system, showing ECG, PPG-based pulse oximetry, and multi-frequency bioelectrical impedance sensing pathways, together with signal acquisition, processing, and physiological parameter extraction for hemodialysis monitoring.

(1) Pulse rate and SpO₂ physiological signal monitoring: The pulse oximeter module (SpO₂ and pulse rate) continuously acquires cardiovascular and oxygenation signals using optical and electrophysiological measurement principles. ECG and PPG signals were synchronously recorded to capture cardiac electrical activity and peripheral blood flow dynamics. These signals were processed to generate continuous pulse rate and SpO₂ distributions during a 4 h monitoring period. Pulse rate was extracted through the peak detection of periodic waveforms, while SpO₂ was calculated from the differential absorption of red and infrared light in PPG signals. Temporal variations in these signals reflect physiological responses during hemodialysis. The resulting time-series data reveal events such as respiratory irregularities, reduced oxygen saturation, and hemodynamic instability, which may indicate abnormal physiological conditions including hypotension or hypoxia. Figure 1 presents the architecture and signal flow of the developed multi-modal physiological sensing system. The system integrates ECG, PPG-based pulse oximetry, and multi-frequency bioelectrical impedance sensing to acquire complementary physiological information during hemodialysis. ECG electrodes acquire cardiac electrical activity, whereas the fingertip pulse oximetry module detects red- and infrared-light-dependent PPG signals for pulse-rate and SpO₂ estimation. The acquired signals are transferred to the signal-processing stage for preprocessing, waveform analysis, peak detection, and physiological parameter extraction. In parallel, the MF-BISA module provides impedance-related information associated with tissue and fluid-status variations. This integrated architecture enables the synchronized interpretation of cardiovascular, oxygenation, and bioimpedance information within a unified hemodialysis monitoring framework.

(2) MF-BISA: MF-BISA measurements are based on bioelectrical impedance sensing, where an alternating current is injected into biological tissues and the voltage response is measured according to Ohm's law. The impedance Z consists of resistance R and reactance X_c , reflecting tissue composition and fluid distribution. To evaluate spatial and physiological variations, impedance measurements were performed at the chest and lower leg, representing central and peripheral regions, respectively. This configuration enables the comparative analysis of fluid redistribution, edema formation, and vascular resistance changes.

A dual-frequency sensing strategy was adopted to improve tissue characterization. A low-frequency current (5 kHz) was applied to the lower leg to mainly measure extracellular water (ECW), while a high-frequency (100 kHz) was used at the chest to penetrate cell membranes and reflect both ECW and ICW. This frequency-dependent method improves sensitivity to physiological changes during hemodialysis. To ensure consistency, all measurements were acquired using the same sensing system under controlled conditions, while standardized procedures minimized calibration errors, baseline drift, and hardware-related variability. To improve measurement consistency, all impedance measurements were acquired using the same sensing system, electrode configuration, and standardized acquisition procedure under controlled conditions. Each measurement was maintained for 1 min to allow signal stabilization before subsequent analysis, thereby reducing the effects of short-term fluctuations and hardware-related variability. However, the quantitative characterization of electrode–skin contact impedance and baseline drift was not independently performed in the present proof-of-concept study; therefore, these factors remain potential sources of measurement uncertainty. The data acquisition protocol used periodic sampling with a 5 min interval. Each measurement session lasted 1 min to allow signal stabilization and reduce noise. The measurement sequence alternated between the chest and lower leg to avoid signal interference and maintain independent regional sampling. This strategy balances temporal resolution and signal robustness, enabling the detection of gradual physiological changes without excessive noise.

Figure 2 illustrates the complete measurement workflow, including electrode placement, alternating acquisition sequence, timing control (1 min measurement with 5 min interval), and the structured process used to generate time-series impedance signals. A total of 40 impedance measurements were obtained, including 20 from the chest and 20 from the lower leg, over approximately 7000 s (116 min). These time-series data were used for subsequent numerical analysis to compare impedance trajectories from different anatomical regions and identify convergence behavior toward physiological equilibrium during hemodialysis. The selected 5 min interval provides sufficient temporal resolution while maintaining measurement stability and efficiency. In addition, the proposed sensing architecture supports integrated physiological and impedance monitoring within a unified acquisition framework, improving synchronization among sensing modalities for continuous dialysis monitoring.

