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Research Article

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Optimizing Electrostatic Precipitator Collection Efficiency: Taguchi Design, Grey Relational Analysis, and Machine Learning Integration

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Abstract:

This study presents a modeling and optimization approach for electrostatic precipitator (ESP) collection efficiency using physics simulations, Taguchi design, gray relational analysis (GRA), and machine learning. A corona discharge and turbulent flow model simulated fluid velocity, electric field, charge density, and particle trajectories in a wire-to-plane ESP. Taguchi L27 simulation run varied electrode radius, gas velocity, and applied voltage, showing voltage as the key efficiency factor, with lower gas velocities and larger electrode radii improving performance. GRA combined multi-size particle efficiencies into a single metric and determined optimal conditions. Machine learning models, Gradient Boosting and Artificial Neural Networks (ANNs), predicted collection efficiency with different strengths such as Gradient Boosting for fine particles and ANN for micron-sized particles. Both models showed limitations for ultra-fine and coarse particles, suggesting the need for expanded datasets. This framework provides a methodology for optimizing ESP performance.

Keywords: Electrostatic Precipitators, Taguchi L27 orthogonal array, Gradient boosting, Artificial Neural network.

1. Introduction:

Electrostatic precipitators (ESPs) are widely employed for particulate matter removal in industrial gas streams because of their high collection efficiency and low operational costs (Li et al. 2019; Pannerselvam et al. 2021). Recent advances have focused on enhancing the ESP performance by integrating detailed physical modeling with data-driven optimization techniques (Zhai et al. 2022; Zheng et al. 2018). Studies have explored the coupling of corona discharge phenomena with turbulent flow dynamics to accurately simulate particle charging and trajectories, which are critical for predicting the collection efficiency across diverse particle size ranges (Yang et al. 2017).

Advances in Physics-Based Modeling of ESPs have significantly enhanced the understanding and prediction of electrostatic precipitator performance by integrating detailed physical phenomena with computational techniques (Kawamoto 2020). Central to these advances is the coupling of corona discharge models with turbulent flow simulations, which enables the comprehensive characterization of the fluid

velocity, electric field distribution, and space charge density within the ESP environment(Ning et al. 2024). This coupling captures the intricate interactions between charged carriers and fluid dynamics, which are critical for accurately modeling the particle charging and trajectory behavior(Zhang et al. 2026).

Corona discharge modeling employs charge conservation equations coupled with Poisson's equation to describe the transport of charge carriers via drift in the electric field and convection with fluid flow(Chuan et al. 2020). While the model simplifies plasma physics by condensing plasma creation and maintenance effects into boundary conditions at the corona electrode, it utilizes Peek's law to impose realistic electric field values necessary for sustaining corona discharge. This approach allows for the predictive simulation of the electric potential and space charge distribution near the electrodes, which are key drivers of particle charging dynamics.

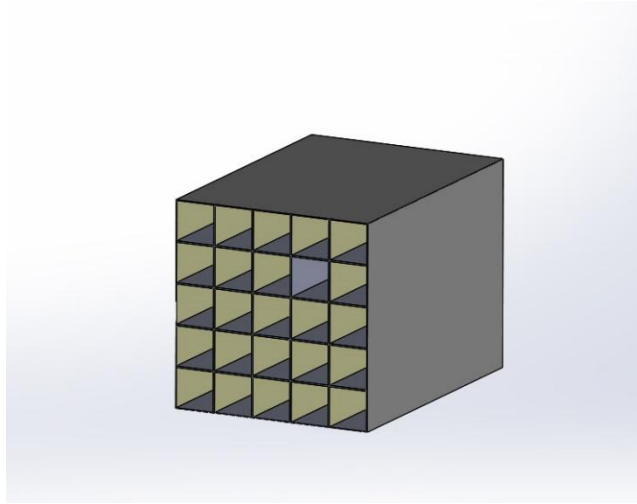
Turbulent flow modeling within the ESP domain solves the Navier-Stokes equations by incorporating electrohydrodynamic forces arising from the interaction of charged particles and electric fields. The fluid velocity and pressure fields obtained influence the particle residence time and transport pathways, affecting the overall collection efficiency (Sonthalia et al. 2019).

Particle tracing models integrate Newton's second law to compute particle trajectories under the combined influence of drag and electric forces (Xu et al. 2024). Advanced drag force modeling incorporates rarefaction effects via the Cunningham-Millikan-Davis correction to account for small particle sizes, while particle charging dynamics are represented using the Lawless model, which calculates charge accumulation based on characteristic charging times and dimensionless charging rates from field and diffusion transport mechanisms. The researcher validated the electrostatic precipitator numerical model against an experimental setup to study current distribution and conducted an analysis on the electrostatic precipitator. However, the effects of operating parameters were not adequately explored using the design of experiments approach to determine the optimal operating point from an energy conservation perspective (Chen et al. 2019).

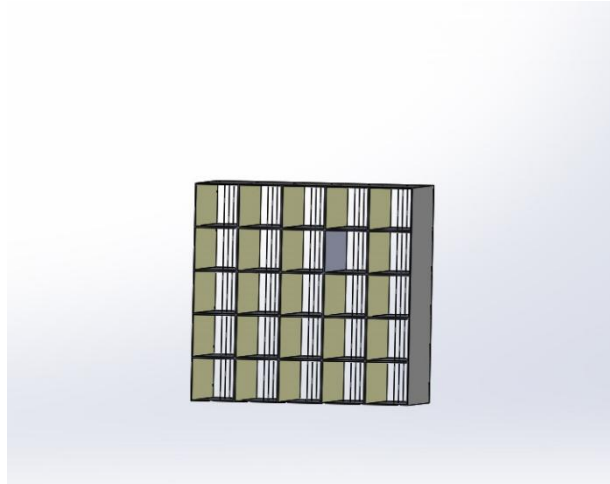
Multi-response optimization approaches, such as grey relational analysis (GRA), have been increasingly adopted to synthesize performance metrics across multiple particle sizes, enabling the identification of optimal operating conditions that balance competing objectives (Sharma et al. 2024; Singh et al. 2024). Concurrently, machine learning techniques, including Gradient Boosting and Artificial Neural Networks (ANN), have shown promise in optimum operating conditions, with algorithmic strengths varying by particle size category (Ajala et al. 2025; Zhu et al. 2020). However, limitations remain in accurately modeling ultra-fine and coarse particle collection due to the complex underlying physics and limited data availability in case of electrostatic precipitators. This study integrates physics simulations, Taguchi design, GRA, and machine learning to optimize ESP collection efficiency, providing insights into operating parameter effects and size-specific predictive modeling from energy conservation point of view.

2. Methodology:

In this research we have modeled several aspects of an electrostatic precipitator using COMSOL Multiphysics 6.1. First, a simplified model for corona discharges coupled with the Turbulent Flow interface is used to compute the fluid velocity, electric field, and space charge density, which are necessary to compute the particle charging and relevant forces acting on particles. After, the Particle Tracing for Fluid Flow interface is used to compute the particle collection efficiency as a function of the particle radius.



(a) 3D View of ESP



(b) Interior View of ESP showing its electrode arrangement

Figure 1: Electrostatic Precipitator Construction showing 3D view and Interior electrode arrangement

2.2 Model Definition:

Figure 1 shows the electrostatic precipitator's cross section in a wire-to-plane configuration. DC voltage is applied to inner electrodes with grounded walls. Particles released from the left inlet are transported with

fluid, accumulate charge, and are deflected toward collecting plates. Table 1 presents the operation conditions.

Table 1: Parameters for Simulation Run

Name	Expression	Value	Description
H	0.1[m]	0.1 metres	Height
Rin	2[mm]	0.002 metres	Electrode radius
W	0.7[m]	0.7 metres	Width
Sp	15[cm]	0.15 metres	Electrode separation
muN	$3e21[1/(V*m*s)]$	$3E21\ 1/(V*m*s)$	Reduced ion mobility

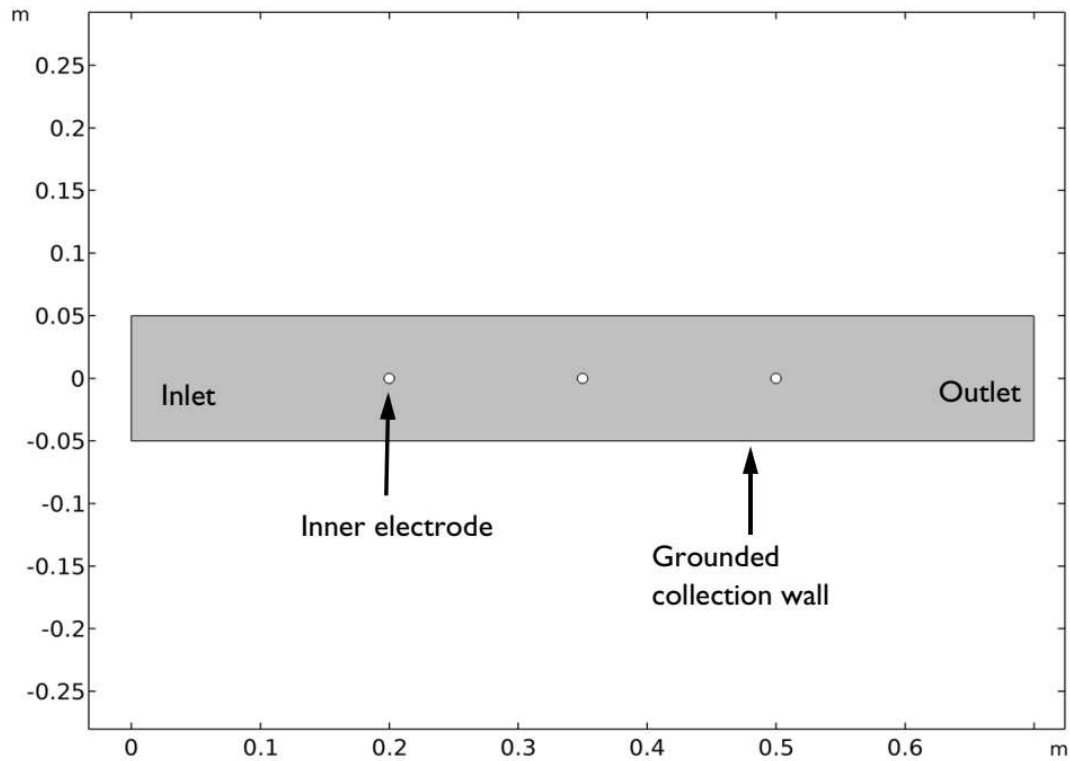


Figure 2: Simulation domain of the electrostatic precipitator

2.3 Corona Model:

The corona model relies on current conservation by charged carriers. The model requires both potential and electric field to be given at the corona electrode, as it does not self-consistently determine the electric field needed for discharge from electron and ion transport principles.

