

Article

Design and Multi-Objective Optimization of a High-Sensitivity Miniaturized Multilayer Flexible Electric Field Sensor for Early Detection of Insulation Degradation

Junpeng Dang ¹, Chuanxu Yang ¹, Yang Li ^{2,*}, Wenlin Wang ¹, Bo Jiang ¹ and Zhensheng Wu ² 

¹ Yuxi Power Supply Bureau, Yunnan Power Grid Co., Ltd., Yuxi 653100, China; 15087706606@139.com (J.D.); 13887725237@139.com (C.Y.); 13577700122@139.com (W.W.); 15108764462@139.com (B.J.)

² School of Electrical Engineering, Beijing Jiaotong University, Beijing 100044, China; zhshwu@bjtu.edu.cn

* Correspondence: 25126470@bjtu.edu.cn

Abstract

To address the difficulty of effectively sensing weakly distorted electric fields generated during the early stage of insulation degradation in power equipment, this paper proposes a miniaturized high-sensitivity multilayer flexible electric field sensor optimized using an improved GOOSE algorithm. First, based on the electric field coupling mechanism, the enhancement effect of the flexible arc-shaped structure on local distorted electric fields is analyzed, and an equivalent model that discretizes the flexible curved surface into parallel-plate micro-elements is established. Furthermore, a multilayer sensor equivalent circuit model considering the effects of parasitic capacitance and conductive ink electrode resistance is developed, and the relationship between sensor sensitivity and structural parameters is derived. Subsequently, an electric field–circuit-coupled simulation model is established in COMSOL Multiphysics to systematically investigate the influence of parameters such as electrode layer number, electrode thickness, dielectric layer thickness, and electrode side length on the output response. The results show that the multilayer structure can effectively improve the equivalent sensing capacitance and electric field coupling capability, while the electrode thickness and dielectric layer thickness exhibit significant nonlinear effects on the output voltage. To achieve the coordinated optimization of high sensitivity and miniaturization, Tent chaotic mapping initialization and nonlinear dynamic adaptive inertia weight are introduced to improve the traditional GOOSE algorithm, and a multi-objective optimization model is constructed with the objectives of maximizing the output voltage and minimizing the electrode area. The optimization results indicate that the improved GOOSE algorithm achieves faster convergence and better optimization stability. Among the Pareto solution sets with different electrode layer numbers, the seven-layer structure exhibits the best size–performance trade-off. The final optimized design achieves an electrode area of only 1.746 mm² and an output voltage of 2.565×10^{-6} V. These results demonstrate that the proposed multilayer flexible structure and improved GOOSE optimization method can significantly enhance the response capability to weak electric fields while maintaining device miniaturization, providing a new sensor design concept and optimization approach for non-contact detection of early-stage insulation degradation in power equipment.



Academic Editor: Roberto Zivieri

Received: 26 June 2026

Revised: 18 July 2026

Accepted: 22 July 2026

Published: 24 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](#)

[Attribution \(CC BY\)](#) license.

Keywords: weakly distorted electric field; flexible electric field sensor; multilayer parallel-plate structure; multi-objective optimization; GOOSE algorithm; insulation condition monitoring

1. Introduction

With the development of power systems toward higher voltage levels, larger capacities, and higher reliability, early monitoring of the insulation condition of power equipment imposes increasingly stringent requirements on sensing technologies. During long-term operation, key equipment such as transformers, cables, switchgear, and insulators is subjected to the combined effects of electrical, thermal, mechanical, and environmental stresses, leading to space charge accumulation, local dielectric degradation, and the evolution of microstructural defects inside insulating materials. Previous studies have investigated space-charge behavior in multilayer oil–paper insulation and reported that space-charge accumulation can distort the local electric field distribution and increase local electrical stress, thereby accelerating insulation degradation and increasing the risk of breakdown [1–4]. However, at the early stage of insulation degradation, power equipment usually does not exhibit obvious fault features such as partial discharge, abnormal temperature rise, or significant leakage current. Instead, the degraded region is often characterized only by local variations in permittivity, conductivity, or charge distribution, which generate low-amplitude and highly localized distorted electric fields in the surrounding space. Therefore, effective sensing of weakly distorted electric fields before fault features are fully developed is a key issue in early insulation condition identification of power equipment.

At present, partial discharge detection, infrared detection, ultraviolet detection, dissolved gas analysis, and ultrasonic detection have been widely used for insulation condition assessment of power equipment. Wen et al. reviewed advanced signal-processing methods for partial-discharge analysis and summarized their role in improving the processing, interpretation, and diagnostic application of partial-discharge signals [5]. Álvarez et al. further combined ultra-high-frequency and high-frequency current detection techniques for online partial discharge monitoring, improving the effectiveness of insulation defect diagnosis [6]. However, partial discharge detection generally relies on the occurrence of discharge processes and requires the discharge signal to reach a certain intensity, making it insufficiently sensitive to early degradation states where obvious discharge has not yet formed. Tao et al. reviewed recent advances and remaining challenges in aging-monitoring and diagnostic techniques for power cables, providing a focused summary of methods used for power cable insulation condition assessment [7]. Nevertheless, these methods mostly use external features after fault development as diagnostic criteria, making it difficult to directly capture weak electric field disturbances caused by early changes in dielectric parameters.

Electric field detection provides a more direct means of characterizing local electric field distortion induced by insulation defects. Gao et al. studied spatial electric field detection for degraded insulators and indicated that insulator degradation can cause changes in the waveform and amplitude of the spatial electric field, enabling insulation condition assessment through non-contact electric field measurement [8]. Liu et al. further investigated high-voltage insulation condition assessment based on electric field detection and suggested that electric field detection offers advantages such as live-line measurement capability, good environmental adaptability, and low cost [9]. However, traditional electric field detection structures usually contain metal electrodes or metallic packages, which may disturb the original electric field distribution in the region under test. Moreover, they still suffer from insufficient sensitivity in detecting weakly distorted electric fields. Mou et al. and Lei et al. proposed MEMS electric field sensors for spatial DC electric field measurement, respectively, improving the miniaturization and integration of electric field sensors [10,11]. However, in practical applications, such sensors are susceptible to surface charge accumulation, packaging structures, and external environmental disturbances, and their stability in weak-field detection still requires further improvement.

Non-contact sensors based on the electric field coupling principle provide a new approach for weak electric field detection. Tan et al. proposed a non-contact adaptive voltage sensor for non-invasive conductor voltage measurement [12]. Xiong et al. adopted multilayer ceramic capacitors to improve the electric field coupling capability of a non-contact voltage sensor, thereby enhancing the output response by increasing the equivalent capacitance [13]. However, the above structures are mainly designed for conductor voltage measurement and usually rely on relatively regular electric field distributions and fixed installation conditions. They have not yet been specifically designed as flexible and miniaturized structures for local weakly distorted electric fields generated by early insulation degradation. For early insulation degradation detection, the sensor should not only exhibit high output sensitivity but also satisfy the requirements of low field disturbance, miniaturization, and adaptability to complex spatial environments.

To improve the response capability of sensors within a limited size, flexible structures and multilayer capacitive structures have gradually attracted attention. Chiurazzi et al. proposed a multilayer flexible capacitive proximity sensor, in which a multi-cell capacitive structure was used to expand the detection range and enhance proximity sensing capability [14]. Fu et al. designed a double-layer flexible capacitive pressure sensor and improved the pressure detection sensitivity and measurement range by modifying the dielectric layer structure [15]. These studies indicate that flexible structures and multilayer capacitive structures can improve the equivalent coupling capability and output response of sensors. However, existing flexible capacitive sensors are mostly intended for pressure, strain, proximity detection, or wearable monitoring, and their sensing targets are mainly mechanical quantities or changes in contact states. They have not been specifically designed for spatially weak, distorted electric fields. Meanwhile, in multilayer parallel-plate structures, the number of electrode layers, electrode thickness, dielectric layer thickness, and lateral size jointly affect the equivalent capacitance, interlayer coupling, parasitic effects, and port output voltage. These factors still lack systematic analysis in weakly distorted electric field detection scenarios.

