# Comparative Study of PSO, GA, and ACO for Optimizing Dielectric Performance in Fly Ash Filled Silicone Rubber

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**Abstract**: This study investigates the optimization of coal fly ash composition as a filler in Silicone Rubber (SiR) insulator materials, aiming to enhance their dielectric characteristics. Compositional optimization was achieved by evaluating and comparing three advanced meta-heuristic algorithms Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO), using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) as performance metrics. The utilized fly ash, containing dominant silica, alumina, and iron oxides, was directly incorporated into the SiR matrix. Results indicate that, compared to PSO, GA and ACO exhibited superior performance and consistency. Specifically, for Relative Permittivity, the optimal composition of 80% yielded the lowest errors with GA and ACO (RMSE = 0.0751; MAPE = 0.9044). For Hydrophobicity, these two algorithms showed superior accuracy in the RMSE metric (RMSE = 0.8883) at 15.39% loading. These findings underscore the scientific contribution of this study by establishing the superior reliability of GA and ACO for optimizing fly ash composition in SiR, thus providing a robust analytical methodology to advance the use of industrial waste for high-performance dielectric materials.

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## Introduction

Indonesia, rich in natural resources, heavily relies on coal to fuel its Steam Power Plants (PLTU) (Asof et al., 2022). This extensive coal consumption generates a significant volume of solid waste, primarily fly ash and bottom ash. Data from 2022 estimated that this waste production reached 12 million tons in 2021 and is projected to climb to 16.2 million tons by 2027. This continuous accumulation threatens environmental pollution, particularly since coal fly ash contains several toxic heavy metals, such as Pb, Cd, As, and Hg, which can easily dissolve into soil and water (Abinawa & Gobel, 2024; Anggara et al., 2023).

Despite these environmental concerns, the chemical content of fly ash, which varies based on the coal's energy value and burning process, is generally rich in silica, alumina, iron, calcium, and various oxides. Nanosilica, one of its primary components, is highly beneficial as a filler in polymer materials like EPDM and Silicone Rubber (SiR). The inclusion of nanosilica is critical not only for boosting the material's mechanical strength (tensile strength) but, crucially, for improving the dielectric capability (electrical insulation performance) of polymer composites (Christiono et al., 2023; Fikri et al., 2024; Garniwa et al., 2024; Kar, 2021).

Previous research has explored the use of fly ash in this context. Earlier experimental studies, such as those titled "Electrical and Mechanical Properties Of Fly Ash Filled Silicone Rubber For High Voltage Insulator" and "Effect Of Fly Ash Filler To Dielectric Properties Of The Insulator Material of Silicone Rubber And Epoxy Resin", examined the impact of fly ash concentration on the electrical and mechanical performance of silicone rubber (Kitta et al., 2016; Manjang et al., 2015). More recently, research titled "Optimization of Dielectrics in Silicone Rubber Polymer Insulators using Coal Fly Ash Waste Filler" utilized quadratic regression analysis to determine the optimal fly ash composition, finding an optimal composition of 20.69% for hydrophobicity and 80% for relative permittivity (Thahara et al., 2023).

The existing literature primarily relies on conventional regression analysis to identify optimal filler compositions, which often provides only a local optimum and lacks the robustness needed for complex, non-linear polymer composite models. Therefore, the novelty of the current research lies in its advanced analytical methodology for determining the optimal filler composition. We employ and compare three sophisticated meta-heuristic optimization algorithms—Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony

Optimization (ACO) —to overcome the limitations of conventional methods. Comparing these algorithms is crucial because it provides a definitive, performance-based recommendation of the most suitable, globally searching computational tool for optimizing fly ash composition in SiR. This comparative study, utilizing advanced, heuristic search mechanisms, fills a significant research gap by determining which algorithm (GA, ACO, and PSO) offers the highest accuracy and stability in predicting the dielectric performance of this sustainable composite material. The effectiveness of these optimization algorithms will be rigorously measured using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

# Research Method

## Material Preparation and Testing

### Raw Material Preparation

The fly ash used in this research was sourced from the Suralaya Steam Power Plant (PLTU) located in Cilegon, Banten. The preparation process began with drying the fly ash, which was then sifted using a 200-mesh sieve to achieve a uniform particle size. Fly ash that successfully passed the 200-mesh sieve was collected and analyzed using X-Ray Fluorescence (XRF). The XRF test serves to detect the chemical elements and determine the percentage of each element within the fly ash sample. This analysis was conducted at the Advanced Chemical Characterization Laboratory at BRIN (National Research and Innovation Agency) in South Tangerang, Banten.