2.4 Domain Equations:

The corona model solves charge carrier transport using charge conservation and Poisson's equations. Transport includes drift in electric field and convection. Without source terms the domain equations are

$$\begin{aligned}\nabla \cdot \mathbf{J} &= 0 \\ \mathbf{J} &= z_q \mu \rho_q \mathbf{E} + \rho_q \mathbf{u} \\ \varepsilon_0 \nabla^2 V &= -\rho_q\end{aligned}$$

where $\mathbf{J}$ (A /m²) is the current density, z_q is the charge number, μ (m² / V · s) is the mobility, ρ_q (C/m³) is the space charge number density, $\mathbf{E}$ is the electric field, $\mathbf{u}$ is the fluid velocity (m/s), V is electric potential, and ε_0 is the vacuum permittivity. This set of equations can be manipulated to obtain the following transport equation

$$\mu \left(\frac{\rho_q^2}{\varepsilon_0} - \nabla V \cdot \nabla \rho_q \right) + \nabla \rho_q \cdot \mathbf{u} = 0$$

Assuming constant mobility, the domain equations contain no plasma creation information. All plasma physics is condensed in the inner electrode boundary conditions.

2.5 Boundary Conditions:

The normal electric field at the corona electrode serves as a boundary condition for Poisson's equation

$$\mathbf{n} \cdot \mathbf{E} = E_0$$

The other boundary conditions for Poisson's equation are $V = 0$ at the collection plates and zero charge at the inlet and outlet. The boundary condition for above equation involves in finding the space charge density ρ_q at the corona electrode, using a Lagrange multiplier, so that the imposed potential V_0 is verified

$$V - V_0 = 0$$

Both potential and electric field are imposed at the corona electrode. To obtain physical results, the field at the wire needs to match reality.

$$E_0 = 3 \times 10^6 \delta \left(1 + \frac{0.03}{\sqrt{\delta r_i}} \right)$$

where E_0 (V/m) is the breakdown electric field, δ is the gas number density normalized to the gas density at 760 torr and 293.15 K, r_i is the radius of the corona electrode.

Turbulent Flow Model

The Turbulent Flow interface is used to solve for the fluid velocity and pressure

$$\rho(\mathbf{u} \cdot \nabla)\mathbf{u} = \nabla \cdot [-p\mathbf{I} + \mu(\nabla\mathbf{u} + (\nabla\mathbf{u})^T)] + \mathbf{F}_{EHD}$$

$$\nabla \cdot \mathbf{u} = 0$$

where μ is the dynamic viscosity (kg/(m · s)), ρ is the fluid density (kg/m³), p is the pressure (Pa), and $\mathbf{F}_{EHD}$ is the electrohydrodynamic force define as

$$\mathbf{F}_{EHD} = \rho_q \mathbf{E}$$

2.6 Particle Tracing Model:

Particle positions are computed by solving second-order motion equations following Newton's second law.

$$\frac{d\mathbf{q}}{dt} = \mathbf{v}$$

$$\frac{d}{dt}(m_p \mathbf{v}) = \mathbf{F}_t$$

where $\mathbf{q}$ is the particle position (m), $\mathbf{v}$ is the particle velocity (m/s), m_p is the particle mass (kg), and $\mathbf{F}_t$ is the total force (N) acting on the particle. In this example the forces acting on the particles are the drag force and the electric force. Rarefaction effects need to be included in the drag force because the particle radius become very small. Here, the drag force $\mathbf{F}_D$ (N) is described with the Cunningham-Millikan-Davis model

$$\mathbf{F}_D = \frac{1}{\tau_p S} m_p (\mathbf{u} - \mathbf{v})$$

where τ_p is the particle velocity response time (s) define as

$$\tau_p = \frac{4\rho_p d_p^2}{3\mu C_D \text{Re}_r}$$

where ρ_p is the density of the particles (kg/m³), d_p is the particle diameter (m), C_D is the drag coefficient, and Re_r is the relative Reynolds number given by the expression

$$\text{Re}_r = \frac{\rho \parallel \mathbf{u} - \mathbf{v} \parallel d_p}{\mu}$$

and S is the drag correction coefficient defined as

$$S = 1 + \text{Kn} \left(C_1 + C_2 \exp \left(-\frac{C_3}{\text{Kn}} \right) \right)$$

where are dimensionless coefficients.

The electric force $\mathbf{F}_e$ (N) acting on the particles is defined as

$$\mathbf{F}_e = eZ\mathbf{E}$$

where e (C) is the elementary charge, and Z is the accumulated charge number on each particle.

The charge accumulated on the particles is computed with the Lawless model

$$\tau_c \frac{dZ}{dt} = \begin{cases} R_f + f_a & (|v_e| \leq |v_s|) \\ R_d f_a & (|v_e| > |v_s|) \end{cases}$$

where τ_c is the characteristic charging time

$$\tau_c = \frac{e^2}{4\pi\rho_q\mu k_B T_i}$$

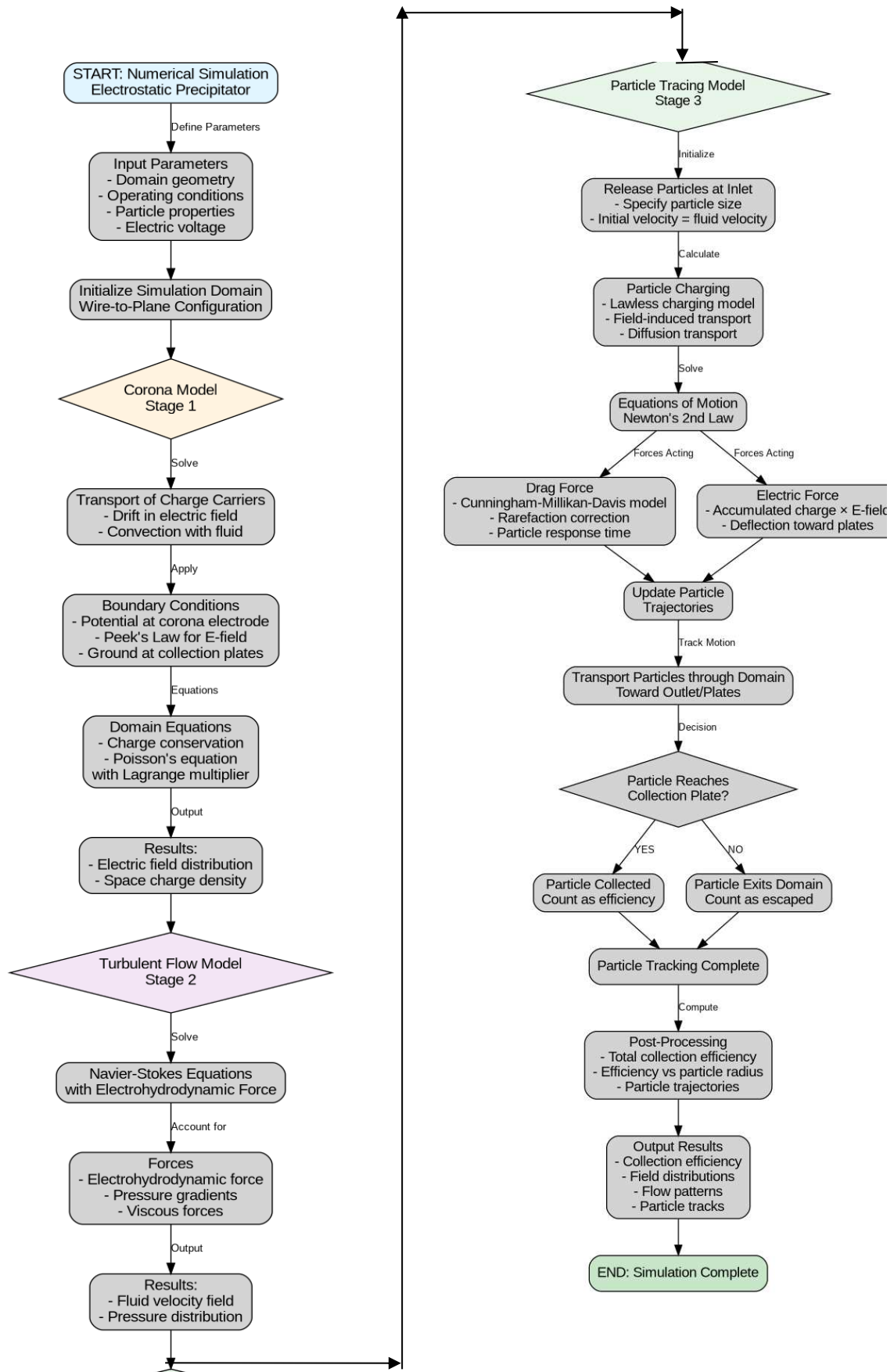
where k_B is the Boltzmann constant, and T_i is the ion temperature. R_f and R_d are the dimensionless charging rates due to field and diffusion transport, respectively, defined as