The structural design of multilayer flexible electric field sensors involves a trade-off between output response and device size. Increasing the number of electrode layers or enlarging the electrode area generally helps improve the output voltage, but it also increases the device size and the complexity of interlayer coupling. Reducing the lateral size is beneficial for miniaturization, but it may decrease the effective sensing capacitance and weak-field output amplitude. Traditional empirical design or single-factor parameter scanning is difficult to simultaneously account for the coupling effects among multiple structural variables, and it is also difficult to obtain comparable trade-off solutions. Reference [16] proposed the Multi-Objective Greylag Goose Optimization algorithm for solving multi-objective optimization problems and obtaining Pareto-optimal solution sets, providing an algorithmic basis for balancing competing optimization objectives. In addition, the GOOSE algorithm realizes global exploration and local exploitation by simulating behaviors such as goose flock cooperation, leadership rotation, and foraging strategy switching [17]. However, the original algorithm may still be affected by strong randomness in the initial population, insufficient local search capability, and limited convergence stability. Zhang and Wang developed an improved Whale Optimization Algorithm by introducing a nonlinear adaptive weight and a golden sine operator, providing a specific example of enhancing the search performance of a metaheuristic algorithm through adaptive weight adjustment and search-strategy modification [18]. Tent-map-based population initialization and iteration-dependent nonlinear inertia-weight strategies have been employed in population-based optimization algorithms to improve initial population diversity and regulate the balance between global exploration and local exploitation [19]. Based on these methodological

considerations, this study introduces Tent chaotic mapping initialization and a nonlinear dynamic adaptive inertia weight into the GOOSE algorithm to improve the stability and convergence efficiency of sensor structural parameter optimization.

To address the above issues, this paper proposes a miniaturized high-sensitivity multilayer parallel-plate flexible electric field sensor for detecting weakly distorted electric fields caused by early insulation degradation in power equipment. The sensor uses a flexible arc-shaped structure to enhance the coupling capability for local distorted electric fields and employs a multilayer parallel-plate stacked structure to improve the equivalent sensing capacitance and output response within a limited size. To accurately describe the output characteristics of the sensor, an equivalent circuit model considering the effects of parasitic capacitance and conductive ink electrode resistance is established [20]. An electric field–circuit-coupled simulation model is then constructed in COMSOL Multiphysics to analyze the effects of the number of electrode layers, electrode thickness, dielectric layer thickness, and electrode side length on the output voltage. On this basis, a multi-objective optimization model is established with the objectives of maximizing the output voltage and minimizing the electrode area, and the Pareto solution sets of the sensor structural parameters are obtained using the improved GOOSE algorithm. The main contributions of this paper are as follows:

- (1) A multilayer parallel-plate flexible electric field sensor structure is proposed to enhance the local coupling capability for weakly distorted electric fields generated by early insulation degradation.
- (2) An equivalent circuit model considering the effects of parasitic capacitance and conductive ink electrode resistance is established, and the relationship between the output voltage and structural parameters is derived.
- (3) The influence mechanisms of the number of electrode layers, electrode thickness, dielectric layer thickness, and electrode side length on the output response are revealed.
- (4) A multi-objective optimization model considering output voltage and electrode area is constructed, and Pareto trade-off solutions under different numbers of electrode layers are obtained.

2. Theoretical Modeling and Structural Optimization of the Sensor

2.1. Capacitive Electric Field Sensing Theory

During the degradation stage of insulating materials, the dielectric anomaly region formed is extremely small, typically on the micrometer scale, and is much smaller than the distance between the anomaly and the external sensor. Therefore, the distorted electric field induced by insulation degradation is very weak. When the spatial dimensions of an insulation anomaly are much smaller than its distance from the sensor, a localized anomaly can be approximated as a point charge located at its center. For an elongated anomaly, when its longitudinal dimension is much larger than both the sensor side length l and the defect-to-sensor distance D , and the sensor is located near the central region of the anomaly, the end effects can be neglected. The elongated charge distribution can therefore be locally approximated as an ideal infinite line charge with a uniform linear charge density λ [21].

For a miniaturized sensor, its thickness is much smaller than the distance from the charge to the electrode plate; therefore, the sensor thickness can be neglected. The length and width of the sensor are both denoted as l , the distance between the electrode plate and the line charge is denoted as D , and the angle between the electric field line and the normal direction of the electrode plate is denoted as θ . The electric field acquisition mechanism of a conventional parallel-plate sensor under the action of a point charge or a line charge is shown in Figure 1.

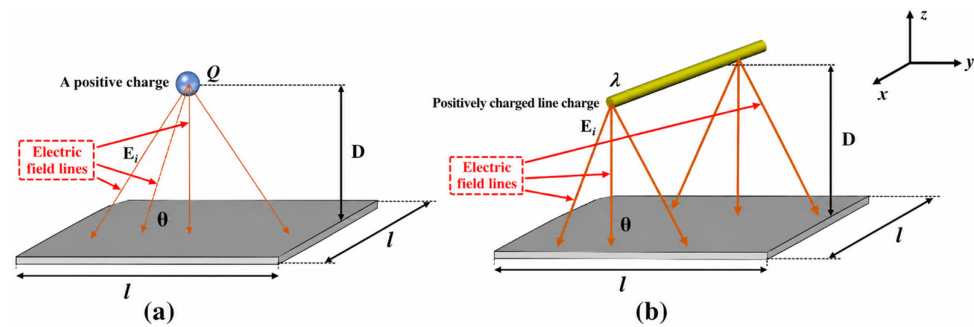


Figure 1. Electric field sensing mechanism of the conventional planar sensor: (a) point-charge model; (b) ideal infinite-line-charge approximation. The finite segment is shown only to schematically indicate the direction of the line-charge distribution.

The point-charge and line-charge models are considered as two independent idealized excitation cases for representing insulation anomalies with different spatial distributions. The electric field intensities E_1 and E_2 generated by a point charge with a total charge Q and an ideal line charge with a linear charge density λ_l , respectively, are expressed as Equation (1):

$$\begin{cases} E_1 = \frac{1}{4\pi\epsilon_0} \frac{Q}{r_p^2} \\ E_2 = \frac{1}{2\pi\epsilon_0} \frac{\lambda}{r_l} \end{cases} \quad (1)$$

where Q is the total point charge with the unit of C, λ_l is the linear charge density of the ideal line charge with the unit of C/m, r_p is the distance from the point charge to the observation point, r_l is the perpendicular distance from the ideal line charge to the observation point, and ϵ_0 is the vacuum permittivity. The two source models are analyzed independently, and no direct numerical comparison is made between Q and λ_l . For the conventional planar sensor, the effective electric field fluxes through the electrode surface under the point-charge and ideal line-charge excitation cases are denoted by μ_1 and μ_2 , respectively. The surface integration is performed over the entire square electrode surface S , which has a side length of l , as expressed in Equation (2).

$$\begin{cases} \mu_1 = \iint_S E_1 \cos \theta dS = \frac{Q}{\pi\epsilon_0} \arctan \left[\frac{l^2}{4D\sqrt{D^2 + \frac{l^2}{2}}} \right] \\ \mu_2 = \iint_S E_2 \cos \theta dS = \frac{\lambda l}{\pi\epsilon_0} \arctan \left(\frac{l}{2D} \right) \end{cases} \quad (2)$$

where S denotes the entire $l \times l$ square electrode surface shown in Figure 1. The integration covers the complete sensing surface of the electrode in both excitation cases. The quantities μ_1 and μ_2 represent the effective electric field fluxes intercepted by the planar sensor under the point-charge and ideal line-charge excitation cases, respectively. Their unit is V·m, equivalent to N·m²/C. These quantities are used to characterize the geometric electric field coupling capability of the sensor under identical source conditions and do not represent local electric field intensities.

The operating principle of a capacitive electric field sensor is based on the capacitive coupling between the external alternating electric field and the sensing electrodes. The electric field induces charge redistribution on the electrodes, thereby producing a displacement current and a corresponding AC voltage across the load resistance [22]. Under an alternating electric field, the time-varying induced charge on the sensing electrodes produces a displacement current whose amplitude is related to the rate of change of the external electric field. Therefore, the electric field excitation can be represented by an

equivalent current source $i_d(t)$. The electrode plates and dielectric layer form a capacitance C_x , which characterizes the charge storage effect. The load resistance R_{load} represents the input impedance of the external measurement circuit and is used to convert the induced current into a measurable voltage signal.

Figure 2 shows the model and equivalent circuit of the conventional parallel-plate sensor, which are used to derive the sensor sensitivity.

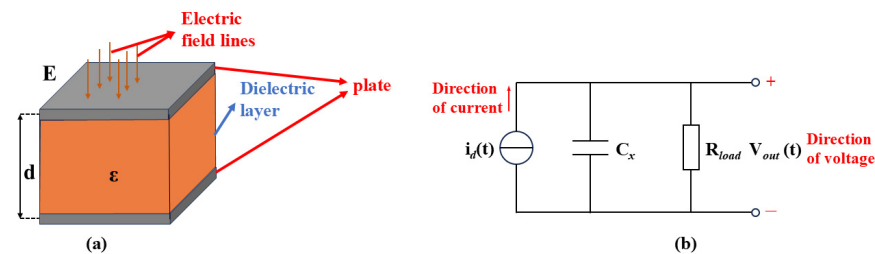


Figure 2. Parallel Plate Sensor: (a) Model Diagram (b) Equivalent Circuit Diagram.

