

Joint Simulation–Measurement Framework for Estimation and Compensation of Distributed Parasitics in a Flexible PCB Sensor Matrix

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Abstract

Distributed sensor networks based on impedance-based pressure sensors can be used for pressure field measurements. However, accurate impedance characterization of such sensor matrices is often compromised by distributed parasitics arising from transmission lines, connectors, and multiplexer switching paths. In this work, a hybrid simulation-measurement approach is presented to compensate for these parasitics in the transmission lines of a nanocomposite pressure sensor matrix fabricated on a flexible printed circuit board (FPCB) with 2×7 nodes for pressure distribution measurement. Impedances between all node pairs were measured from 50 kHz to 1 MHz using an Analog Discovery 2 impedance analyzer. After compensation, the proposed method was validated under multiple loading conditions of the sensor matrix, demonstrating good agreement between the corrected and expected impedance responses. Across the investigated frequency range, the RMS relative error in impedance magnitude across all measurements remained below 8%, with a forward-model RMS relative error of approximately 2.5% and an inverse reconstruction error below 10%, demonstrating the effectiveness of the parasitic compensation framework. This approach enables reliable extraction of intrinsic impedance, providing a foundation for subsequent analysis and applications such as machine-learning-based interpretation of sensor data.

Keywords: Flexible PCB, simulation-measurement framework, compensation of distributed parasitics, impedance network

1 Introduction

Distributed sensor networks based on impedance-based pressure sensors are used in flexible systems for measuring pressure fields, tactile sensing, and human–machine interfaces [1–3]. The accurate characterization of such sensor arrays requires the accurate measurement of the electrical impedance between sensor nodes. However, measurements are often distorted by distributed parasitics arising from transmission lines, connectors, and multiplexers used for sequential node interrogation [4, 5]. These parasitics introduce resistive, inductive, and capacitive coupling that obscures the intrinsic behavior of the actual (= de-embedded) sensor network and can compromise subsequent data-driven analysis or control applications [2, 6].

Various approaches have been proposed to model parasitic effects in electronic interconnects and sensor networks and to remove artifacts due to their presence. Data-driven extraction techniques and curve-fitting methods

based on measured responses provide valuable insight into parasitic contributions but often rely on simplified equivalent circuits or specific test structures, which may limit their accuracy and generalizability [4, 7].

Hybrid estimation methods, which combine physics-based simulations with experimental measurements, provide a flexible and practical framework for identifying parasitic elements while preserving the intrinsic response of the network, particularly in impedance networks implemented on flexible substrates where distributed parasitics along densely routed transmission lines are complex and difficult to model accurately [4, 8].

In this work, we present a joint simulation–measurement framework for compensating distributed parasitics in a flexible nanocomposite pressure sensor matrix. The method leverages measured impedance matrices and physics-informed circuit simulation to reconstruct the intrinsic sensor behavior, enabling more accurate sensor characterization and downstream data analysis.

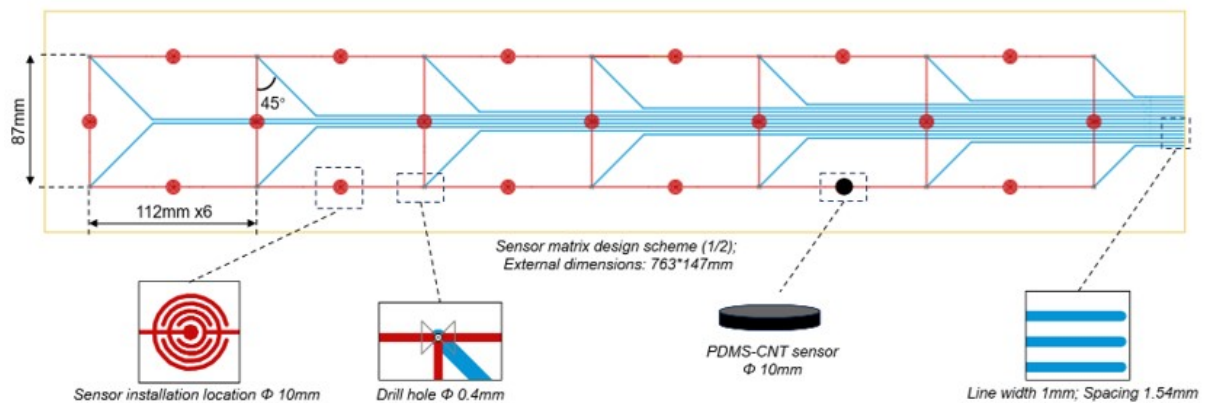


Fig. 1: Layout of the flexible PCB-based pressure sensor matrix.