$$R_f = \frac{v_s}{4\varepsilon_0} \left(1 - \frac{v_e}{v_s}\right)^2$$

$$R_d = \frac{v_e - v_s}{\exp(v_e - v_s) - 1}$$

where

$$v_e = \frac{Ze^2}{4\pi\varepsilon_0 r_p k_B T_i}$$



Flowchart 1: Numerical Simulation Methodology for Electrostatic Precipitator

3. Results and Discussion:

Figure 3, 4, and 5 show fluid velocity, electrostatic potential, and space charge density from the corona model coupled with Turbulent Flow interface. Particle trajectories were computed using this data. The corona and fluid models were fully coupled, yet fluid velocity remains unaffected by electrohydrodynamic force, with drift velocity exceeding fluid velocity in key regions. Space charge density was higher near inner electrodes where corona discharge was luminous, causing faster particle charge accumulation due to large charge densities and electric fields.

Figures 6-9 show particle trajectories and charges accumulated in particles of several radii. Particles are released at the left and transported toward the right outlet. The particles become charged along their trajectory, with electric forces deflecting them toward the wall. Particle radius influences the balance of drag and electric forces, affecting trajectory and precipitator collection efficiency. Figures 10-11 show particle collection efficiency and average charge at the last time step versus particle radius. Collection efficiency was higher at extreme particle dimensions. Larger particles are collected efficiently due to greater electric charge, while smaller particles are collected efficiently due to less drag force. Between these extremes, drag force dominates trajectories, resulting in lines parallel to collection plates and low collection efficiency.

Partial charging becomes important in the small-particle branch. A model describing partial charging should capture the random nature of particles having charges of 1 or 0. In the present model, particles can be charged between 0 and 1, potentially causing inaccurate collection efficiency for small particles. These models reveal size-dependent behaviors: larger particles achieve higher collection efficiency through greater charge accumulation and electrostatic forces, while smaller particles benefit from reduced drag forces. Intermediate particles show lower efficiency due to dominant drag force limiting plate deflection. The models show limitations in capturing partial charging for ultrafine particles, where charge quantization is significant. The coupled corona and fluid models showed electrohydrodynamic forces minimally affected fluid velocity, suggesting future computational efficiency through model uncoupling.

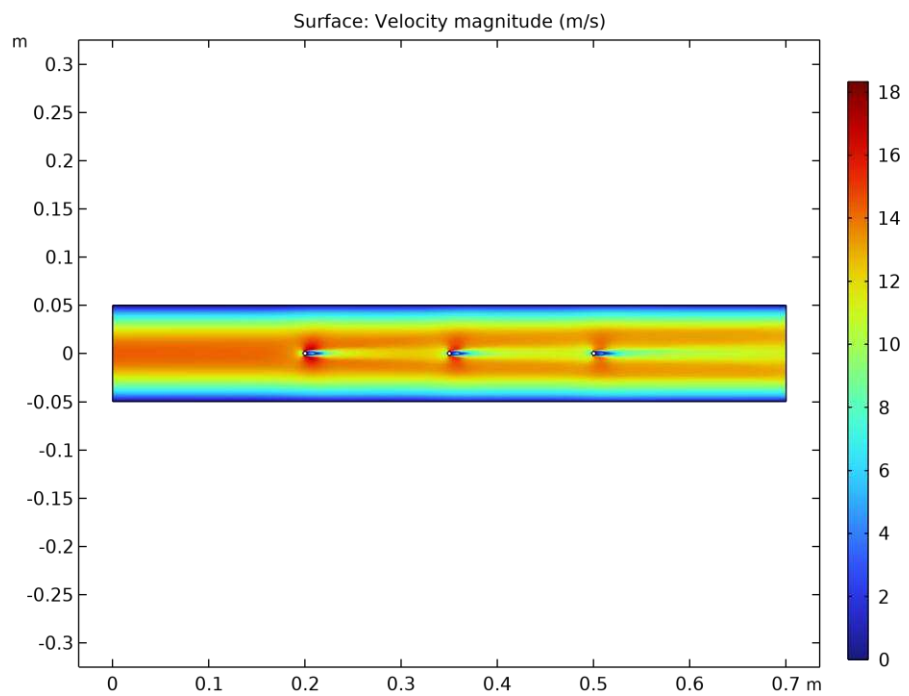


Figure 3: Velocity magnitude of the flow in electrostatic precipitator

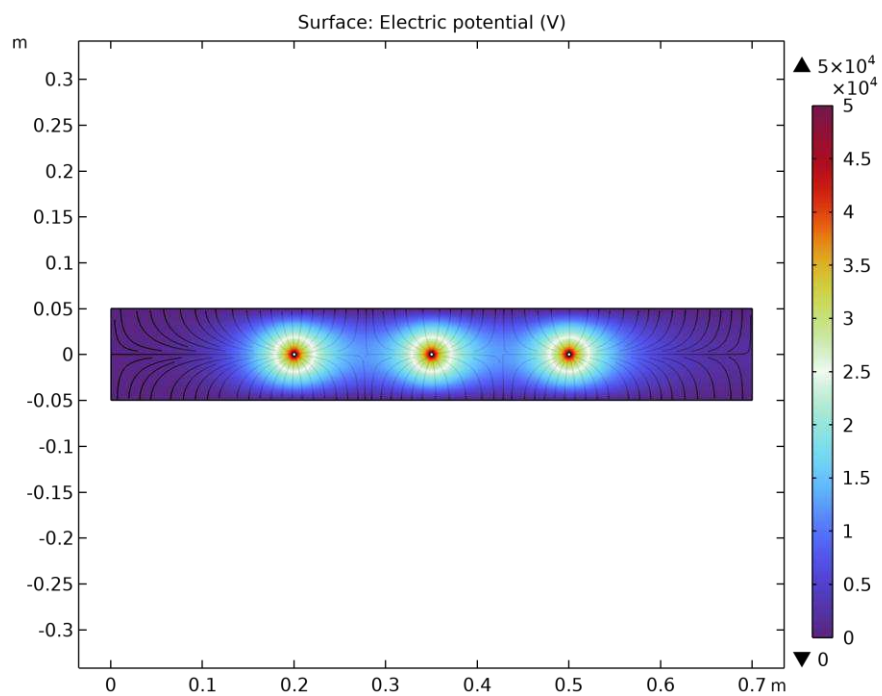


Figure 4: Electric Potential lines around electrodes in Electrostatic Precipitator