In Figure 2a, d denotes the spacing between the two parallel plates, while $V_{OUT}(t)$ in Figure 2b represents the output voltage of the sensor. The expression for the capacitance C_x is given in Equation (3):

$$C_x = \frac{\epsilon S}{d} \quad (3)$$

where S is the effective overlapping area of the two electrode plates, with the unit of m^2 . For the square electrode considered in this study, $S = l^2$. In insulation degradation detection applications for power equipment, sensor sensitivity is a core performance parameter, as it directly determines the system's capability to detect weak signals. Based on the above analysis, the sensor sensitivity $H_1(\omega)$ can be derived as Equation (4).

$$H_1(\omega) = \frac{V_{out}(t)}{E} = \frac{dj\omega C_x R_{load}}{1 + j\omega C_x R_{load}} \quad (4)$$

where ω is the variation frequency of the external electric field E , and the magnitude of the sensitivity can be written as Equation (5).

$$|H_1(\omega)| = \frac{d\omega C_x R_{load}}{\sqrt{1 + (\omega R_{load} C_x)^2}} = \frac{d\omega \epsilon S R_{load}}{\sqrt{(d)^2 + (\omega R_{load} \epsilon S)^2}} \quad (5)$$

2.2. Optimization of Sensor Flexibility

To address the low collection efficiency of parallel-plate sensors for distorted electric fields generated during the degradation stage of insulating materials, the sensor is designed as a flexible arc-shaped structure with the same length.

The electric field acquisition mechanism of the flexible sensor is shown in Figure 3.

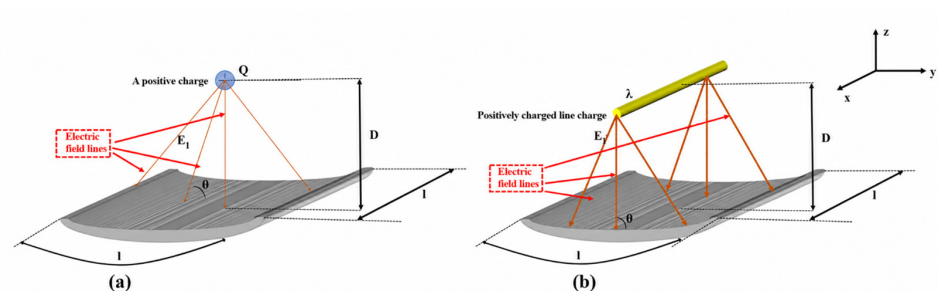


Figure 3. Electric field acquisition mechanism of the flexible sensor: (a) point charge; (b) line charge.

For the idealized flexible sensor shown in Figure 3, the sensing surface is assumed to conform to the electric field distribution. The point-charge case is represented by a spherical surface segment centered on the point charge, while the ideal line-charge case is represented by a cylindrical surface segment coaxial with the line charge. Therefore, the local normal direction of each surface element is parallel to the electric field direction, giving $\theta = 0$ and $\cos \theta = 1$. The sensing surface also remains at a constant distance D from the corresponding charge source, and its total area remains $S = l^2$. Accordingly, the effective electric field fluxes coupled through the flexible sensing surface are expressed as Equation (6).

$$\begin{cases} \nu_1 = \iint_S E_1 \cos \theta dS = \frac{Ql^2}{4\pi\epsilon_0 D^2} \\ \nu_2 = \iint_S E_2 \cos \theta dS = \frac{\lambda l^2}{2\pi\epsilon_0 D} \end{cases} \quad (6)$$

where ν_1 and ν_2 denote the effective electric field fluxes coupled by the flexible sensor under the point-charge and ideal line-charge excitation cases, respectively. Both quantities have the unit of V·m. Equation (6) is based on an ideal conformal-surface approximation and is used to compare the geometric coupling capabilities of the planar and flexible sensor structures under identical charge-source conditions.

To compare the electric field acquisition capabilities of the two structures, their ratios, η_1 and η_2 , are defined by Equation (7).

$$\begin{cases} \eta_1 = \frac{\mu_1}{\nu_1} = \frac{4D^2}{l^2} \arctan \left[\frac{l^2}{4D\sqrt{D^2 + \frac{l^2}{2}}} \right] \\ \eta_2 = \frac{\mu_2}{\nu_2} = \frac{2D}{\sqrt{4D^2 + l^2}} \end{cases} \quad (7)$$

According to Equation (7), when $D \gg l$:

$$\begin{cases} \eta_1 = \frac{4D^2}{l^2} \arctan \left[\frac{l^2}{4D\sqrt{D^2 + \frac{l^2}{2}}} \right] = \frac{4D^2}{l^2} \times \frac{l^2}{4D\sqrt{D^2}} = 1 \\ \eta_2 = \frac{2D}{\sqrt{4D^2 + l^2}} = \frac{2D}{\sqrt{4D^2}} = 1 \end{cases} \quad (8)$$

In all other cases, η_1 and η_2 are less than 1. The above analysis indicates that the normal direction of the flexible sensor can remain aligned with the direction of the electric field lines of the distorted electric field. This geometric optimization enables the sensor to couple a higher effective electric flux under the same projected area, thereby significantly improving the acquisition efficiency and integrity of the electric field signal.

2.3. Multilayer Parallel-Plate Structure Optimization

On the basis of the enhanced electric field coupling capability provided by the flexible structure, a single-layer electrode remains limited by its effective sensing area, making it difficult to simultaneously achieve miniaturization and a high output response [23]. Therefore, a multilayer electrode stacking structure is further introduced in this paper.

It should be noted that, in the distorted electric field generated by insulation degradation, the normal direction at each point on the surface of the flexible sensor is approximately aligned with the direction of the local electric field line. Therefore, the flexible curved surface can be discretized into numerous infinitesimal elements, each of which can be regarded as a local parallel-plate unit. Since each infinitesimal element satisfies the parallel-plate sensing mechanism, the flexible multilayer structure can be theoretically equivalent to a model composed of multiple parallel-plate units [24,25]. Based on this equivalent concept, the improved multilayer parallel-plate sensor model and its equivalent circuit are established, as shown in Figure 4.

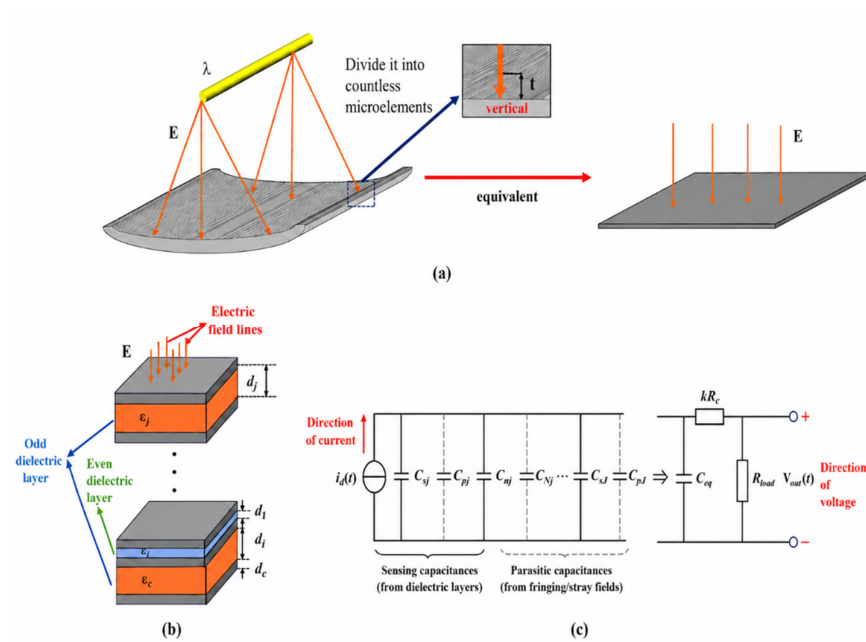


Figure 4. Multilayer flexible electric field sensor: (a) equivalent schematic of infinitesimal elements in the flexible structure; (b) multilayer parallel-plate model; (c) expanded and simplified equivalent circuits of the multilayer structure, in which the sensing capacitances and parasitic capacitances are separately identified.