2 Sensor matrix and measuring setup

Our sensor matrix was developed as part of a versatile rehabilitation and care-assistance system aimed at supporting both macro- and micro-positioning of patients in outpatient care. It comprises 19 sensors arranged in a 2×7 node grid and is fabricated from a composite of polydimethylsiloxane (PDMS) and carbon nanotubes (CNTs), as shown in Fig. 1. The PDMS–CNT pressure sensors operate via a piezoresistive mechanism: conductive CNTs are dispersed within the elastomeric PDMS matrix, which provides mechanical flexibility. When external pressure is applied, the PDMS deforms elastically, reducing the distance between CNTs and increasing both contact points and tunneling pathways, thereby decreasing the overall electrical impedance. Upon release of pressure, the PDMS returns to its original shape, restoring the CNT spacing and electrical resistance. The matrix enables the high-resolution measurement of pressure distributions, which is essential for monitoring and assisting patient positioning, providing real-time feedback for safe and effective rehabilitation and care interventions [9].

The sensor matrix layout is specifically designed for electrical impedance tomography (EIT) to estimate the pressure distribution. Unlike direct sensor readout, EIT exploits the relationships between node impedances to reconstruct a high-resolution pressure map, allowing more “pixels” of information than the number of impedance measurements. This approach reduces the number of direct measurements required, but it also prevents access to individual sensor signals, making the determination of parasitic elements in the transmission lines particularly challenging. To

accurately estimate these parasitics, all possible node-pair combinations must be characterized. For the 14 nodes considered here, this corresponds to $14 \times 13/2 = 91$ impedance measurements. These measurements were conducted over a frequency range from 50 kHz to 1 MHz at 5 discrete frequencies using an Analog Discovery 2 impedance analyzer (AD2), providing representative coverage of the electrical behavior of the sensor network. The AD2 was interfaced with a personal computer via USB, and data acquisition was automated through a custom Python-based measurement script. A broad frequency range is generally desirable to capture the frequency-dependent response of the sensor system. However, the AD2 employs a reference resistor whose value must be comparable to that of the device under test (DUT) to ensure accurate measurements [10].

At lower frequencies, the impedance magnitude of the sensor network increases to the megaohm range, while the available reference resistor is limited to approximately 10 k Ω . This mismatch leads to reduced measurement accuracy and increased uncertainty in the low-frequency regime. Consequently, the usable frequency range is constrained by the measurement system, and frequencies below 50 kHz are excluded from the analysis.

The measurement setup is illustrated in Fig. 2.

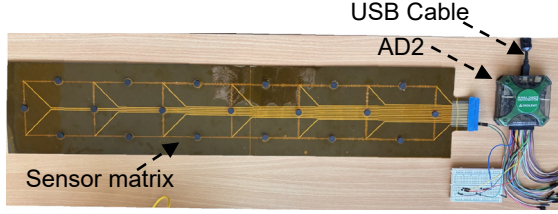


Fig. 2: Impedance measurement setup.

3 Hybrid Estimation of Intrinsic Sensor Impedance

To determine the distributed parasitic impedances in the transmission lines, the intrinsic (ideal) impedances between node pairs are required. Since they are not directly accessible from measurements, they are obtained through numerical simulation based on impedance network theory [11].

As the individual sensor impedances cannot be measured directly due to the multiplexed network configuration, an indirect estimation approach is adopted. Impedances between node pairs are measured under two distinct loading conditions: (i) a no-load condition and (ii) a loaded condition with an applied pressure of 1.25 bar.

Under the no-load condition, impedances are measured for all 91 node pair combinations at 5 discrete frequencies, resulting in a total of 455 complex values, denoted as $Z_{meas}(\omega)$. Under the loaded condition, each sensor is sequentially subjected to a pressure of 1.25 bar, and only the impedance of the node pair directly connected to the activated sensor is measured. This results in 19 impedance measurements per frequency, corresponding to 95 impedance values in total, denoted as $Z_1(\omega)$.

Between these two measurement conditions, only the sensor impedances vary whereas the distributed parasitic impedances associated with the transmission lines and measurement setup remain unchanged. This enables the formulation of an inverse estimation problem, where the intrinsic sensor parameters (modeled as frequency-dependent RC elements) are identified by minimizing the difference between measured and simulated impedance responses across both loading conditions.