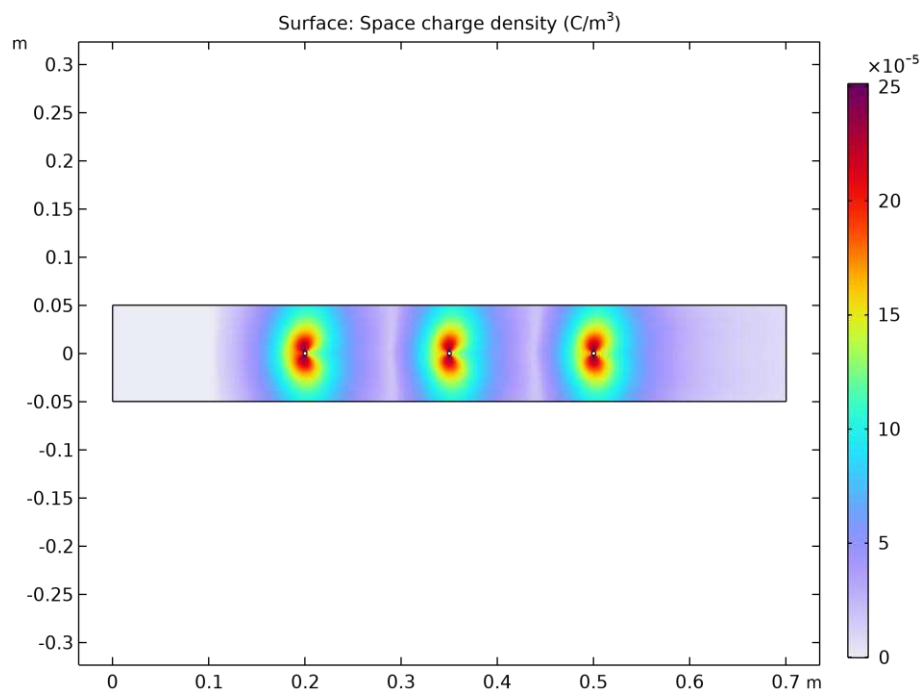


Figure 5: Space Charge Density in Electrostatic Precipitator

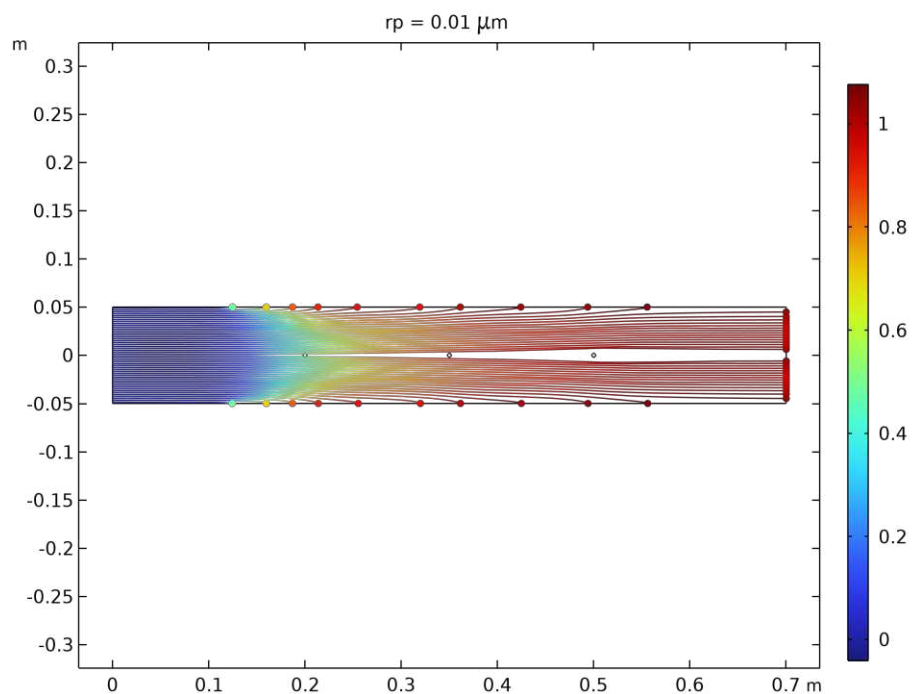


Figure 6: Particle trajectories with the charge number along the trajectory expressed in color for particles with a radius of 0.01 μm .

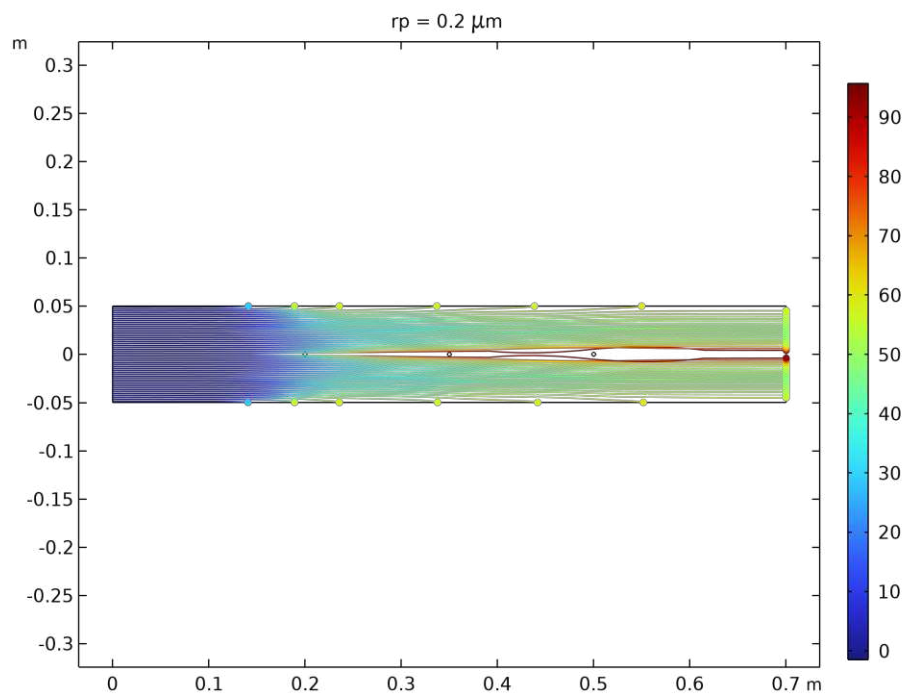


Figure 7: Particle trajectories with the charge number along the trajectory expressed in color for particles with a radius of $0.2 \mu\text{m}$.

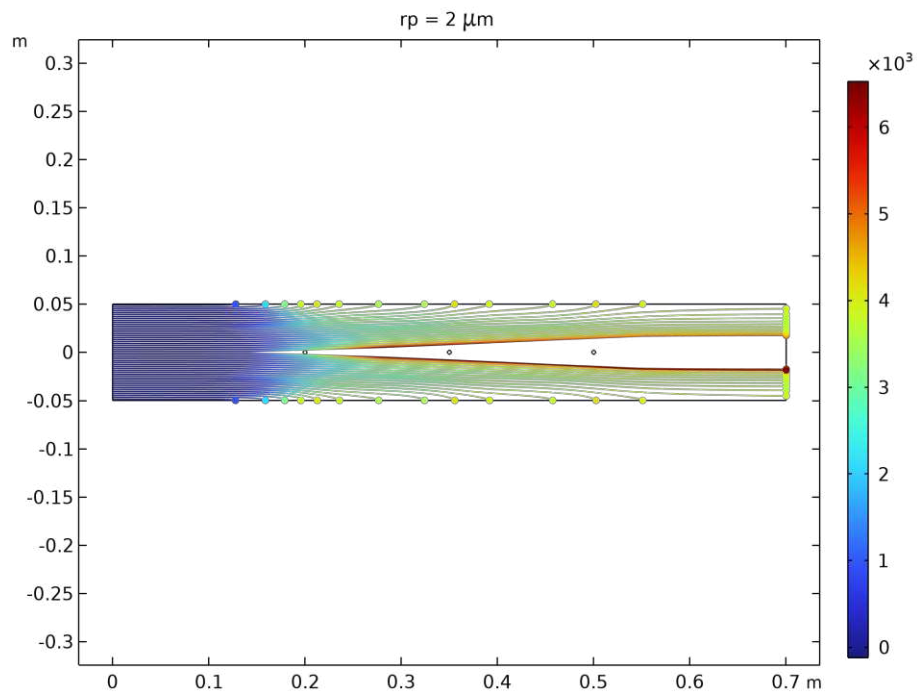


Figure 8: Particle trajectories with the charge number along the trajectory expressed in color for particles with a radius of $2 \mu\text{m}$.

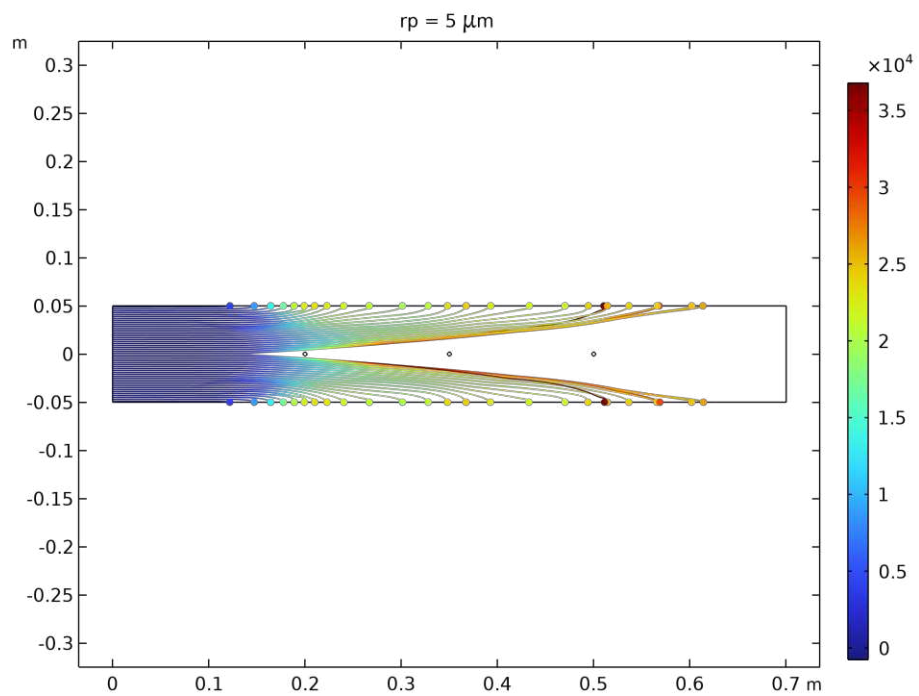


Figure 9: Particle trajectories with the charge number along the trajectory expressed in color for particles with a radius of $5 \mu\text{m}$.