Figure 4a shows the equivalent schematic, illustrating the equivalence process from the flexible curved structure to local parallel-plate units. This equivalent treatment preserves the electric field coupling characteristics of the flexible structure while facilitating the establishment of an analytical model for the multilayer sensor. In Figure 4b, the sensor model consists of n electrode layers, where d_i denotes the plate spacing of the odd-layer sensing units, d_j denotes the plate spacing of the even-layer sensing units, ϵ_i denotes the dielectric permittivity of the odd-layer sensing units, ϵ_j denotes the dielectric permittivity of the even-layer sensing units, and d_c denotes the electrode thickness. In Figure 4c, C_i and C_j represent the capacitances of the odd-layer and even-layer sensing units, respectively, with the parasitic capacitance effect taken into account.

In the expanded equivalent circuit shown in Figure 4c, $C_{s,i}$ and $C_{s,j}$ denote the sensing capacitances formed by the adjacent electrodes and dielectric layers of the two types of sensing units, respectively. $C_{p,i}$ and $C_{p,j}$ denote the corresponding lumped parasitic capacitances caused mainly by electrode-edge fringing fields and unintended coupling between nonadjacent electrodes. The sensing capacitances and parasitic capacitances are shown separately to clarify their respective physical meanings. In the simplified equivalent circuit, C_i and C_j denote the corresponding effective branch capacitances after the parasitic-capacitance effects are incorporated, and the complete multilayer capacitance network is further simplified as the overall equivalent capacitance C_{eq} .

In addition, the conductive-ink electrode resistance R_c is introduced to characterize the conductor loss in the electrodes, and κ is a dimensionless positive correction coefficient used to approximately relate the effective resistance of the multilayer electrode network to R_c .

In the alternating multilayer structure, adjacent sensing units produce induced-voltage contributions with opposite polarities relative to the defined output-voltage direction. Therefore, d_{eq} is introduced as a signed equivalent differential spacing rather than the total physical thickness of the sensor. Under the adopted sign convention, the contributions of the units with spacing d_i are positive, whereas those of the units with spacing d_j are negative. For an odd number n of electrode layers, the numbers of these two types of

units are $(n + 1)/2$ and $(n - 1)/2$, respectively. Similarly, the capacitance terms associated with the two alternating sensing-unit groups contribute with opposite signs relative to the defined output-voltage polarity. The subtraction in C_{eq} therefore represents a signed differential combination of the capacitance contributions, rather than the direct subtraction of passive physical capacitors. Each individual sensing capacitance remains positive. The equivalent spacing d_{eq} , the equivalent capacitance C_{eq} , and the electrode resistance R_c can be expressed as Equation (9):

$$\begin{cases} d_{eq} = \frac{n+1}{2}d_i - \frac{n-1}{2}d_j \\ C_{eq} = S\left(\frac{(n+1)}{2}\frac{\epsilon_i}{d_i} - \frac{(n-1)}{2}\frac{\epsilon_j}{d_j}\right) \\ R_c = \frac{\rho l_c}{S_c} = \frac{\gamma}{d_c} \end{cases} \quad (9)$$

d_{eq} denotes the signed equivalent differential spacing determined by the opposite-polarity contributions of the alternating sensing units; it does not represent the total geometric thickness of the multilayer sensor and S_c is the cross-sectional area of the electrode plate, ρ is the resistivity of the conductive ink, l_c is the length of the conductive ink electrode, and γ is a constant.

Where S_c is the effective cross-sectional area of the conductive path, ρ is the resistivity of the conductive ink, l_c is the effective current-path length, and d_c is the electrode thickness. For an electrode with an effective conductive width w_c , $S_c = w_c d_c$. Therefore, γ is defined as $\gamma = \rho l_c / w_c$, and the electrode resistance can be written as $R_c = \gamma / d_c$. The coefficient γ is a lumped material–geometry parameter with the unit of $\Omega \cdot \text{m}$. Under the adopted output-polarity convention, the differential equivalent capacitance remains positive when $(n + 1)\epsilon_i / (2d_i) > (n - 1)\epsilon_j / (2d_j)$, or equivalently, when $(n + 1)\epsilon_i d_j > (n - 1)\epsilon_j d_i$. This condition is imposed on the admissible design domain. Equality corresponds to zero net differential coupling. If the inequality is reversed, the sign indicates a reversal of the output polarity rather than a negative passive capacitance, and the physical equivalent-capacitance magnitude is given by $|C_{eq}|$. Based on the above analysis, the sensor sensitivity and its magnitude can be expressed as Equation (10):

$$\begin{cases} H(\omega) = \frac{V_{out}(t)}{E} = \frac{j\omega d_{eq} C_{eq} R_{load}}{1 + j\omega(R_{load} + \kappa \frac{\gamma}{d_c})C_{eq}} \\ |H(\omega)| = \frac{SR_{load}\omega(\frac{n+1}{2}d_i - \frac{n-1}{2}d_j)(\frac{(n+1)}{2}\frac{\epsilon_i}{d_i} - \frac{(n-1)}{2}\frac{\epsilon_j}{d_j})d_c}{\sqrt{(d_c)^2 + [\omega(R_{load} + \kappa \frac{\gamma}{d_c})S(\frac{n+1}{2}\frac{\epsilon_i}{d_i} - \frac{n-1}{2}\frac{\epsilon_j}{d_j})]^2}} \end{cases} \quad (10)$$

3. Parameter Optimization Method Based on the Improved GOOSE Algorithm

To improve the sensor's detection capability for weakly distorted electric fields generated during the insulation degradation stage while maintaining miniaturization, it is necessary to optimize the key structural parameters of the sensor. In this paper, the maximization of the sensor output voltage and the minimization of device size are taken as the optimization objectives, and an improved multi-objective GOOSE algorithm is used to optimize the sensor structural parameters. The five parameters d_i , d_j , d_c , n , and l are selected as the variables to be optimized. In addition, n is constrained to be an odd integer greater than or equal to 1, and the constraint expressed in Equation (11) must also be satisfied.

$$h_c - (n + 1)d_c = \frac{(n + 1)}{2}d_i + \frac{(n - 1)}{2}d_j \quad (11)$$

where h_s denotes the overall thickness of the multilayer sensor. Let $n \in \{1, 3, 5, 7, 9\}$. The above problem can then be abstracted as Equation (12).

$$\begin{cases} X = (d_i, d_j, d_c, n) \\ F = F(d_i, d_j, d_c, n) \\ X_{\min} \leq X \leq X_{\max} \\ \text{Max} : M = M(X) \\ 1 \leq n, n \equiv 1(\text{mod}2) \end{cases} \quad (12)$$

X denotes the optimization variables, M and A are the objective functions, F represents the constraint in Equation (11), and $X_{\min}$ and $X_{\max}$ denote the lower and upper bounds of the optimization variables, respectively.

The GOOSE optimization algorithm first initializes the population. The position of each goose, namely the optimization variable, is defined as the matrix $X = [X_1, X_2, \dots, X_m]$. The fitness value of each goose position is then determined in each iteration using a normalized benchmark function. The fitness of each goose position in the search space is calculated and compared with those of the other goose positions to identify the best fitness value and the corresponding best position. The algorithm then enters the exploitation and exploration stages. A random parameter β is generated; if β falls between 0.5 and 1.0, the algorithm enters the exploitation stage; otherwise, it enters the exploration stage. The above stages are repeated until the maximum number of iterations is reached. After the iteration process is completed, the algorithm outputs the optimal goose position.

However, the basic GOOSE algorithm suffers from strong randomness in population initialization and a relatively rigid balance strategy between exploration and exploitation. To overcome these limitations, this paper improves the original GOOSE algorithm in two aspects. First, a Tent chaotic mapping initialization strategy is introduced to enhance the diversity and ergodicity of the initial population. Second, a nonlinear dynamic adaptive inertia weight is introduced to dynamically adjust the search capability of the algorithm at different iteration stages.

In the population initialization stage, Tent chaotic mapping is adopted to generate the initial population, and its mapping relationship is defined as Equation (13).

$$x_{n+1} = f(x_n) = \begin{cases} x_n / \alpha, x_n \in [0, \alpha) \\ (1 - x_n) / (1 - \alpha), x_n \in [\alpha, 1) \end{cases} \quad (13)$$

where x_n is the chaotic value at the current iteration step, x_{n+1} is the chaotic value at the next iteration step, and α is the initialization coefficient, $\alpha \in [0, 1]$, and the initialized solution vector can be written as Equation (14).

$$X^0 = X_t + x_n(X_{\max} - X_{\min}) \quad (14)$$

where X^0 denotes the population initialized using the Tent chaotic map, and the mapping operation is performed elementwise within the variable bounds defined by $X_{\min}$ and $X_{\max}$.