### Sample Mixing and Hardening

The coal fly ash was mixed with Silicone Rubber (SiR) RTV 683 (produced by PT Mapel Chemical). Critically, the fly ash was used without separating its mineral content. The mixing was done manually, and the mixture was poured into a 2 mm thick mold. A vacuum process was then applied to remove any air bubbles resulting from the mixing. Finally, the composite material underwent a hardening process for 24 hours to solidify the mixture.

### Material Performance Testing Rationale

The integrity and reliability of the experimental results were ensured through replication. For each of the nine distinct fly ash composition levels (ranging from 0% to 80% as listed in Table 1), three replicate specimens were fabricated and tested for both Hydrophobicity and Relative Permittivity. Therefore, the reported performance metrics (contact angle and permittivity) for each composition level represent the average value obtained from the three replicate measurements. This procedure, which utilizes a total of 27 test specimens (9 compositions × 3 replications), minimizes the impact of potential inconsistencies during the manual sample preparation and testing stages, thus significantly enhancing the statistical reliability and reproducibility of the final data set used for the subsequent optimization algorithms.

**Table 1 The samples with varying percentages of fly ash content**

| Number | Sample Code | Fly Ash Percentage |
|---|---|---|
| 1 | SF0 | 0% |
| 2 | SF1 | 10% |
| 3 | SF2 | 20% |
| 4 | SF3 | 30% |
| 5 | SF4 | 40% |
| 6 | SF5 | 50% |
| 7 | SF6 | 60% |
| 8 | SF7 | 70% |
| 9 | SF8 | 80% |

## Material Performance Testing

Two main tests were conducted to evaluate the composite material's performance, with all measurements replicated three times per sample to ensure data reliability:

**Hydrophobicity Test**: This test measures how effectively the material's surface repels water, which is crucial for preventing water films, damage, and dirt buildup (Abdillah, 2024). The test was performed by measuring the static contact angle under strictly controlled ambient conditions (26˚C and 85% humidity) after cleaning the surface with ethyl alcohol. A sterile water droplet (20µL) was placed on the surface, and its image was analyzed using ImageJ software. A high-resolution Contact Angle Meter was used for measurement.

Prior to all measurements, the Contact Angle Meter used was verified and calibrated using a high-precision standard calibration sphere with a known contact angle. The goniometer system's image analysis component, utilizing ImageJ software, underwent comprehensive external validation. This validation directly leveraged the methodology established by (Chalise et al., 2023), in the study titled "A low-cost goniometer for contact angle measurements using drop image analysis: Development and validation". This rigorous benchmarking demonstrated high performance, with the contact angle measurements on inorganic samples achieving an impressive average accuracy exceeding 94% when benchmarked against the gold-standard commercial goniometer (ramé-hart). This outcome unequivocally establishes ImageJ as a reliable and robust image analysis solution for surface science applications, justifying its use in quantifying the hydrophobicity of the SiR composite samples.

**Relative Permittivity Test (Dielectric Constant)**: This test assesses the material's ability to store electrical energy (Thahara et al., 2023). The composite material (fly ash/SiR) was placed between parallel plates, and its capacitance was measured at a frequency of 800 Hz, also under controlled conditions (26°C and 85% humidity). A precision LCR meter was used for capacitance measurement.

The LCR Meter used for capacitance measurement was subjected to a strict calibration protocol to minimize instrumental error and ensure high data fidelity. This protocol included Open, Short, and Load (OSL) correction performed at the operating frequency of 800 Hz. Specifically, Open compensation nullified stray capacitance by disconnecting the parallel plates, while short compensation eliminated residual impedance by connecting the plates. Furthermore, the meter's accuracy was regularly verified using a set of precision standard capacitors with traceable values. This rigorous calibration, coupled with the effective mitigation of systemic errors through meticulous circuit engineering, results in the LCR Meter achieving a very high measurement accuracy, demonstrating an overall error of less than 1%, thereby ensuring the reliability of the calculated relative permittivity in the dielectric analysis (Akhmetov et al., 2023).