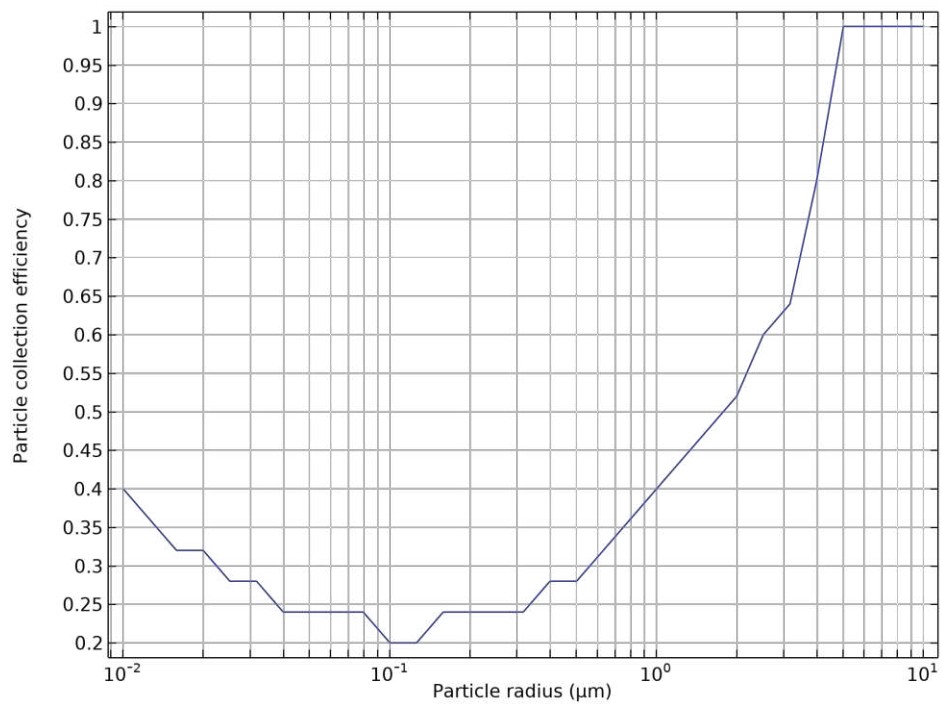


Figure 10: Particle collection efficiency as a function of the particle radius

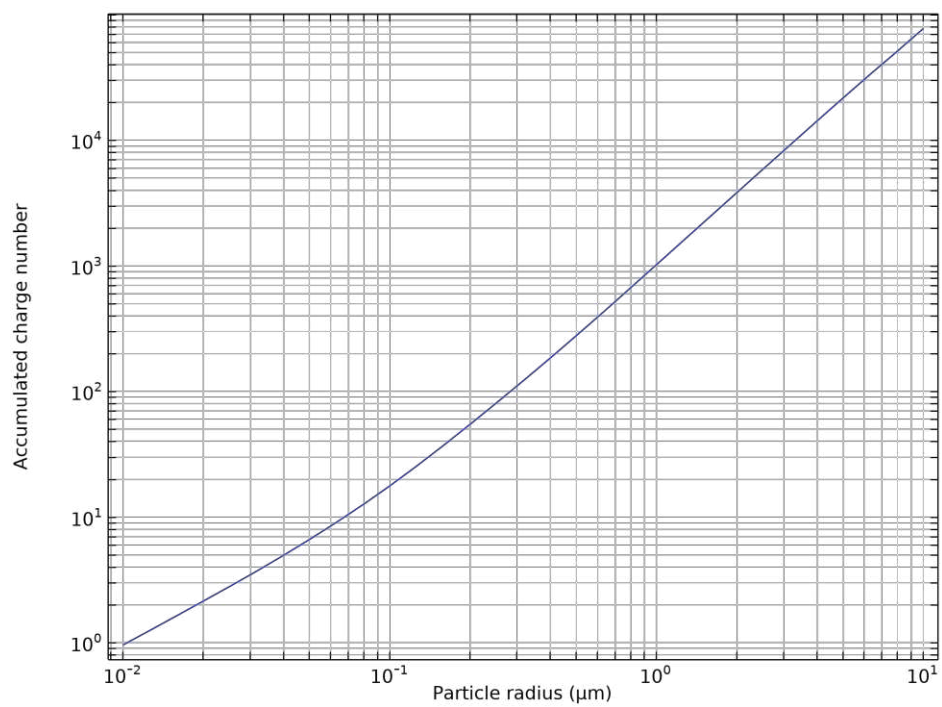


Figure 11: Average charge accumulated per particle at the last time step as a function of the particle radius

Run	Radius (m)	Velocity (m/s)	Voltage (KV)	Eff _{10⁻²}	Eff _{10⁻³}	Eff _{10⁰}	Eff _{10¹}
1.0	0.0005	10	10	0.080	0.020	0.100	0.150
2.0	0.0005	10	30	0.300	0.150	0.240	0.630
3.0	0.0005	10	50	0.550	0.290	0.450	1.000
4.0	0.0005	30	10	0.060	0.040	0.040	0.080
5.0	0.0005	30	30	0.078	0.130	0.182	0.260
6.0	0.0005	30	50	0.090	0.150	0.210	0.300
7.0	0.0005	50	10	0.060	0.100	0.140	0.200
8.0	0.0005	50	30	0.100	0.040	0.080	0.220
9.0	0.0005	50	50	0.060	0.100	0.140	0.200
10.0	0.0010	10	10	0.084	0.140	0.196	0.280
11.0	0.0010	10	30	0.132	0.220	0.308	0.440
12.0	0.0010	10	50	0.180	0.300	0.420	0.600
13.0	0.0010	30	10	0.072	0.120	0.168	0.240
14.0	0.0010	30	30	0.096	0.160	0.224	0.320
15.0	0.0010	30	50	0.120	0.200	0.280	0.400
16.0	0.0010	50	10	0.060	0.100	0.140	0.200
17.0	0.0010	50	30	0.060	0.100	0.140	0.200
18.0	0.0010	50	50	0.060	0.100	0.140	0.200
19.0	0.0020	10	10	0.108	0.180	0.252	0.360
20.0	0.0020	10	30	0.204	0.340	0.476	0.680
21.0	0.0020	10	50	0.300	0.500	0.700	1.000
22.0	0.0020	30	10	0.084	0.140	0.196	0.280
23.0	0.0020	30	30	0.132	0.220	0.308	0.440
24.0	0.0020	30	50	0.180	0.300	0.420	0.600
25.0	0.0020	50	10	0.400	0.200	0.400	1.000
26.0	0.0020	50	30	0.180	0.100	0.180	0.550
27.0	0.0020	50	50	0.120	0.080	0.120	0.370

Table 2: Taguchi L27 orthogonal array design matrix and collection efficiency responses for electrostatic precipitator simulation. The process parameters included the electrode radius (m), velocity (m/s), and voltage (V). The collection efficiencies were measured at four particle size scales: Eff_{10⁻²}, Eff_{10⁻¹}, Eff_{10⁰}, and Eff_{10¹}. The maximum efficiency values for each particle size category are highlighted.

The simulated results from the Taguchi L27 orthogonal array design are shown in Table 2, presenting collection efficiency responses for all parameter combinations across four particle sizes. The data showed efficiencies ranging from 0.040-1.000 based on electrode radius, gas velocity, and applied voltage combinations, demonstrating the importance of parameter optimization for maximum collection efficiency.

Among the 27 experimental runs, Run 21 (electrode radius = 0.0020 m, gas velocity = 10 m/s, applied voltage = 50 KV) achieved perfect collection efficiency ($\eta = 1.000$) for both fine particles (Eff_{10⁻¹}) and coarse particles (Eff_{10¹}), as shown in Table 2. This configuration combines maximum radius and voltage with minimum velocity. Run 3 and Run 25 also achieved maximum efficiency ($\eta = 1.000$) for coarse particles (Eff_{10¹}), showing multiple parameter combinations can achieve excellent coarse particle collection.

Analysis of the data showed voltage was the dominant controlling parameter. Collection efficiency increased with voltage across particle sizes when examining parameter sets with constant radius and

velocity but varying voltage (Runs 1-3, $r = 0.0005$ mm, $u = 10$ m/s). For coarsest particles (Eff_{10}^1), efficiency increased from 0.150 at 10 KV to 0.630 at 30 KV to 1.000 at 50 KV, a 567% improvement. Electrode radius showed a secondary effect, with larger radii enhancing performance under favorable voltage conditions. Gas velocity had an inverse relationship with collection efficiency, with lower velocities (10 m/s) performing better than higher velocities (50 m/s) due to extended particle residence time.

The collection efficiency showed strong particle size dependency across the four size fractions in Table 2. Coarse particles (Eff_{10}^1 , $d_p = 10$ μm) showed the highest mean collection efficiency (0.415 ± 0.263), with perfect collection ($\eta = 1.000$) in five runs. This aligns with electrostatic precipitation principles, where larger particles acquire greater charge and experience stronger forces. Ultrafine particles ($\text{Eff}_{0.2}^2$, $d_p = 0.01$ μm) showed the lowest efficiencies (mean = 0.133 ± 0.097), ranging from 0.060 to 0.550, reflecting the challenge of capturing nanometer-sized particles where charging efficiency is limited. Statistical analysis of the 27 experimental runs showed significant performance variation across the design space. The coefficient of variation ranges from 60-73% across response variables, with $\text{Eff}_{0.2}^2$ showing highest variability (CV = 73%) and Eff_{10}^1 showing lower variability (CV = 63%). This variability confirms collection efficiency's sensitivity to parameter selection and validates using Design of Experiments methodology. The worst performance occurred in Run 4 ($r = 0.0005$ mm, $u = 30$ m/s, $V = 10$ V), achieving only 4-8% collection efficiency across particle sizes.

Given the multi-response optimization problem with four competing efficiency objectives across particle sizes, gray relational analysis (GRA) was used to identify the optimal compromise solution. GRA converts the response variables into a single composite performance metric (Grey Relational Grade) to determine globally optimal operating conditions, as detailed in the following section.