Each sensor is modeled as a parallel RC element:

$$Z_i^{(k)}(\omega) = \frac{R_i}{1 + j\omega R_i C_i} \quad (1)$$

where $k=0$ and $k=1$ respectively denote the unloaded and loaded case and i runs from 1 to 19.

Let

$$Z_{simu}^{(0)}(\omega) = f(Z_i^{(0)}(\omega)) \quad (2)$$

denote the simulated pairwise impedance vector (size $M=91$) under no-load condition obtained from the impedance network mode [11]. Then the parasitic admittance is estimated by

$$Y_{CP}(\omega) = \frac{1}{Z_{meas}(\omega)} - \frac{1}{Z_{simu}(\omega)} \quad (3)$$

where $Z_{meas}(\omega)$ is associated with impedance measurements under no-load condition. For each sensor i , a hybrid state is constructed:

$$Z_i^{(k)}(\omega) = \begin{cases} Z_i^{(1)}(\omega), & k = i \\ Z_i^{(0)}(\omega), & k \neq i \end{cases} \quad (4)$$

When one sensor is pressed, the corresponding intrinsic impedances between node pairs can be simulated:

$$Z_{simu}^{(k)}(\omega) = f(Z_i^{(k)}(\omega)). \quad (5)$$

Let $p(i)$ denote the node pair corresponding to sensor i which is pressed. The residual is defined in the admittance domain:

$$r_i(\omega) = \frac{1}{Z_{1,i}(\omega)} - \frac{1}{Z_{simu,p(i)}^k(\omega)} - Y_{CP,p(i)}(\omega). \quad (6)$$

As the impedance magnitude varies by decades between different frequencies the relative residual is used:

$$\tilde{r}_i(\omega) = \frac{r_i(\omega)}{|Z_{1,i}(\omega)|}. \quad (7)$$

The unknown parameters are:

$$\theta = \{R_i^0, C_i^0, R_i^1, C_i^1\}_{i=1}^{19}. \quad (8)$$

The objective is to minimize the total residual over all sensors and frequencies:

$$\min_{\theta} \sum_{\omega, i} (\text{Re}(\tilde{r}_i(\omega))^2 + \text{Im}(\tilde{r}_i(\omega))^2). \quad (9)$$

The dataset used for parameter estimation comprises 455 impedance measurements under no-load conditions and 95 values under loaded conditions, yielding a total of 550 observations across multiple frequencies. These measurements are employed to estimate 76 parameters corresponding to the sensor work, resulting in an overdetermined optimization problem. It is noteworthy that under a load of 1.25 bar, the impedance of the pressure-sensitive elements decreases significantly, becoming approximately one order of magnitude smaller than both the parasitic

impedance and the corresponding no-load sensor impedance [9]. In this regime, the measured impedance is predominantly determined by the sensor response and can therefore serve as an approximation of the intrinsic sensor impedance. In the proposed framework, this approximation is not directly used for parameter identification; rather, it provides physically meaningful initial values for the optimization. This initialization improves convergence and mitigates the risk of non-physical local minima in the subsequent nonlinear estimation process.

The reconstruction accuracy of the proposed model is evaluated by comparing measured and reconstructed pairwise impedances across all frequencies. As shown in Fig. 3, the relative errors in impedance magnitude remain below 10% and phase error below 10 degrees over the entire frequency range. These results demonstrate that the proposed hybrid estimation framework provides an accurate reconstruction of the impedance magnitude and a reasonable approximation of the phase response.

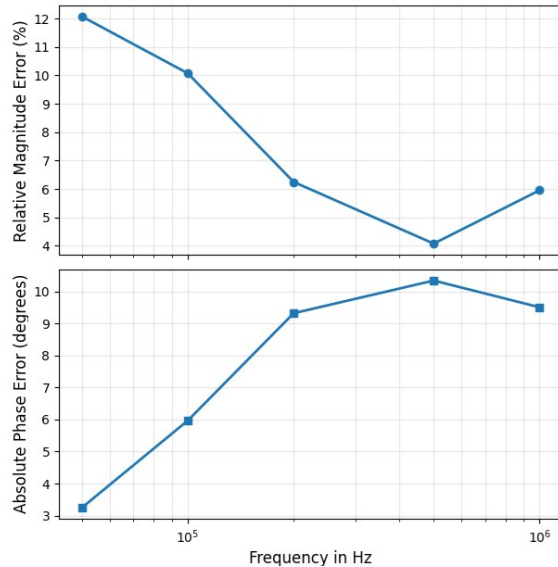


Fig. 3: Relative impedance magnitude error (top) and phase error (bottom) across all frequencies.