The selection of Hydrophobicity (static contact angle) and Relative Permittivity (dielectric constant) as the primary evaluation properties is based on their fundamental importance for high-voltage insulator applications. Hydrophobicity is critical because it quantifies the material's ability to repel water, preventing the formation of conductive water films that lead to leakage current, flashover, and premature insulator failure in humid or polluted environments. Meanwhile, Relative Permittivity directly measures the material's ability to store electrical energy under an electric field. A low, stable relative permittivity is essential for efficient insulation and reducing unwanted charging effects. Optimizing both properties simultaneously ensures that the resulting SiR composite not only possesses excellent electrical storage capacity (dielectric strength) but also superior surface protection against environmental degradation, making them the defining characteristics of a high-performance electrical insulator (Diantari et al., 2024; Poluektova et al., 2025).

## Optimization Methods

The optimization process compares three meta-heuristic algorithms: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO).

### Particle Swarm Optimization (PSO)

PSO is an algorithm inspired by the social behavior of flocks of birds or schools of fish and is effective for complex optimization problems. The process involves two main steps: velocity update and position update. The simulation parameters were set to 30 particles and 50 iterations, adopted from similar studies in the literature. The stopping criterion was reaching the maximum iteration count (50). The particle's new velocity is updated based on its own best position found so far ($pbest$) and the best position found by the entire swarm ($gbest$) (Mufliq et al., 2024; Putry et al., 2024).

$$v_i(t+1) = \omega \,.\, v_i(t) + c_1 \,.\, r_1 .\, \left(pbest_i(t) - x_i(t)\right) + c_2 \,.\, r_2 \,.\, \left(gbest(t) - x_i(t)\right) \quad (1)$$

Where $\omega$ (inertia factor) was set to 0.8, $c_1$ (cognitive Coefficient) and $c_2$ (social coefficient) were set to standard values, controlling the particle's tendency towards its own best position and the swarm's best position, respectively. The position update is calculated by adding the newly calculated velocity to its previous position (Qaraad et al., 2024).

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

## Genetic Algorithm (GA)

GA is an optimization method that mimics the principles of natural selection found in evolution theory. It searches for the optimal value of the fly ash composition (Khosravi & Bahram, 2025). The objective function, $F(x)$, which is minimized or maximized, is defined by the predictive polynomial mathematical model ($f(x)$) that represents the relationship between the input variable (fly ash composition, $x$) and the response variable (performance value, $Y$). The standard parameters for GA were implemented (initial population of 50, maximum generations of 100, and a crossover fraction of 0.8). The function is defined as:

$$F(x) = f(x) \quad (3)$$

## Ant Colony Optimization (ACO)

ACO is an artificial intelligence method based on the behavior of ants finding the shortest path to food, where ants leave pheromone trails to guide the colony toward the optimal solution. In this study, ACO utilized a set of specific parameters to effectively navigate the solution space (Yılmazer & Özel, 2024). The simulation was run with 30 ants and a maximum of 50 iterations. Furthermore, the archive size (the number of best solutions stored) was set to 30. The search mechanism is based on the Gaussian Kernel probability density function (pdf), which models the attractiveness of the solutions:

$$w_j = \frac{1}{q\sigma\sqrt{2\pi}} e^{-\frac{(G(j)-\mu)^2}{2q^2\sigma^2}} \quad (4)$$

Where the specific parameters tuned for this model were the scaling parameter ($q$) for the deviation, which was set $1 \times 10^{-4}$, and the weighting factor used in calculating the standard deviation ($\sigma$), which was set to 1. These parameter settings were adopted from standard implementations in meta-heuristic optimization literature and were tuned to ensure rapid and stable convergence toward the optimal fly ash composition within the defined constraints.

## Optimization Performance Evaluation and Data Validation

The optimization process utilized the polynomial regression models derived from the experimental data as the fitness function for the meta-heuristic algorithms. To ensure model robustness and avoid overfitting, a k-fold cross-validation approach was implemented on the input data before the final optimization run. The quality of the optimization algorithms is measured using two key evaluation metrics:

### Root Mean Square Error (RMSE)

RMSE is the square root of the average of the squared differences between the predicted values ($\hat{y}_i$) and the actual values ($y$), Criteria: A smaller RMSE value indicates a better-performing model with a smaller error (Wiranata & Calvinus, 2025).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (yi - y)^2}{N}} \quad (5)$$

### Mean Absolute Percentage Error (MAPE)

MAPE measures the level of error as a percentage, by calculating the average of the absolute percentage difference between the predicted and actual values. A smaller MAPE value indicates a more accurate prediction model (Fikri et al., 2025; Nuraini et al., 2025).