Run	X ₁	X ₂	X ₃	X ₄
1.0	0.040816	0.000000	0.099909	0.076087
2.0	0.489796	0.270833	0.303030	0.597826
3.0	1.000000	0.562500	0.621212	1.000000
4.0	0.000000	0.041667	0.000000	0.000000
5.0	0.036735	0.229167	0.215152	0.195652
6.0	0.061224	0.270833	0.257576	0.239130
7.0	0.000000	0.166667	0.151515	0.130435
8.0	0.081633	0.041667	0.060606	0.152174
9.0	0.000000	0.166667	0.151515	0.130435
10.0	0.048980	0.250000	0.236364	0.217391
11.0	0.146939	0.416667	0.406061	0.391304
12.0	0.244898	0.583333	0.575758	0.565217
13.0	0.024490	0.208333	0.193939	0.173913
14.0	0.073469	0.291667	0.278788	0.260870
15.0	0.122449	0.375000	0.363636	0.347826
16.0	0.000000	0.166667	0.151515	0.130435
17.0	0.000000	0.166667	0.151515	0.130435
18.0	0.000000	0.166667	0.151515	0.130435
19.0	0.097959	0.333333	0.321212	0.304348
20.0	0.293878	0.666667	0.660606	0.652174
21.0	0.489796	1.000000	1.000000	1.000000
22.0	0.048980	0.250000	0.236364	0.217391
23.0	0.146939	0.416667	0.406061	0.391304
24.0	0.244898	0.583333	0.575758	0.565217
25.0	0.693878	0.375000	0.545455	1.000000
26.0	0.244898	0.166667	0.212121	0.510870
27.0	0.122449	0.125000	0.121212	0.315217

Run	GRC ₁	GRC ₂	GRC ₃	GRC ₄
1.0	0.342857	0.333333	0.354839	0.351145
2.0	0.494949	0.406780	0.417722	0.554217
3.0	1.000000	0.533333	0.568966	1.000000
4.0	0.333333	0.342857	0.333333	0.333333
5.0	0.341702	0.393443	0.389151	0.383333
6.0	0.347518	0.406780	0.402439	0.396552
7.0	0.333333	0.375000	0.370787	0.365079
8.0	0.352518	0.342857	0.347368	0.370968
9.0	0.333333	0.375000	0.370787	0.365079
10.0	0.344585	0.400000	0.395683	0.389831
11.0	0.369532	0.461538	0.457064	0.450980
12.0	0.398374	0.545455	0.540984	0.534884
13.0	0.338866	0.387097	0.382831	0.377049
14.0	0.350501	0.413793	0.409429	0.403509
15.0	0.362963	0.444444	0.440000	0.433962
16.0	0.333333	0.375000	0.370787	0.365079
17.0	0.333333	0.375000	0.370787	0.365079
18.0	0.333333	0.375000	0.370787	0.365079
19.0	0.356623	0.428571	0.424165	0.418182
20.0	0.414552	0.600000	0.595668	0.589744
21.0	0.494949	1.000000	1.000000	1.000000
22.0	0.344585	0.400000	0.395683	0.389831
23.0	0.369532	0.461538	0.457064	0.450980
24.0	0.398374	0.545455	0.540984	0.534884
25.0	0.620253	0.444444	0.523810	1.000000
26.0	0.398374	0.375000	0.388235	0.505495
27.0	0.362963	0.363636	0.362637	0.422018

Run	GRG	Rank
1.0	0.345494	26
2.0	0.468417	7
3.0	0.775575	2
4.0	0.335714	27
5.0	0.376907	18
6.0	0.388322	14
7.0	0.361050	20
8.0	0.353428	25
9.0	0.361050	20
10.0	0.382525	15
11.0	0.434779	8
12.0	0.504924	5
13.0	0.371461	19
14.0	0.394308	13
15.0	0.420342	10
16.0	0.361050	20
17.0	0.361050	20
18.0	0.361050	20
19.0	0.406885	12
20.0	0.549991	4
21.0	0.873737	1
22.0	0.382525	15
23.0	0.434779	8
24.0	0.504924	5
25.0	0.647127	3
26.0	0.416776	11
27.0	0.377814	17

Table 3: Grey Analysis dataset for Taguchi L27 Simulation Run

Grey Relational Analysis - Performance Rankings and Distribution



Figure 12: Comprehensive Grey Relational Analysis of Taguchi L27 optimization study. (A) Rankings: (a) GRG values for all runs with top three highlighted, (b) best vs. worst comparison, (c) GRG distribution.

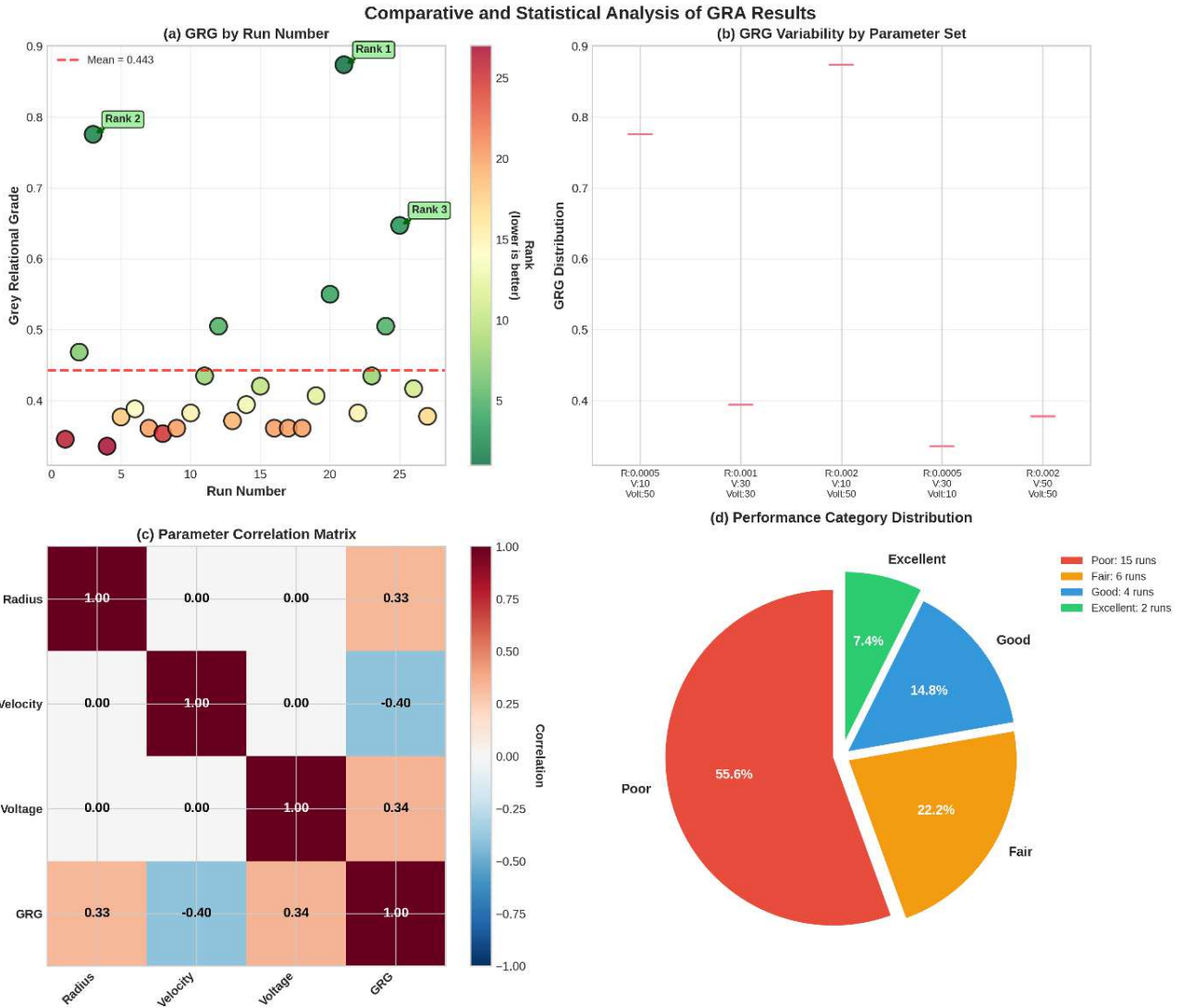


Figure 13: Parameter Effects: (a) main effects plot, (b-d) distribution by radius, velocity, and voltage. (D) 3D Analysis: (a-b) parameter space visualization, (c) contour map, (d) parallel coordinates. Color coding: green = high performance; red = low performance. Top performers (Runs 21, 3, and 25) were consistently marked.