3. Results and Discussion

Multi-modal physiological waveforms were analyzed within a unified time-domain framework to evaluate temporal relationships among ECG, respiratory signal (RESP),

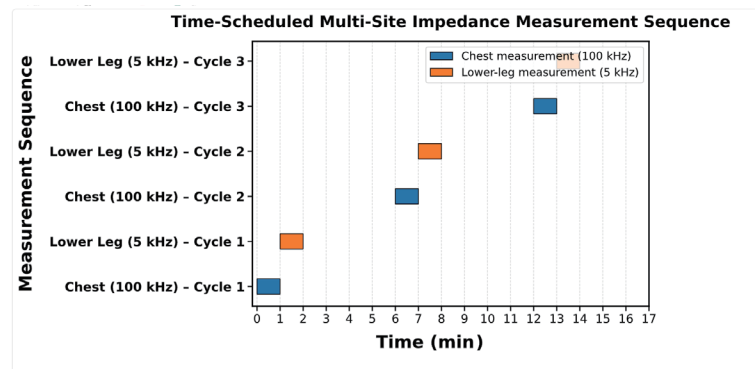


Fig. 2. (Color online) Measurement procedure for time-scheduled multi-site bioelectrical impedance sensing during hemodialysis. Impedance measurements were alternately acquired from the chest at 100 kHz and the lower leg at 5 kHz to characterize central and peripheral fluid-related impedance variations, respectively. Each measurement lasted 1 min, with a 5 min interval between successive measurements. A total of 40 impedance measurements, including 20 chest and 20 lower-leg measurements, were obtained for the subsequent time-series analysis of impedance variations and crossover behavior.

impedance cardiography (ICG), pulse rate, and SpO₂ signals during hemodialysis. Signal synchronization enables the quantitative interpretation of physiological variations and inter-signal correlations.

(1) The comparison of ECG and ICG waveforms shows that the maximum ICG peak (C wave) appears after the ECG QRS complex, while the O wave occurs after the T wave, as shown in Fig. 3. This temporal delay indicates that impedance variations follow cardiac electrical excitation and reflect mechanical responses such as ventricular filling and early diastolic activity. From a sensing perspective, ECG captures electrical activity, whereas ICG reflects subsequent hemodynamic responses. Short-duration ECG signals (16 s) were transformed into the frequency domain by Fourier analysis to extract dominant spectral components. RESP and ICG signals were analyzed simultaneously to characterize respiratory and impedance-related periodicity. This time–frequency representation improves signal interpretation by separating overlapping physiological rhythms and enhancing the robustness of multi-sensor analysis. The synchronized time-domain waveforms of ECG, RESP, and ICG for comparative physiological analysis are shown in Fig. 4.

(2) The comparison of ECG waveforms under normal and abnormal conditions indicates that sharp Q-wave deflections may correspond to myocardial infarction, elevated R-wave amplitudes are associated with ventricular hypertrophy, and negative T-wave deviations suggest myocardial ischemia. Although abnormal cases were not included in this study, the proposed sensing framework demonstrates the feasibility of integrating ECG with SpO₂ and impedance signals for physiological anomaly detection. Future work will incorporate additional sensing parameters and longer observation periods to improve diagnostic capability and system robustness. To evaluate long-term physiological responses, the observation duration was extended to 5 h, focusing on SpO₂ and pulse rate variations during hemodialysis. The corresponding waveform distributions are presented in Fig. 5, where both signals exhibit clear temporal trends.