In the exploitation and exploration stages of the algorithm, a nonlinear dynamic adaptive inertia weight is introduced during each generation of the random number β to dynamically balance the global exploration and local exploitation capabilities of the algorithm. This mechanism enables the algorithm to maintain a larger inertia weight in the early stage of iteration, thereby promoting global exploration. In the later stage of iteration, the inertia weight decreases to enhance local exploitation around potential

optimal solution regions. The expression of the nonlinear dynamic inertia weight Λ is given in Equation (15):

$$\Lambda = 2 - \frac{2}{1 + e^{[-10\tau(\frac{2t}{N}-1)]}} \quad (15)$$

where τ is a uniformly distributed random number generated in the interval $[0, 1]$, t denotes the current iteration number, and N denotes the preset maximum number of iterations.

Through the above two improvements, the algorithm enhances population diversity during the initialization stage and dynamically adjusts the global exploration and local exploitation capabilities during the iterative process, thereby improving the convergence speed and optimization stability.

The flowchart of the improved GOOSE algorithm is shown in Figure 5.

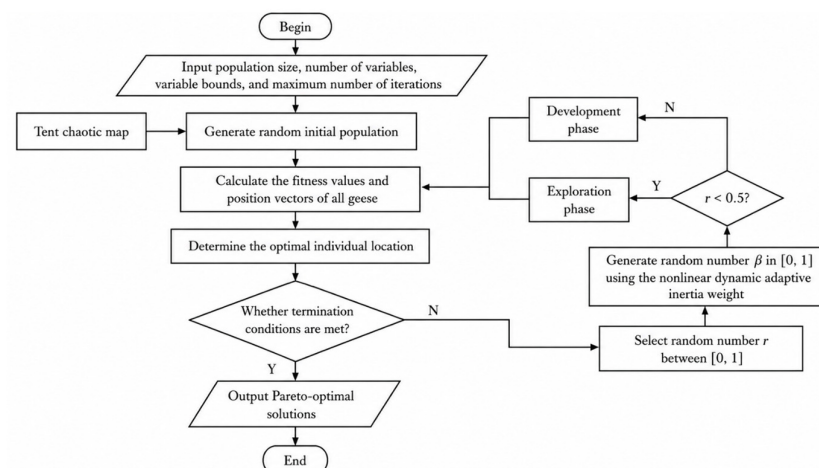


Figure 5. Improved GOOSE algorithm process.

4. Simulation Design and Optimization of Sensors

An electric field–circuit-coupled model was established using COMSOL Multiphysics 6.3 (COMSOL AB, Stockholm, Sweden) to compare the basic parallel-plate structure, the three-layer structure, and the five-layer structure. The effects of structural parameters on the output voltage and sensor size were analyzed to provide a basis for subsequent multi-objective optimization.

Conductive ink was used as the electrode material, while polytetrafluoroethylene (PTFE) with a relative permittivity of 2 and polyvinylidene fluoride (PVDF) with a relative permittivity of 10 were selected as the dielectric materials. The applied electric field was set to 1000 V/m along the z-axis.

The electric field–circuit-coupled model was established in COMSOL Multiphysics 6.3 using the Electric Currents and Electrical Circuit interfaces under a frequency-domain study. The sensor was placed at the center of a spherical air domain, and the outer boundary conditions were configured to generate a uniform electric field of 1000 V/m along the z-axis. The remaining external boundaries were treated as electrically insulating boundaries. For the capacitive electric field sensor, the two electrode groups were defined as electrical terminals and coupled to the external circuit through the terminal connections. A 1 MΩ load resistor was connected between the two terminals, allowing the electric field-induced current to generate a voltage drop across the resistor. The terminal current calculated by the Electric Currents interface was transferred to the Electrical Circuit interface, and the resulting terminal voltage was coupled back to the field model. A voltage probe was placed across the load resistor, and the measured voltage difference was taken as the sensor output

voltage. Under identical external electric field conditions, this output voltage was used to evaluate and compare the sensitivity of different sensor structures.

A mesh-independence study was conducted by progressively refining the computational mesh while keeping all other simulation settings unchanged. Local mesh refinement was applied to the thin electrode and dielectric layers and their interfaces. The output voltage across the load resistance was used as the convergence quantity, and the mesh was considered sufficiently converged when further refinement resulted in a relative output-voltage variation of less than 1%. The final converged mesh was used in all subsequent simulations.

The simulation models of the sensors are shown in Figure 6.

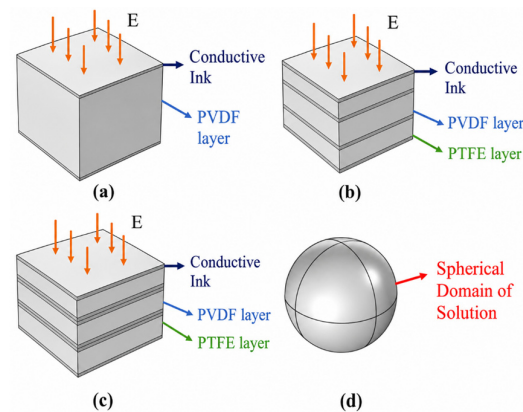


Figure 6. COMSOL simulation model: (a) Traditional structure (b) three-layer structure (c) five-layer structure (d) spherical solution domain.

A logarithmic frequency sweep with 12 frequency points was performed over the range of 10–300 Hz, and the variation in the output voltage of sensors with different numbers of layers as a function of frequency is shown in Figure 7.

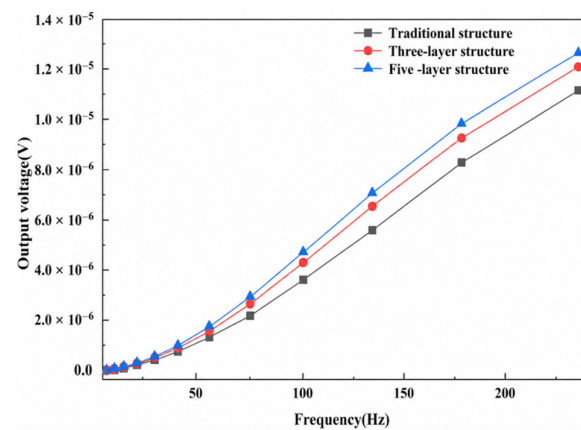


Figure 7. Relationship between output voltage and frequency for flexible capacitive electric field sensors with three different numbers of layers.

Across the entire frequency range, the five-layer structure consistently produced a higher output voltage than the three-layer structure and the conventional single-layer structure. The obvious differences in output voltage among structures with different numbers of layers indicate that the number of sensor layers has a significant influence on the electric field coupling capability. Based on this analysis, the number of layers n was introduced as a discrete design variable in the subsequent multi-objective optimization model and jointly optimized with the other structural parameters.

With the sensor length and width kept identical and constant and the total thickness fixed, the effects of electrode spacing and electrode thickness on the output voltage were first analyzed. The parameters of the three sensor structures are listed in Table 1.

Table 1. Parameters of the three sensor structures with constant length and width.

Sensor Length and Width/mm	Sensor Thickness /mm	Radius of Spherical Solution Domain/mm
1	0.8	3

Under a 50 Hz electric field, the relationship between the output voltage of the three sensors and the electrode thickness is shown in Figure 8.

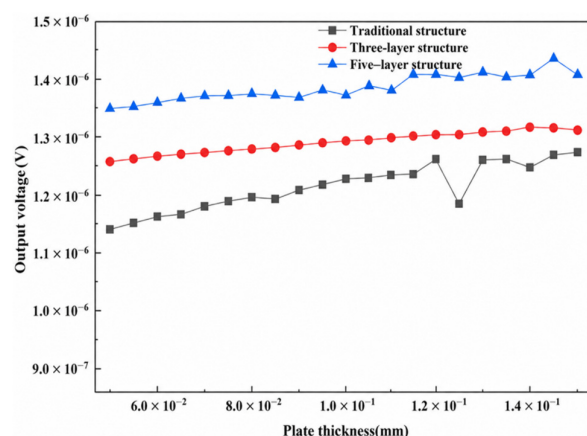


Figure 8. Relationship between output voltage and electrode thickness for the three sensors.