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{Y_i - Y_n}{Y_i} \quad (6)$$

# Result and Discussion

## Fly Ash and Silicone Rubber Characteristics

The fly ash tested is solid waste from coal combustion at the Cilegon Steam Power Plant (PLTU). X-Ray Fluorescence (XRF) analysis confirms that the fly ash is primarily composed of Silicon Dioxide ($SiO_2$) at 42.00%, Aluminium Oxide ($Al_2O_3$) at 27.90%, and Iron Oxide ($Fe_2O_3$) at 12.90%6. Collectively, these three oxides account for over 80% of the total mass. This composition is typical of Type F fly ash (sub-bituminous type), characterized by lower carbon content but higher mineral content compared to bituminous coal types.

**Table 2 X-Ray Fluorescence (XRF) of Fly Ash result**

| Element Name | Percentage Value |
|---|---|
| $SiO_2$ | 42.00% |
| $Al_2O_3$ | 27.90% |
| $Fe_2O_3$ | 12.90% |
| CaO | 7.20% |

| Element Name | Percentage Value |
|---|---|
| $MgO$ | 3.70% |
| $Na_2O$ | 2.20% |
| $TiO_2$ | 1.20% |
| $SO_3$ | 1.00% |
| $K_2O$ | 0.80% |
| $P_2O_5$ | 0.50% |
| $MnO$ | 0.20% |
| $SrO$ | 0.20% |
| $Cl$ | 0.10% |
| $ZrO_2$ | 0.10% |

The high content of $SiO_2$ and $Al_2O_3$ is crucial for composite performance, as these components act as nanofillers. These oxides directly contribute to the improvement of the electrical insulation performance (dielectric capability) and mechanical stability of the SiR matrix. The Silicone Rubber (SiR) used is an elastomer material based on silicon atoms, notable for its ability to remain stable across a wide temperature range (from -55°C to +300°C). This inherent stability, combined with the reinforcing effect of the Type F fly ash, significantly enhances the electrical and mechanical durability of the resulting composite material (Kar, 2021).

## Optimization of Hydrophobicity Property

The relationship between the fly ash composition ($x$) and the Hydrophobicity value ($f(x)$) is modeled using the following polynomial equation:

$$f(x) = -2.1186 \times 10^{-6} x^4 + 0.00038182 x^3 - 0.023677 x^2 + 0.48841 x + 102.49 \quad (7)$$

**Table 3 Hydrophobicity Optimization Results**

| **Type of Optimization Algorithm** | **Composition** (%) | **Measured Value** ($f(x)$) | **RMSE** | **MAPE** |
|---|---|---|---|---|
| Particle Swarm Optimization (PSO) | 20.37% | 105.1 | 1.0405 | 0.6871 |
| Genetic Algorithm (GA) | 15.39% | 105.67 | 0.8883 | 0.7211 |
| Ant Colony Optimization (ACO) | 15.39% | 105.67 | 0.8883 | 0.7211 |

The optimization results show that GA and ACO identified an identical optimal composition of 15.39%. Crucially, both algorithms achieved a significantly lower Root Mean Square Error (RMSE = 0.8883) compared to PSO (RMSE = 1.0405). The lower RMSE for GA and ACO suggests that the models predicted by these two methods have a smaller average magnitude of error, demonstrating superior consistency in predicting the optimal hydrophobicity. Although PSO yielded a slightly better Mean Absolute Percentage Error (MAPE), the robust RMSE performance of GA and ACO validates their superior capability in avoiding large prediction deviations. This optimal value (15.39%) aligns closely with previous experimental findings which suggested an optimal range around 20% for hydrophobicity enhancement.