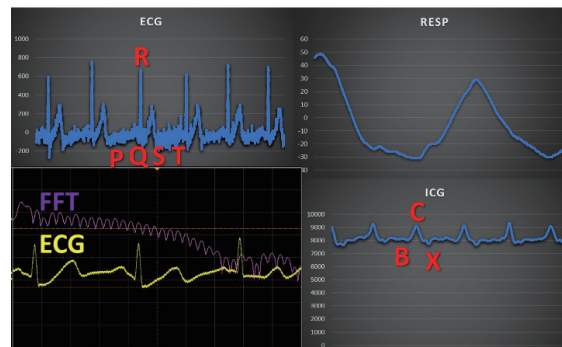


Fig. 3. (Color online) ECG/RESP/ICG with Fourier transform.

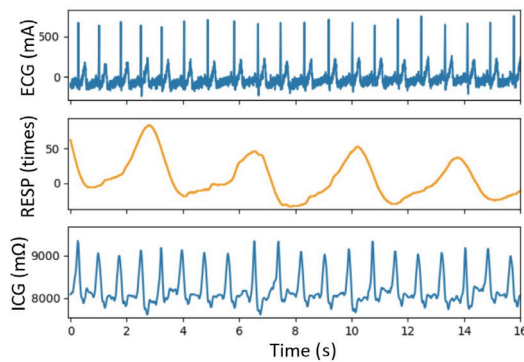


Fig. 4. (Color online) Synchronized time-domain waveforms of ECG, RESP, and ICG signals, illustrating the temporal alignment and interaction among cardiac electrical activity, respiratory dynamics, and impedance variations.

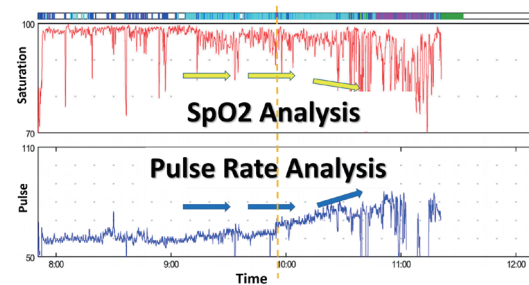


Fig. 5. (Color online) SpO2 and heart rate (pulse rate) curve distributions.

These synchronized physiological variations indicate that oxygenation status and cardiovascular responses are strongly coupled during fluid removal. The observed signal trends demonstrate that multi-modal sensing provides a more comprehensive physiological assessment than single-parameter monitoring. The SpO2 and pulse rate curves show a clear turning point near 9:30, where SpO2 decreases to approximately 80% while pulse rate increases above 100 bpm. This inverse relationship reflects compensatory regulation under hypoxic conditions, where increased heart rate helps maintain oxygen delivery. From a sensing perspective, the coupling between these signals provides more reliable indicators of physiological stress than single-signal observation. During the initial ~2 h of treatment, the decreasing SpO2 and increasing pulse rate further confirm the sensitivity of these signals to dynamic physiological changes. The corresponding impedance (ICG) signals were processed using temporal averaging to improve stability. Measurements were sampled every 10 s and averaged over 1 min intervals, generating smoothed trajectories that reduce noise while preserving overall trends. Figure 6

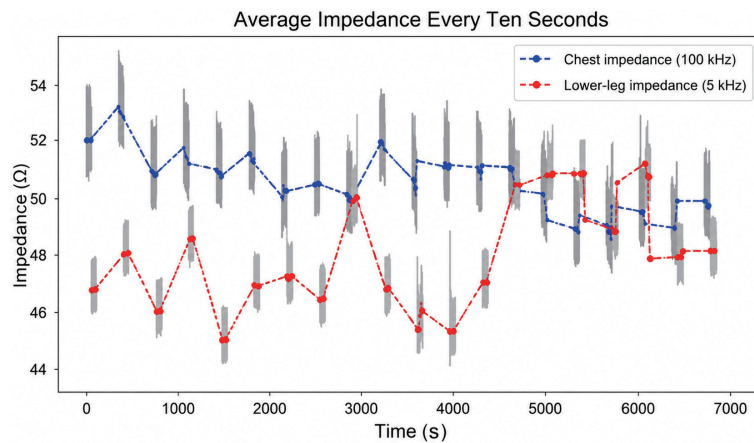


Fig. 6. (Color online) Temporal impedance variations measured at the chest (100 kHz) and lower leg (5 kHz) during hemodialysis. The initially upper trace represents the chest impedance measurement, whereas the initially lower trace represents the lower-leg impedance measurement. The convergence and crossover of the two trajectories indicate temporal changes in the impedance relationship between the central and peripheral measurement regions.