Figure 8 shows that the electrode thickness has a pronounced effect on the sensor output voltage, and the relationship is not simply linear. When the electrode is relatively thin, the cross-sectional area of the conductive ink electrode is small, resulting in a large equivalent resistance. Consequently, considerable ohmic loss occurs during the transfer of induced current through the electrode, leading to a low output voltage at the load terminal. As the electrode thickness increases, the electrode resistance decreases and the charge transfer efficiency improves, thereby increasing the output voltage. However, a further increase in electrode thickness compresses the effective thickness of the dielectric layer and enhances interlayer parasitic coupling and fringing-field distortion, causing the output response to approach saturation or even decrease. Therefore, the effect of electrode thickness on the output voltage reflects a competing relationship between reduced conductor loss and enhanced parasitic coupling, indicating the existence of an appropriate optimal thickness range.

Since the PVDF layer thickness in the multilayer structure significantly affects the electric field distribution and equivalent capacitance, the relationship between the output voltage and PVDF layer thickness for the three-layer and five-layer structures was further analyzed, as shown in Figure 9.

Figure 9 shows that the PVDF layer thickness also has a non-monotonic effect on the output voltage. Owing to the high relative permittivity of PVDF, increasing the PVDF layer thickness at relatively small thicknesses increases the proportion of the high-permittivity material, enhances electric field concentration within the dielectric layer, and improves the capability for induced charge accumulation, thereby increasing the output voltage. However, when the PVDF layer becomes excessively thick, part of the electric field is overly confined within the high-permittivity dielectric, weakening the effective penetration of

the external distorted electric field toward the internal electrodes. Meanwhile, the internal potential gradient in the multilayer structure decreases, suppressing the increase in induced current and leading to a reduction in the output voltage. Therefore, an optimal PVDF layer thickness exists, which essentially reflects the balance between electric field concentration and electric field penetration. Compared with the relatively smooth dependence of the three-layer structure, the five-layer structure exhibits small local fluctuations because it contains more electrode–dielectric interfaces and internal capacitive branches. Variations in the PVDF layer thickness simultaneously affect the effective capacitance, electric field distribution, interlayer shielding, and parasitic coupling among the sensing layers. The competition among these effects results in local redistribution of the electric field and induced charge, making the five-layer output response more sensitive to thickness variation. Therefore, the fluctuations in Figure 9 should be understood as local non-monotonic variations rather than periodic oscillations.

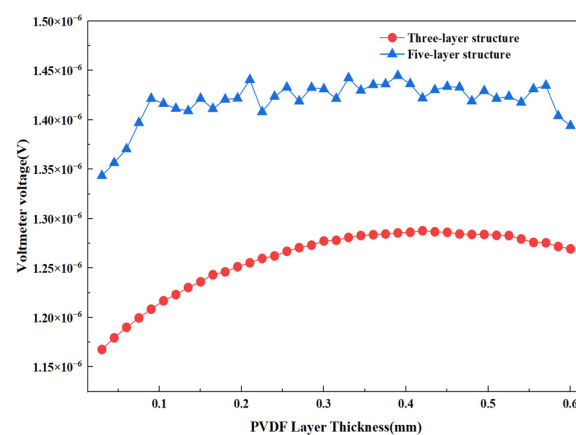


Figure 9. Relationship between output voltage and PVDF layer thickness for the two improved sensors.

With the electrode spacing and electrode thickness kept identical and constant, the overall sensor thickness was fixed at 0.8 mm for all structures to ensure a fair comparison under the same size constraint. The effect of the sensor length and width on the output voltage was then analyzed. The parameters of the conventional parallel-plate sensor are listed in Table 2, while those of the three-layer and five-layer sensors are listed in Table 3.

Table 2. Parameters of the conventional parallel-plate structure with constant electrode spacing and electrode thickness.

Electrode Plate Layer Thickness/mm	PVDF Layer Thickness/mm	Sensor Thickness/mm	Radius of Spherical Solution Domain/mm
0.2	0.6	0.8	3

Table 3. Parameters of the three-layer and five-layer structures with constant electrode spacing and electrode thickness.

Electrode Plate Layer Thickness/mm	PVDF Layer Thickness/mm	Sensor Thickness/mm	Radius of Spherical Solution Domain/mm
0.145	0.4	0.8	3

Under a 50 Hz electric field, the relationship between the output voltage of the three sensors and the electrode side length l is shown in Figure 10.

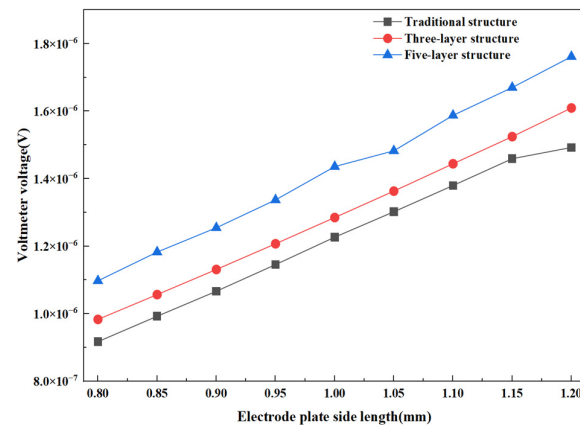


Figure 10. Relationship between output voltage and electrode side length for the three sensor structures.

Figure 10 shows that, when the other structural parameters remain unchanged, the electrode side length l is generally positively correlated with the output voltage. From the perspective of electric field acquisition, a larger electrode area provides a stronger capability to intercept electric flux, thereby generating a higher induced current and output voltage. However, increasing the electrode side length also enlarges the overall sensor size, which is unfavorable for installation and deployment on complex power equipment surfaces. Therefore, an inherent trade-off exists between output voltage enhancement and structural miniaturization, which provides the main motivation for subsequent structural parameter optimization using a multi-objective optimization algorithm.

The above analysis aims to verify the influence of each structural parameter on the sensor output performance and to reveal the coupling relationships among these parameters, rather than to determine a single optimal structure. Based on the identified influence characteristics of the variables, a multi-objective optimization model is further constructed. The improved multi-objective GOOSE algorithm is then employed to jointly optimize the above variables and obtain the Pareto-optimal solution set of the sensor structural parameters.

To evaluate the convergence performance of the improved GOOSE algorithm, the conventional GOOSE algorithm and the improved GOOSE algorithm were compared under the same conditions. The magnitude of the sensor output was selected as the fitness function for algorithm performance evaluation. The initial population size of both algorithms was set to 30, and the maximum number of iterations was set to 500. Figure 11 shows the convergence curves of the two algorithms.

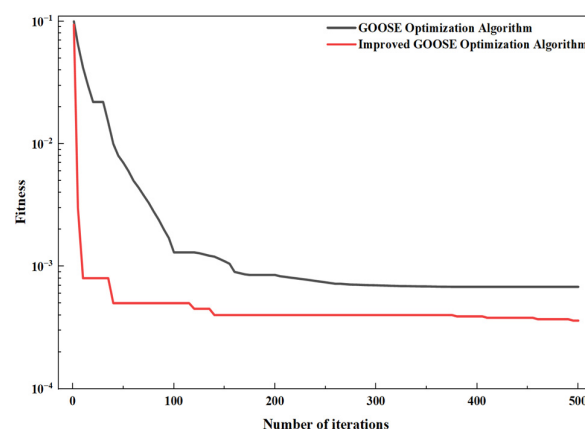


Figure 11. Algorithm convergence curves.

As shown in Figure 11, both algorithms gradually converge as the number of iterations increases. However, compared with the conventional GOOSE algorithm, the improved

GOOSE algorithm exhibits a lower initial fitness value, a faster convergence rate, and better convergence performance. This indicates that Tent chaotic initialization and the adaptive weight mechanism can effectively enhance the global search capability and optimization accuracy of the algorithm.

Based on the above convergence analysis, the improved multi-objective GOOSE algorithm was further employed to optimize the structural parameters of the multilayer flexible electric field sensor, with the aim of simultaneously satisfying the requirements of miniaturization and high sensitivity. The preceding comparison among the conventional single-layer, three-layer, and five-layer structures has verified the enhancement effect of multilayer stacking on the output response and the five-layer structure exhibits the best performance. To further analyze the size–performance trade-off of multilayer structures with higher numbers of layers, five-layer, seven-layer, and nine-layer structures were selected for Pareto front comparison. With electrode area minimization and output voltage maximization as the optimization objectives, the population size was set to 30 and the maximum number of iterations was set to 50. The Pareto solution sets obtained for sensors with different numbers of layers are shown in Figure 12.