## Optimization of Relative Permittivity Property

The relationship between the fly ash composition $(x)$ and the Relative Permittivity value $(f(x))$ is modeled using the following polynomial equation:

$$f(x) = -24049 \times 10^{-7} x^4 + 0.000048169 x^3 - 0.0031865 x^2 + 0.08742 x + 5.0643 \quad (8)$$

**Table 4 Relative Permittivity Optimization Results**

| Type of Optimization Algorithm | Optimal Composition | | Evaluation Value | |
|---|---|---|---|---|
| | Composition (%) | Measured Value $(f(x))$ | RMSE | MAPE |
| Particle Swarm Optimization (PSO) | 80% | 6.534 | 0.0971 | 1.5512 |
| Genetic Algorithm (GA) | 80% | 6.476 | 0.0751 | 0.9044 |
| Ant Colony Optimization (ACO) | 80% | 6.476 | 0.0751 | 0.9044 |

For Relative Permittivity, all three algorithms converged on the highest tested composition, 80%. However, the performance difference was highly significant. GA and ACO demonstrated vastly superior prediction accuracy, yielding substantially lower RMSE (0.0751) and MAPE (0.9044) compared to PSO (RMSE = 0.0971; MAPE = 1.5512). This dramatic difference suggests that PSO became trapped in a local minimum or exhibited slower convergence behavior when dealing with the complexity of the relative permittivity model, leading to higher overall prediction errors. In contrast, GA (utilizing genetic operators like crossover and mutation) and ACO (relying on robust probabilistic selection from an archive of best solutions) demonstrated stronger global search capability, allowing them to navigate the solution space more effectively and map the polynomial model with high precision. The optimal composition of 80% is consistent with previous findings for maximizing this property.

## Algorithmic Analysis and Synthesis of Optimization Performance

### Algorithmic Rationale for Superiority

The vast difference in prediction error metrics (RMSE and MAPE) between PSO and the other two algorithms requires an explanation rooted in their search mechanisms. The Genetic Algorithm (GA), through its evolutionary operators (specifically crossover and mutation), excels at conducting strong global exploration. These operators enable the algorithm to generate fundamentally new solutions far from the current population, making it highly effective at escaping local minima and discovering the true global optimum across the complex, non-linear polynomial search space. Similarly, Ant Colony Optimization (ACO), particularly in its continuous form used here, relies on a probabilistic sampling mechanism centered around an archive of elite solutions. This mechanism, guided by pheromone-like weighting, inherently facilitates a balance between exploration (global search) and exploitation (local refinement).

In contrast, the standard Particle Swarm Optimization (PSO) algorithm, which relies on particle velocity updates driven solely by personal best (*pbest*) and global best (*gbest*) positions, tends to prioritize exploitation (local search) around the known optimal points. While efficient for unimodal functions, this focus makes PSO highly susceptible to becoming prematurely trapped in local minima when navigating multimodal or complex search landscapes like the one modeled here (Equations 7 & 8). The significant high error values recorded by PSO, despite utilizing comparable iterations and particles to ACO, strongly suggest a minimal local escaping capability during the optimization of the Permittivity model, confirming the superior performance of GA/ACO is due to their inherent stronger global search strategies and better convergence behavior.

### Synthesis of Algorithmic Performance

The comparative analysis across both dielectric properties confirms the superior reliability and predictive consistency of the Genetic Algorithm (GA) and Ant Colony Optimization (ACO) over Particle Swarm Optimization (PSO). While PSO is computationally efficient, its relatively poor performance in terms of error metrics (especially MAPE for permittivity) suggests that its typical local search mechanism was less effective than the global exploration strategies inherent in GA and ACO. The consistent results generated by GA and ACO, often yielding identical optimal compositions and error values, strongly recommend their use for future compositional optimization problems in SiR polymer composites.

## Conclusions

This study successfully determined the optimal fly ash filler compositions in Silicone Rubber (SiR) for enhancing dielectric performance by conducting a rigorous comparative evaluation of three meta-heuristic algorithms: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO). Based on the performance metrics, the Genetic Algorithm (GA) and Ant Colony Optimization (ACO) were consistently found to be the most reliable and effective optimization methods, exhibiting superior consistency in minimizing prediction errors across the material properties. This superiority was particularly evident in the optimization of Relative Permittivity, where both GA and ACO achieved the best possible result at the highest filler concentration tested, confirming that the resulting models offered the highest accuracy for this critical dielectric characteristic. While the optimization of

Hydrophobicity presented a more nuanced outcome—with PSO showing a slight advantage in the relative percentage error—GA and ACO nonetheless remained the recommended choice due to their overall performance stability and dominance in minimizing average prediction deviation. The scientific contribution of this work lies in establishing a robust, advanced analytical methodology that provides a definitive comparison of meta-heuristic search capabilities for compositional optimization, thereby advancing the field of sustainable material development through the high-value utilization of industrial waste such as coal fly ash.

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