presents the raw and averaged impedance data obtained from the chest and lower leg, allowing a direct comparison of regional variations. The initially upper trace represents the chest impedance measured at 100 kHz, whereas the initially lower trace represents the lower-leg impedance measured at 5 kHz. Their temporal variations and subsequent crossover behavior reflect differences in impedance responses between the central and peripheral measurement regions during hemodialysis.

The impedance crossover behavior may reflect transient stabilization between central and peripheral fluid redistributions during dialysis. It should be emphasized that the measured bioelectrical impedance does not represent a single physiological condition but results from the combined effects of several physiological and measurement-related factors. In the present hemodialysis setting, dialysis-induced changes in regional fluid distribution and tissue hydration are considered the dominant contributors to the observed impedance trajectories because fluid removal directly alters tissue water content and electrical conductivity. The lower-leg measurement at 5 kHz is expected to be particularly sensitive to extracellular fluid changes, whereas the chest measurement at 100 kHz includes contributions from both extracellular and intracellular fluid compartments. Nevertheless, electrolyte concentration, tissue composition, vascular changes, individual anatomy, electrode placement, and electrode–skin contact may also affect the measured impedance. Therefore, the convergence of the two impedance trajectories should be interpreted as a multi-factorial sensing feature associated primarily with fluid redistribution rather than as a direct measurement of a single physiological state. This sensing characteristic suggests that impedance convergence can serve as a useful feature for real-time dialysis monitoring systems. The impedance curves show multiple crossover points, particularly around 3000 and 5000 s, with another projected crossing near 7000 s. These points occur when

chest and lower-leg impedance values converge, indicating temporary equilibrium in electrical properties between central and peripheral regions. From a physiological perspective, this convergence suggests balanced fluid distribution and similar conductivity characteristics between body segments. From a signal-processing viewpoint, these crossover points can be interpreted as equilibrium states within a dynamic multi-variable system. To further quantify these trends, polynomial curve fitting was applied to the impedance trajectories, as illustrated in Fig. 7.

The polynomial fitting approach improves the interpretation of physiological impedance trajectories by suppressing local fluctuations and highlighting long-term trends. This numerical modeling strategy may support future automated dialysis monitoring and decision-support systems. The fitted curves capture global impedance variations while reducing sensitivity to local noise. The results indicate a convergence point near 7000 s (1.94 h), suggesting that the physiological system approaches a stable equilibrium at this stage, providing a quantitative reference for determining dialysis termination timing. In the present study, the first-degree polynomial was selected primarily for trend estimation rather than for the detailed reconstruction of nonlinear physiological dynamics. The linear model provides a simple and interpretable representation of the overall increasing or decreasing impedance tendency and facilitates the identification of the convergence between the chest and lower-leg impedance trajectories. Given the limited number of measurements and the relatively short observation interval, increasing model complexity may improve local fitting but also increase sensitivity to short-term fluctuations and the risk of overfitting. Therefore, the first-degree model was considered