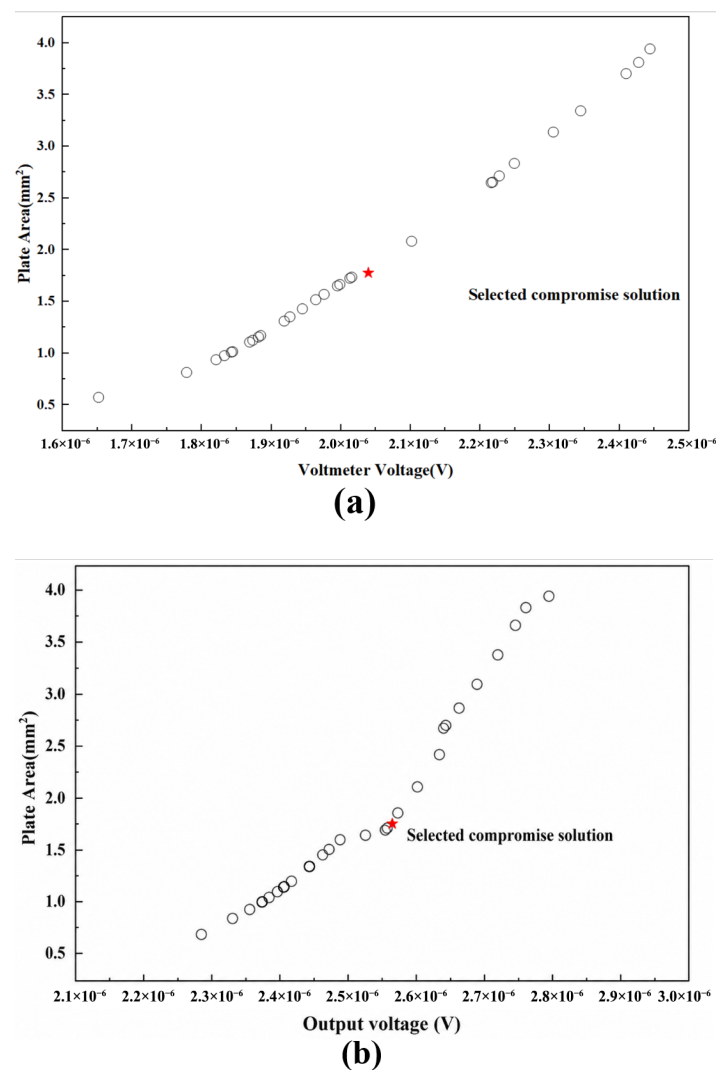


Figure 12. Cont.

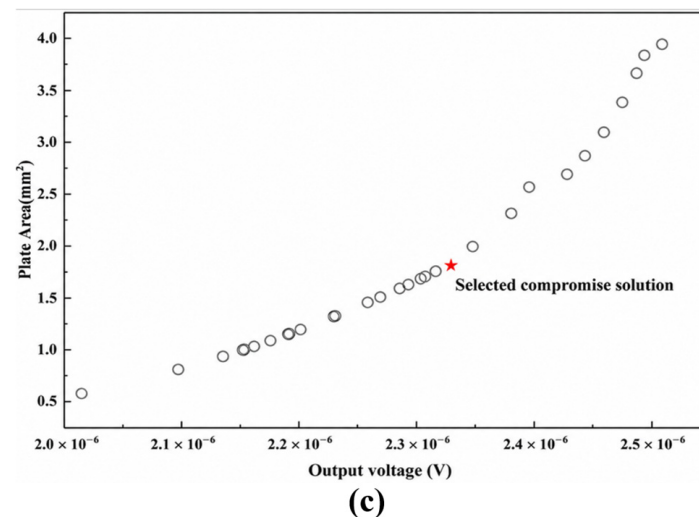


Figure 12. Pareto-optimal solution sets and compromise optimal solutions: (a) five-layer structure; (b) seven-layer structure; (c) nine-layer structure.

Figure 12 presents the Pareto fronts obtained from the parameter optimization of the five-layer, seven-layer, and nine-layer structures, with the output voltage plotted on the horizontal axis and the electrode area on the vertical axis. Overall, compared with the five-layer structure, the Pareto front of the seven-layer structure shifts further toward the lower-right region, indicating that a higher output voltage can be achieved under the same electrode area, or a smaller structural size can be obtained under the same output voltage. However, when the number of electrode layers increases to nine, the Pareto front does not continue to move toward the high-performance region, and some solutions even exhibit degradation. This indicates that simply increasing the number of electrode layers does not necessarily lead to better performance.

This phenomenon can be attributed to the competing effects introduced by the multilayer structure. On the one hand, increasing the number of layers improves the electric field coupling capability by increasing the equivalent capacitance. On the other hand, it also introduces internal electric field shielding and parasitic coupling. When the number of electrode layers becomes excessive, the external distorted electric field gradually attenuates after passing through the upper electrodes, resulting in a weaker effective electric field sensed by the deeper electrodes. Meanwhile, the increase in parasitic capacitance paths makes it more difficult for part of the induced charge to be effectively transferred to the output terminal. Therefore, the performance improvement of the multilayer structure is jointly constrained by capacitance enhancement, shielding effects, and parasitic coupling. Overall, the seven-layer structure provides the best trade-off between output voltage enhancement and electrode area control.

The selected compromise solution in Figure 12 was finally adopted as the optimized design, and the corresponding structural parameters are listed in Table 4.

Table 4. Final optimized design obtained from the Pareto front.

Electrode Plate Layer Thickness/mm	PVDF Layer Thickness/mm	Number of Sensor Electrode Layers	PTFE Layer Thickness/mm	Sensor Length and Width/mm
0.138	0.422	7	0.240	1.321

With the optimized structural parameters listed in Table 4, the corresponding electrode area and output voltage are 1.746 mm² and 2.565×10^{-6} V, respectively, as shown in Figure 12b. Under the applied electric field intensity of 1000 V/m, this output voltage corresponds to an electric field-to-voltage sensitivity of 2.565×10^{-9} V/(V/m), or equiva-

lently $2.565 \mu\text{V}/(\text{kV}/\text{m})$. These results verify the effectiveness of the proposed multilayer flexible structure and the improved GOOSE algorithm in simultaneously achieving sensor miniaturization and high sensitivity.

5. Conclusions

This study focused on the insufficient sensing capability for weakly distorted electric fields generated during the early stage of insulation degradation in power equipment, and investigated the theoretical modeling, simulation analysis, and multi-objective optimization of a multilayer parallel-plate flexible electric field sensor. Theoretical analysis shows that the flexible arc-shaped structure improves the alignment between the surface normal of the sensor and the direction of the local electric field lines, thereby enhancing the effective coupling capability for weakly distorted electric fields. Based on the equivalent representation of the flexible curved surface as local parallel-plate infinitesimal elements, a multilayer equivalent circuit model was established. This model can characterize the effects of parasitic capacitance and conductive ink electrode resistance on the sensor output response, providing a theoretical basis for subsequent structural parameter analysis.

The electric field–circuit-coupled simulation results indicate that the multilayer parallel-plate stacked structure can improve the equivalent sensing capacitance and output voltage within a limited size. However, the performance enhancement does not increase monotonically with the number of electrode layers. Both electrode thickness and dielectric layer thickness exhibit non-monotonic effects on the output voltage, reflecting the combined influence of conductor loss, dielectric field concentration, field penetration capability, and parasitic coupling. Increasing the electrode side length improves the electric field interception capability and output voltage, but also increases the device area, revealing an inherent trade-off between output response enhancement and sensor miniaturization.

The algorithm comparison results show that, after introducing the Tent chaotic mapping initialization strategy and the nonlinear dynamic adaptive inertia weight, the improved GOOSE algorithm outperforms the original GOOSE algorithm in terms of convergence speed and optimization stability. The Pareto solution sets obtained using the improved algorithm further demonstrate that, as the number of electrode layers increases from a single layer to seven layers, the sensor output response gradually improves under the same electrode area. However, when the number of electrode layers increases to nine, enhanced internal shielding and parasitic coupling cause the output response to approach saturation and even degrade, indicating that simply increasing the number of layers does not necessarily lead to better performance.

By comprehensively comparing the Pareto solution sets under different numbers of electrode layers, the seven-layer structure exhibits a better compromise between output voltage enhancement and electrode area control. The selected compromise solution on the Pareto front was finally adopted as the optimized design, achieving an output voltage of $2.565 \times 10^{-6} \text{ V}$ with an electrode area of 1.746 mm^2 . These results indicate that the multilayer electrode stacked structure should be designed by balancing equivalent capacitance enhancement, internal shielding effects, and parasitic coupling. Within the scope of the present theoretical modeling and simulation study, the proposed multilayer parallel-plate flexible structure and improved GOOSE-based multi-objective optimization method provide a design reference for miniaturized weakly distorted electric field sensors. Their capability for detecting actual insulation degradation remains to be verified through prototype development and experimental testing.