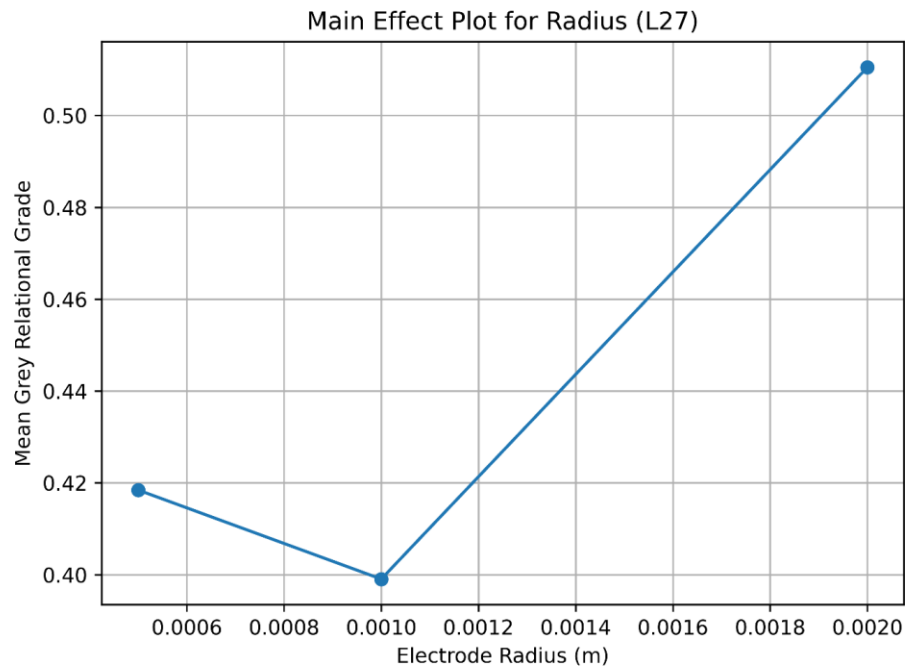


Figure 14: Effect of Electrode radius on Mean Grey Relational Grade

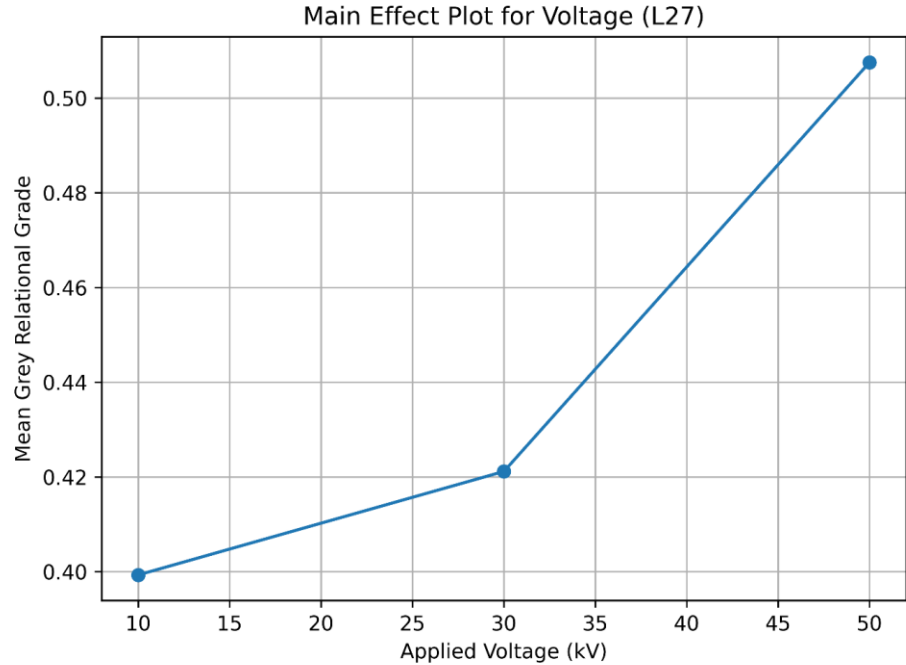


Figure 15: Effect of Applied Voltage (KV) on Mean Grey Relational Grade

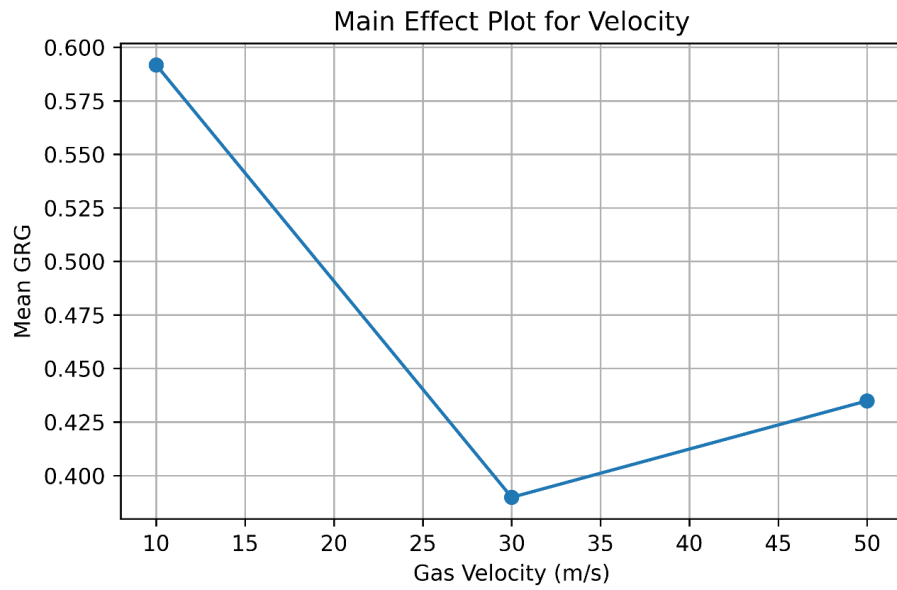


Figure 16: Effect of Gas Velocity on Mean Grey Relational Grade

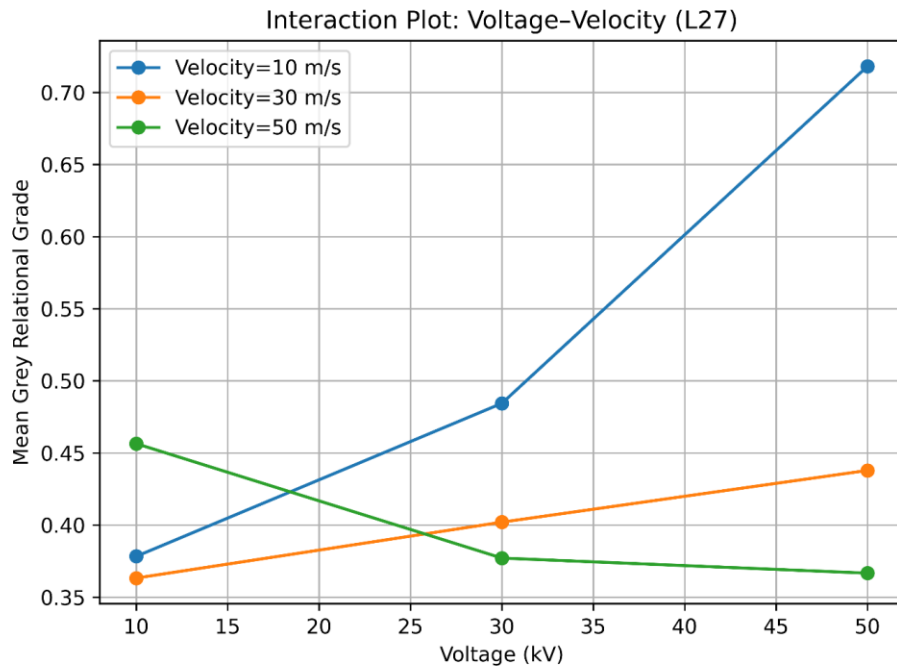


Figure 17: Interaction between Applied Voltage and gas Velocity on Mean Grey relational Grade

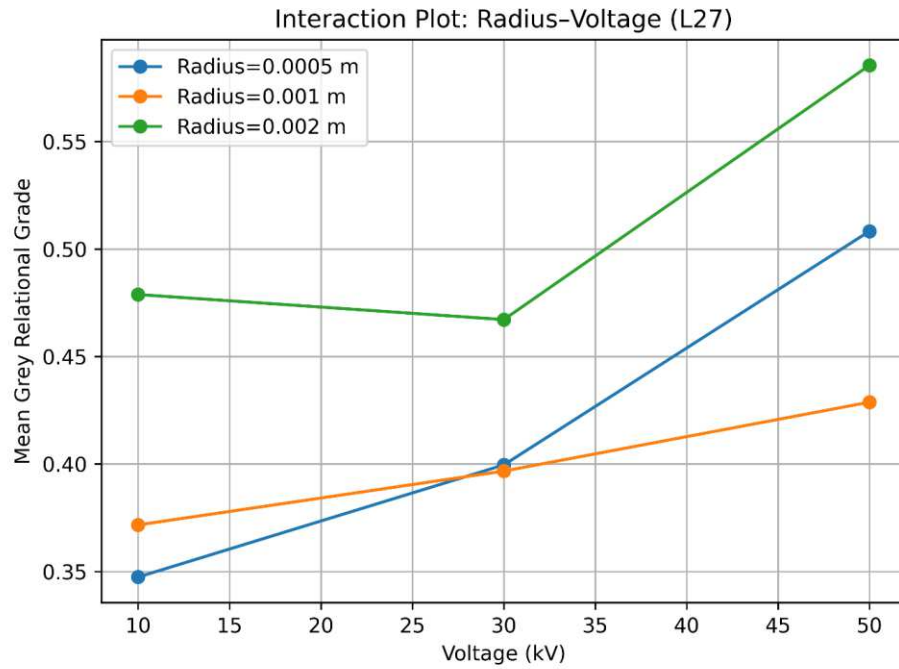


Figure 18: Interaction between Applied Voltage and gas Electrode radius on Mean Grey relational Grade

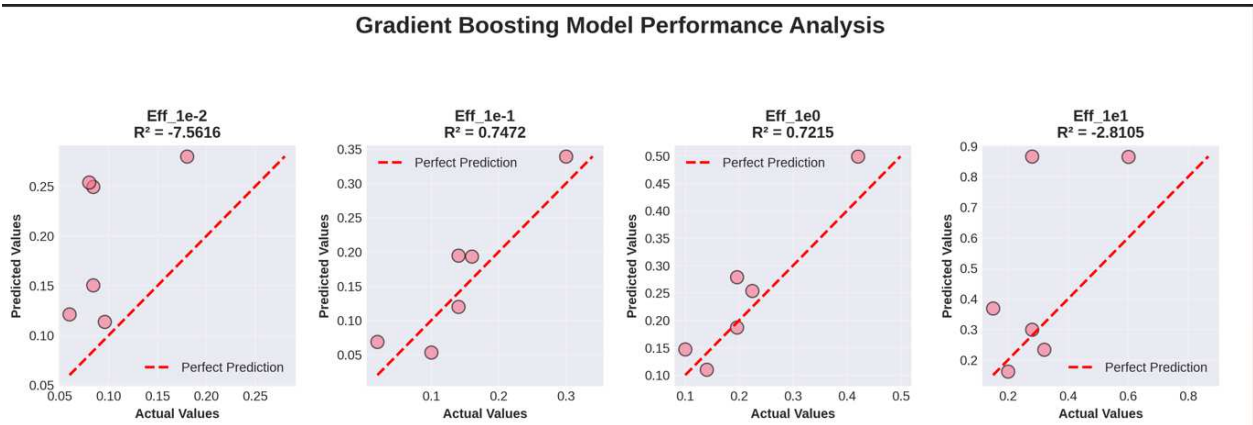


Figure 19: Comparison of Simulated results with Gradient Boosting Model Performance Analysis