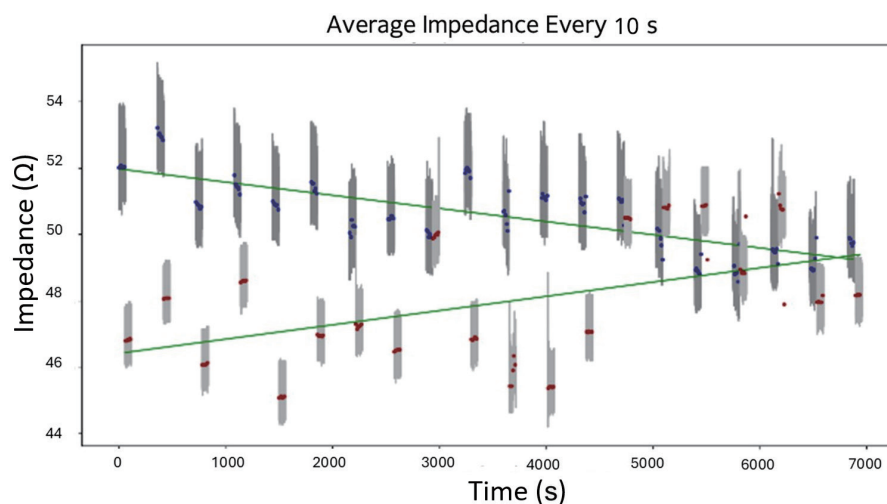


Fig. 7. (Color online) First-degree polynomial fitting of the chest and lower-leg impedance trajectories over the experimentally measured interval (0–7000 s). The fitted curves are used to characterize the convergence behavior within the available measurement period; no extrapolation beyond 7000 s was performed.

appropriate for the preliminary proof-of-concept analysis. Nevertheless, nonlinear physiological variations may not be fully represented by this model. Future studies with larger datasets will compare linear, higher-order polynomial, and spline-based models using quantitative fitting metrics such as the coefficient of determination (R^2) and root mean square error ($RMSE$) to determine the most appropriate model for impedance trajectory analysis.

Although higher-order polynomial models provide greater flexibility and fitting accuracy, careful model selection is necessary to avoid overfitting physiological data. From an engineering perspective, crossover-point identification can be treated as a feature extraction problem in time-series analysis. These crossover points represent critical transition states in system dynamics and may serve as decision indicators. The integration of multi-modal sensing signals (pulse rate, SpO₂, and MF-BISA) further improves robustness by reducing reliance on a single signal and enhancing the reliability of physiological assessment. The results demonstrate that combining pulse rate, SpO₂, and MF-BISA enables continuous physiological monitoring and provides a data-driven approach for determining dialysis timing. The observed coupling among oxygenation, cardiovascular response, and impedance convergence suggests a consistent multi-sensor pattern associated with fluid redistribution during hemodialysis.

Note that the impedance measurements were terminated at approximately 7000 s (116 min); therefore, the subsequent impedance trajectories over a complete hemodialysis session were not experimentally recorded. Although the fitted trends indicate the convergence of the chest and lower-leg impedance trajectories near the end of the measurement period, extrapolation beyond the measured interval may introduce substantial uncertainty because fluid redistribution can continue to vary during dialysis. Accordingly, the present crossover behavior should be interpreted only within the experimentally observed time range. Future studies will extend MF-BISA measurements throughout the complete dialysis session to determine whether the two regional impedance trajectories remain convergent, diverge again, or exhibit additional crossover behavior after 7000 s. However, bioimpedance interpretation remains complex and may depend on measurement configuration, individual variability, and clinical conditions. Therefore, further validation using larger datasets and more diverse populations is required.

Bioimpedance interpretation remains complex and may depend on measurement configuration, individual variability, and clinical conditions. The present results should therefore be regarded as a preliminary proof-of-concept demonstration of the proposed sensing framework rather than a statistical validation of a universal dialysis endpoint. The repeatability of the observed impedance crossover behavior across different patients and repeated dialysis sessions remains to be established. Future studies will include larger patient cohorts and repeated measurements to evaluate inter-subject and intra-subject variabilities. In addition, the crossover timing will be compared with conventional clinical indicators, including ultrafiltration volume, pre- and post-dialysis body weights, and relevant biochemical markers, to determine its physiological consistency and clinical significance. Further validation using larger datasets and more diverse populations is required.