It should be noted that the present study is limited to theoretical modeling, equivalent-circuit analysis, COMSOL simulation, and numerical optimization. A physical prototype has not yet been fabricated, and the predicted sensor response and optimized structural

parameters have not been experimentally validated using controlled electric field tests or actual insulation-degradation samples. Therefore, practical factors such as manufacturing tolerances, electrode–dielectric interface characteristics, measurement noise, environmental disturbances, and long-term stability remain to be evaluated through subsequent prototype development, calibration, and experimental testing. Future work will focus on prototype fabrication, controlled electric field testing, and validation under representative insulation-degradation conditions. Alternative flexible dielectric and electrode materials will also be investigated to further improve the sensor sensitivity, mechanical adaptability, manufacturability, and long-term stability.

Author Contributions: Conceptualization, J.D. and C.Y.; methodology, Y.L.; software, Y.L.; formal analysis, Y.L.; investigation, B.J.; resources, J.D.; data curation, Z.W.; writing—original draft preparation, Y.L.; writing—review and editing, Z.W.; visualization, B.J.; supervision, C.Y.; project administration, W.W.; funding acquisition, Z.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. The COMSOL model files and the underlying numerical data are available from the corresponding author upon reasonable request.

Conflicts of Interest: Authors Junpeng Dang, Chuanxu Yang, Wenlin Wang, and Bo Jiang were employed by Yuxi Power Supply Bureau, Yunnan Power Grid Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Jani, C.Y.; Vora, S.C. Establishing correlation between material properties and space charge dynamics in oil-impregnated paper insulations. *IEEE Trans. Dielectr. Electr. Insul.* **2026**, *33*, 1672–1681. [[CrossRef](#)]
2. Wang, Y.; Xiong, Y.; Wang, Z.; Lu, W. Characterization of Space Charge Accumulations in Alternative Gas-to-Liquid Oil-Immersed Paper Insulation Under Polarity Reversal Voltage Scenarios. *Energies* **2025**, *18*, 3152. [[CrossRef](#)]
3. Deng, J.; Xie, Z.; Ge, H.; Xue, X.; Gao, C.; Cheng, J.; Zhou, H.; Pan, Z.; Lyu, G.; Wu, H. Effect of Temperature and Electric Field Strength on Carrier Mobility of Oil-Impregnated Pressboard Under DC Voltage. *Energies* **2024**, *17*, 5338. [[CrossRef](#)]
4. Zhu, Y.; Li, S.; Min, D.; Li, S.; Cui, H.; Chen, G. Space charge modulated electrical breakdown of oil-impregnated paper insulation subjected to AC–DC combined voltages. *Energies* **2018**, *11*, 1547. [[CrossRef](#)]
5. Wen, H.; Abu Talip, M.S.; Othman, M.; Azam, S.M.K.; Mohamad, M.; Ibrahim, M.F.; Arof, H.; Ababneh, A. Advanced Signal Processing Methods for Partial Discharge Analysis: A Review. *Sensors* **2025**, *25*, 7318. [[CrossRef](#)]
6. Álvarez, F.; Garnacho, F.; Ortego, J.; Sánchez-Urán, M.Á. Application of HFCT and UHF sensors in on-line partial discharge measurements for insulation diagnosis of high voltage equipment. *Sensors* **2015**, *15*, 7360–7387. [[CrossRef](#)]
7. Tao, J.; Rehman, S.U.; Ali, R.; Raza, S.A. Advancement and challenges: A review of power cable aging monitoring and diagnostic techniques. *Renew. Sustain. Energy Rev.* **2025**, *222*, 115970. [[CrossRef](#)]
8. Gao, S.; Jia, J.; Huang, X.; Liu, Y.; Zhang, B.; Zhang, Y.; Geng, J. Research on electric field detection of degraded insulators based on a sensitive detection method under complex operating conditions. *Appl. Sci.* **2022**, *12*, 5680. [[CrossRef](#)]
9. Liu, Y. Analysis of the detection method of insulators deterioration based on optical electric field sensors. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2021; Volume 714, p. 042047. [[CrossRef](#)]
10. Mou, Y.; Yu, Z.; Huang, K.; Ma, Q.; Zeng, R.; Wang, Z. Research on a novel MEMS sensor for spatial DC electric field measurements in an ion flows field. *Sensors* **2018**, *18*, 1740. [[CrossRef](#)] [[PubMed](#)]
11. Lei, Y.; Qiu, Z.; Tan, Y.; Lu, C.; Song, R.; Yang, Q. Research on spatial electric field measurement of DC line with MEMS electric field sensor. In *Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2024; Volume 2843, p. 012018. [[CrossRef](#)]
12. Tan, X.; Zhang, W.; He, M.; Li, W.; Ao, G.; Zhou, F. Non-contact adaptive voltage sensor based on electric field coupling principle. *Sensors* **2023**, *23*, 8316. [[CrossRef](#)] [[PubMed](#)]

13. Xiong, Q.; Zhang, J.; Li, J.; Tang, Y.; Zhang, Q.; Zhou, T.; Zhuang, Z.; Ji, S. Voltage sensor design with multi-layer ceramic capacitors based on electric field coupling principle and differential input structure. *Sens. Actuators A Phys.* **2025**, *391*, 116672. [\[CrossRef\]](#)
14. Chiurazzi, M.; Garozzo, G.G.; Dario, P.; Ciuti, G. Novel capacitive-based sensor technology for augmented proximity detection. *IEEE Sens. J.* **2020**, *20*, 6624–6633. [\[CrossRef\]](#)
15. Fu, B.; Wang, Z.; Chen, K.; Mao, Z.; Wang, H.; Ju, B.; Peng, Y. Dual-layer flexible capacitance sensor with wide range and high sensitivity. *Actuators* **2025**, *14*, 251. [\[CrossRef\]](#)
16. Sharma, A.; Gupta, K.; Jangir, K.; Jain, P.; Malakar, P. Multi-objective greylag goose optimization. In *Proceedings of the 2024 2nd International Conference on Advancement in Computation & Computer Technologies (InCACCT)*; IEEE: New York, NY, USA, 2024; pp. 374–379. [\[CrossRef\]](#)
17. Hamad, R.K.; Rashid, T.A. GOOSE algorithm: A powerful optimization tool for real-world engineering challenges and beyond. *Evol. Syst.* **2024**, *15*, 1249–1274. [\[CrossRef\]](#)
18. Zhang, J.; Wang, J.S. Improved whale optimization algorithm based on nonlinear adaptive weight and golden sine operator. *IEEE Access* **2020**, *8*, 77013–77048. [\[CrossRef\]](#)
19. Sun, G.; Shang, Y.; Yuan, K.; Gao, H. An Improved Whale Optimization Algorithm Based on Nonlinear Parameters and Feedback Mechanism. *Int. J. Comput. Intell. Syst.* **2022**, *15*, 38. [\[CrossRef\]](#)
20. Kalscheuer, T.; Zimmermann, U.; Sparr, H.; Ekspong, A.P.; Lindblad, A. An Improved Equivalent Circuit for Electric Field Sensors in Geophysical Exploration. *Geophys. Prospect.* **2025**, *73*, e70047. [\[CrossRef\]](#)
21. Wang, T.; He, K.; Cao, F.; Chen, B.; Xie, L.; Lu, J. Mesh-Based Charge Simulation Method and Its Applications to Electrostatic Electric Field Computation. *High Volt.* **2026**, *11*, 399–409. [\[CrossRef\]](#)
22. Peng, H.; Liu, H.; Shang, K.; Li, G.; Zhao, L. Design and Simulation Test of Non-Contact Voltage Sensor. *Sensors* **2025**, *25*, 3118. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Zhu, Y.; Wu, D.; Jiang, H.; Zhang, W.; Shen, L.; Sun, J.; Zhuang, J.; Xu, H.; Huang, Y. A new strategy for fabricating a stacked flexible capacitive sensor. *Funct. Compos. Mater.* **2024**, *5*, 9. [\[CrossRef\]](#)
24. Fu, H.; Zhao, Z.; Jiang, J.; Chen, Y.; Zhang, H.; Li, H.; Liang, G. Tunable flexible capacitive sensor for dynamic pressure monitoring. *Microsyst. Nanoeng.* **2026**, *12*, 110. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Ghanbari, A.; Colakoglu, A.A.; Serjouei, A.; Chakrabarty, S.; Ichiyama, R.M.; Culmer, P.R.; Alazmani, A. Customized batch fabrication of highly sensitive thin capacitive soft sensors based on high dielectric constant composite polymers. *Sci. Rep.* **2026**, *16*, 1543. [\[CrossRef\]](#) [\[PubMed\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.