4 Extraction and Validation of Distributed Parasitic Admittances

With the pairwise impedances obtained from simulation, the corresponding parasitic admittance $Y_{CP}(\omega)$ can be calculated by Eqn. (3). In general, distributed parasitics in transmission lines may include resistive, inductive, and capacitive components. However, in the present setup, the lines are shorter than 1 m, and the operating frequency range is limited to 1 MHz. Under these conditions, the inductive and resistive contributions are relatively small

compared to the capacitive coupling effects and can therefore be neglected in a first-order approximation.

Consequently, the distributed parasitics are modeled using a leaky capacitive representation that accounts for both capacitive coupling and conductive leakage effects. Specifically, each parasitic path is described by a shunt combination of a coupling capacitance $C_p(k)$ and a leakage conductance $G_p(k)$, resulting in a frequency-dependent admittance of the form

$$Y_{CP}^{(k)}(\omega) = G_p^{(k)} + j\omega C_p^{(k)}, \quad k = 1, \dots, 19. \quad (10)$$

Since each pairwise impedance measurement corresponds to an independent signal path within the multiplexed network, the associated parasitic effects are assumed to be independent for each node pair. Accordingly, the distributed parasitic model is parameterized by 91 independent pairs of parameters ($C_p(k)$, $G_p(k)$), each corresponding to one node pair.

The estimation of these parameters is formulated as a nonlinear least-squares optimization problem in the complex domain. For all frequencies ω and node pairs k , the model parameters are obtained by minimizing the normalized difference between the modeled parasitic admittance and the measured admittance:

$$\min_{C_p, G_p} \sum_{\omega, k} \left\| \frac{Y_{model}^{(k)}(\omega) - Y_{meas}^{(k)}(\omega)}{Y_{meas}^{(k)}(\omega)} \right\|^2. \quad (11)$$

Here, $Y_{meas}(\omega)$ is obtained from the measured impedance by subtracting the simulated intrinsic network response, and $Y_{model}(\omega)$ is given by the parametric leaky capacitive model. The normalization by $Y_{meas}(\omega)$ ensures balanced weighting across frequencies and measurement channels.

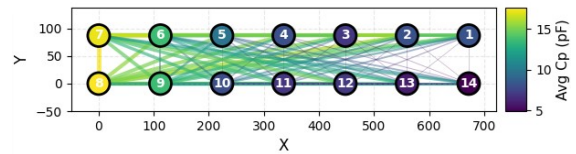


Fig. 4: Physical layout of coupling capacitance in the transmission lines (line thickness & color = coupling strength)

The extracted coupling capacitances $C_p(k)$ of the transmission lines are mapped onto the sensor matrix, as illustrated in Fig. 4. It can be observed that $C_p(k)$ strongly depends on the length of the transmission lines. In particular, the connections associated with nodes 7 and 8, which define the longest transmission paths, show the highest coupling capacitance values.

This trend is consistent with the physical expectation that longer transmission lines introduce larger parasitic capacitances. Therefore, the extracted results not only provide a good numerical fit but also demonstrate clear physical consistency with the underlying system geometry. In contrast, the extracted conductance $G_p(k)$ does not show a clear correlation with the transmission line length. As a result, it is not included in the spatial visualization.

With the extracted coupling capacitances $C_p(k)$, a measured pairwise impedance can be accurately reconstructed from the simulated intrinsic impedance. Conversely, the intrinsic impedance can be recovered from the parasitic-affected measurements through the proposed correction method. Over the entire frequency range, the RMS relative error in impedance magnitude across all measurements was 2.5% for the forward reconstruction of $Z_{meas}(\omega)$ and 7.7% for the inverse reconstruction of the intrinsic impedance $Z_{simu}(\omega)$.

To further validate the estimated parasitic parameters, an additional load condition was introduced in which two sensors were simultaneously pressed. Under this condition, all pairwise impedances were measured and reconstructed across the full frequency range. The reconstructed results strongly agree with the measurements, confirming the validity and robustness of the proposed model. Results at 100 kHz are presented in Figs. 5–7.

5 Conclusion

The proposed inversion, or de-embedding, framework provides a robust and generalizable method for the extraction of distributed parasitics in flexible PCB sensor matrices. By suppressing the parasitic influence, the framework enables the recovery of the intrinsic impedance response that can be directly utilized for subsequent analysis and machine-learning-based modeling of distributed impedance sensors and flexible electronic systems.