Because baseline impedance, body composition, fluid overload, vascular condition, and fluid-removal response may differ among patients, the crossover time observed in the present study should not be regarded as a fixed threshold applicable to all individuals. A future

personalized monitoring strategy can therefore employ adaptive thresholding on the basis of each patient's baseline impedance and temporal changes in chest and lower-leg impedances rather than using a predetermined crossover time. Complementary physiological information, such as pulse rate and SpO₂ trends, can also be incorporated to improve the robustness of patient-specific assessment. Such an adaptive approach may allow the decision criterion to be dynamically adjusted according to individual physiological responses during dialysis. However, the development and clinical validation of this personalized thresholding strategy will require larger patient cohorts and repeated dialysis sessions. Future work should extend MF-BISA applications, incorporate advanced analytics such as machine learning, and optimize sensor design and measurement protocols to improve accuracy and reproducibility.

In addition to physiological variability, the measurement uncertainty associated with electrode–skin contact impedance, baseline drift, and sensor placement should be considered when interpreting bioimpedance trajectories. These factors were controlled through a standardized measurement procedure but were not independently quantified. Future validation will include systematic calibration, repeated measurements under identical conditions, and quantitative error and repeatability analyses to evaluate measurement accuracy and reproducibility. From a clinical sensing perspective, impedance monitoring provides a real-time alternative to conventional body-weight assessment. Unlike discrete measurements, impedance sensing continuously tracks changes in tissue conductivity, enabling the more accurate evaluation of fluid removal during hemodialysis. This capability highlights the potential of sensor-based approaches to improve clinical decision-making and patient safety.

4. Conclusions

In this study, we demonstrated a sensor-driven multi-modal physiological monitoring framework integrating pulse rate, SpO₂, and MF-BISA signals for hemodialysis assessment. The proposed sensing system enables the synchronized monitoring of cardiovascular activity, oxygenation status, respiratory behavior, and impedance dynamics in real time. The results showed that during approximately 2 h of hemodialysis, SpO₂ decreases while pulse rate increases, reflecting compensatory physiological responses under fluid and oxygenation stress. These coupled variations highlight the importance of multi-modal sensing for capturing dynamic physiological changes. In the MF-BISA analysis, impedance trajectories from different anatomical locations converge at approximately 7000 s (1.94 h), forming a crossover point that may reflect a transient equilibrium in fluid distribution. From a signal analysis perspective, this crossover behavior represents a potentially useful sensing feature for monitoring dialysis-related fluid redistribution. However, the observed crossover time should not be interpreted as a clinically established dialysis termination point at this stage. Validation across multiple patients and repeated dialysis sessions, together with the comparison against conventional clinical indicators such as ultrafiltration volume, body-weight change, and biochemical markers, will be required before its clinical applicability can be established. Future studies will further investigate patient-specific adaptive thresholds based on individual baseline impedance and multi-modal physiological responses to support personalized dialysis monitoring. In this study, we also

demonstrated that signal preprocessing and curve fitting enhance the interpretability of physiological data by enabling the reliable detection of trends and critical features. Compared with conventional body-weight-based assessment, impedance monitoring provides continuous and non-invasive insight into fluid redistribution, offering improved temporal resolution for clinical evaluation. Impedance interpretation remains dependent on individual variability and measurement conditions, and further validation with larger datasets is required. Future work should incorporate advanced analytical methods, such as machine learning, to improve feature extraction and decision accuracy. Overall, in this work, we established a sensor-driven monitoring framework linking physiological signal acquisition, data processing, and clinical interpretation, providing a practical basis for real-time hemodialysis monitoring and contributing to the advancement of clinical sensing technologies. The proposed sensing framework also demonstrates the potential for future integration with intelligent healthcare systems, wearable sensing devices, and machine-learning-assisted clinical decision support platforms for personalized dialysis management. Furthermore, the proposed sensing methodology may support the future development of intelligent dialysis platforms incorporating cloud-based monitoring, wearable healthcare sensors, and real-time physiological analytics for personalized and adaptive treatment control.

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