The normalization strategy in the admittance domain ensures balanced weighting across frequencies and measurement channels, leading to stable and physically meaningful parameter estimation.

The achieved reconstruction accuracy demonstrates the effectiveness of the method, with RMS relative error of 2.5% in impedance magnitude across all measurements for the forward reconstruction and 7.7% for the inverse reconstruction of the intrinsic impedance.

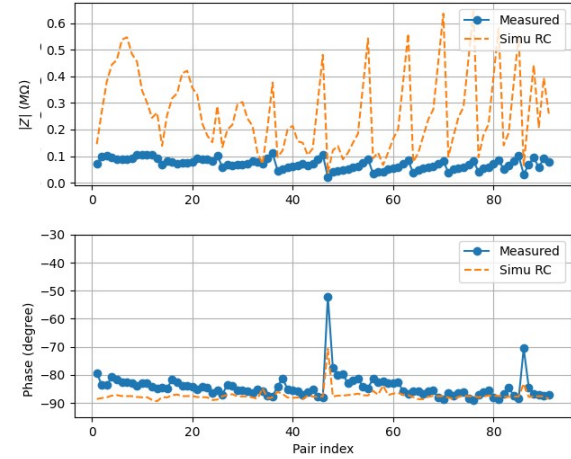


Fig. 5: Measured and simulated impedance magnitudes (top) and impedance phases (bottom) between selected nodes in the distributed-sensor matrix at 100 kHz without taking distributed parasitics into account.

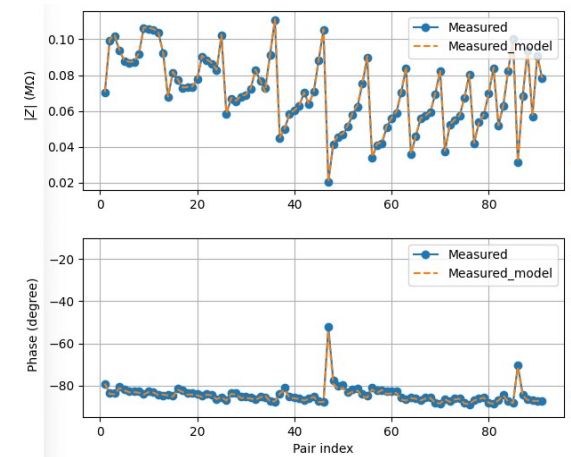


Fig. 6: Comparison of measured and modeled impedance magnitudes (top) and phases (bottom) between all node pairs in the distributed sensor matrix at 100 kHz.

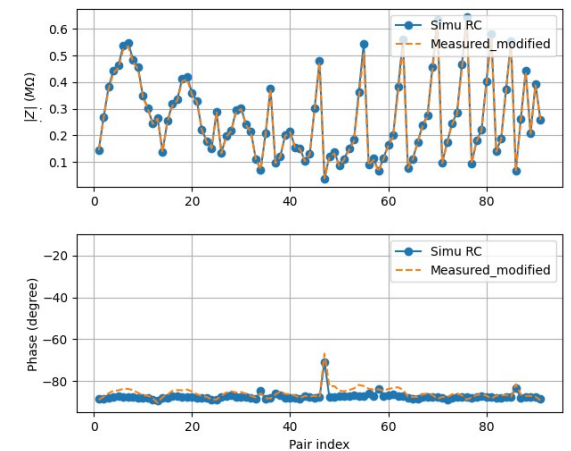


Fig. 7: Comparison of de-embedded measured impedances (= measured impedances with parasitic influences removed) with simulated impedances. Top: impedance magnitudes. Bottom: phases.

Furthermore, validation under a new load condition confirms the generalizability of the estimated parameters and highlights the effectiveness of the parasitic compensation in recovering the intrinsic impedance response.

Overall, the proposed de-embedding framework provides a robust and scalable solution for modeling distributed parasitics in flexible electronic systems. By enabling accurate extraction of intrinsic impedance characteristics, it establishes a reliable foundation for subsequent analysis and machine-learning-based signal processing for distributed impedance sensors.

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Declaration of Generative AI Use

While preparing this work, the authors used ChatGPT to check for possible spelling and grammatical errors. In addition, prompts such as “Improve it” were used to ensure the quality of the text. After using this service, the authors reviewed and edited the content as needed. They assume full responsibility for the content of the manuscript.

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