ANN vs Gradient Boosting: Comprehensive Comparison

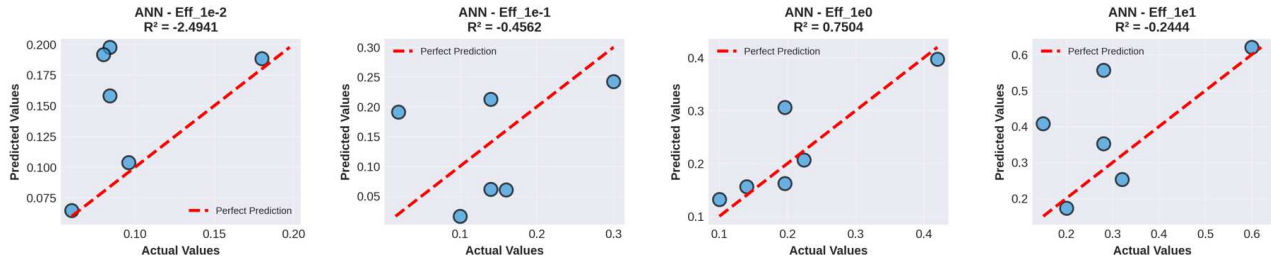


Figure 20: Comparison of Simulated results with Artificial Neural Network Analysis

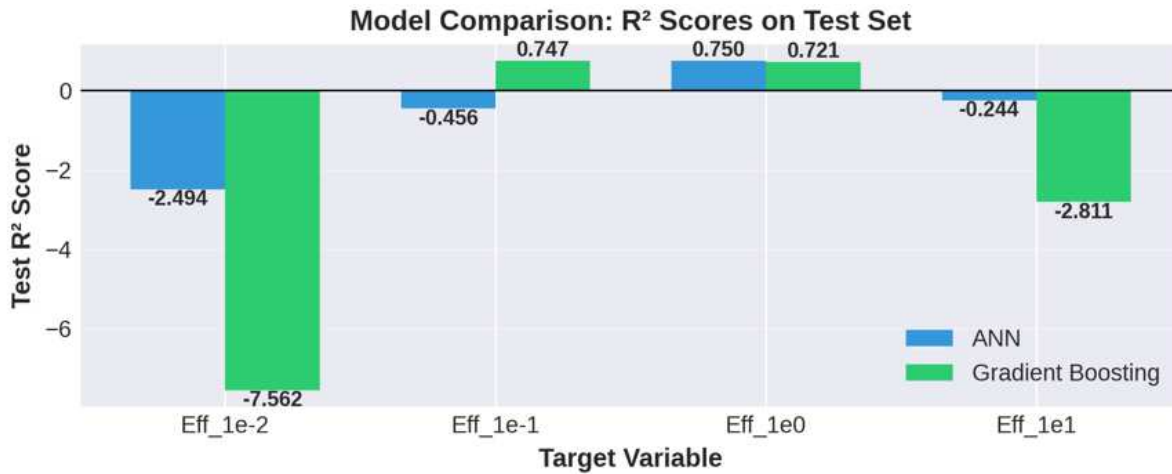


Figure 21: ANN Vs Gradient Boosting Model Comparison

Machine learning models were utilized to predict collection efficiency across four particle sizes using Taguchi L27 data. Gradient Boosting and Artificial Neural Network approaches were used, with model effectiveness evaluated on a test set ($n=6$) distinct from the training data ($n=21$). Figure 19 shows the Gradient Boosting model's performance, with excellent accuracy for fine particles ($\text{Eff}_{10^{-1}}$: $R^2 = 0.75$) and strong performance for micron-sized particles (Eff_{10^0} : $R^2 = 0.72$). However, the model failed for ultra-fine ($\text{Eff}_{10^{-2}}$: $R^2 = -7.56$) and coarse particles (Eff_{10^1} : $R^2 = -2.81$), with negative R^2 values indicating worse predictions than mean-based forecasts. The ANN models (Figure 20) exhibited complementary performance. The optimal ANN (50-25 neurons, 2 layers) achieved excellent predictions for micron-sized particles (Eff_{10^0} : $R^2 = 0.75$), slightly exceeding Gradient Boosting. However, ANN performance declined for fine particles ($\text{Eff}_{10^{-1}}$: $R^2 = -0.46$), a 264% loss compared to Gradient Boosting. A direct comparison (Figure 21) revealed model-target interactions. Gradient Boosting was superior for fine particles (+264% advantage), while ANN had a marginal advantage for micron particles (+4%). Both models were inadequate

for extreme sizes ($\text{Eff}_{10^{-2}}$, Eff_{10^1}), but ANN showed better accuracy in these failure modes (67-91% improved R^2 despite remaining negative). These results show that algorithm selection for multi-response optimization must be target-specific. For fine-particle collection, Gradient Boosting models provided reliable predictions ($R^2 = 0.75$). For micron particle optimization, either algorithm is acceptable, with a slight preference for ANN. Predictions for extreme sizes remain unreliable with current data ($n=21$), likely requiring datasets over 100 samples to capture the complex physics of diffusion-dominated (ultra-fine) and inertia-dominated (coarse) collection mechanisms.

4. Conclusion:

This study formulated a unified model amalgamating physics-based simulations, Taguchi experimental design, grey relational analysis (GRA), and machine learning to optimize ESP collection efficiency across multiple particle sizes. The coupled corona discharge and turbulent flow model quantified fluid velocity, electric field, and space charge density, permitting evaluation of particle charging dynamics and trajectories. Taguchi L27 simulation identified applied voltage as the principal component affecting collection efficiency, with larger electrode radii and lower gas velocities enhancing positively. GRA synthesized multi-size particle efficiencies into a single performance metric, steering identification of optimal operating conditions. Machine learning models exhibited target-specific predictive capabilities such as Gradient Boosting outperformed in fine particle prediction, while Artificial Neural Networks performed better for micron-sized particles. Both models exhibited limitations for ultra-fine and coarse particles, indicating the need for expanded datasets to encapsulate complex collection physics. The Outcomes provide a framework for ESP performance optimization, linking physical processes with data-driven approaches and furnishing insights for future experimental and modeling studies aimed at improving particulate matter removal efficiency.

References:

- Ajala, Adewole Adetoro, Oluwatosin Lawrence Adeoye, Olawale Moshood Salami, and Ayoola Yusuf Jimoh. 2025. An examination of daily CO₂ emissions prediction through a comparative analysis of machine learning, deep learning, and statistical models. *Environmental Science and Pollution Research* 32: 2510–2535. <https://doi.org/10.1007/s11356-024-35764-8>.
- Chen, Bing, Hongjiao Li, Yuzhong He, Baiqian Liu, and Lijie Zhang. 2019. Study on performance of electrostatic precipitator under multi-physics coupling. *Environmental Science and Pollution Research* 26: 35023–35033. <https://doi.org/10.1007/s11356-019-06623-8>.
- Chuan, Li, Liu Zhi, Wang Pengyu, Zhang Ming, Yang Yong, and Yu Kexun. 2020. A hybrid approach for corona discharge in needle electrode configuration: in a large-scale space. *Plasma Sources Science and Technology* 29: 045011. <https://doi.org/10.1088/1361-6595/ab708b>.
- Kawamoto, Hiroyuki. 2020. Improved Electrostatic Precipitator in Martian Environment. *Journal of Aerospace Engineering* 33. [https://doi.org/10.1061/\(asce\)as.1943-5525.0001127](https://doi.org/10.1061/(asce)as.1943-5525.0001127).
- Li, Xiaodong, Chenyang Zhou, Jingwei Li, Shengyong Lu, and Jianhua Yan. 2019. Distribution and emission characteristics of filterable and condensable particulate matter before and after a low-temperature electrostatic precipitator. *Environmental Science and Pollution Research* 26: 12798–12806. <https://doi.org/10.1007/s11356-019-04570-y>.
- Ning, Liwei, Nan Wang, Jun Fu, Yi Ma, Shuo Gu, and Milan Cheng. 2024. Effect of High-Voltage Electrostatic Precipitator Dust Collection Plate Structure on Collection Efficiency. *ACS Omega* 9: 37396–37407. <https://doi.org/10.1021/acsomega.4c06500>.
- Pannerselvam, Anandhraj, Mohana Sundaram Kuppusamy, Jayaraman Shanmugapriyan, Vishnu Kumar Kaliappan, and Ravishankar Sathyamurthy. 2021. Experimental investigation of removal of flue gas emissions exhaust from municipal solid waste incinerator using photovoltaic-based electrostatic precipitator. *Environmental Science and Pollution Research* 29: 11209–11218. <https://doi.org/10.1007/s11356-021-16378-w>.
- Sharma, Radhika, Sushma Pardeshi, Jowin Joseph, Debishree Khan, Asha Chelani, and Rita Dhodapkar. 2024. Integrated analytical hierarchy process-grey relational analysis approach for mechanical recycling scenarios of plastics waste in India. *Environmental Science and Pollution Research* 31: 23106–23119. <https://doi.org/10.1007/s11356-024-32632-3>.
- Singh, Yashvir, Nishant Kumar Singh, Abhishek Sharma, Pravin P Patil, Irfan Anjum Badruddin, and Sarfaraz Kamangar. 2024. Biodiesel production and exploring properties of *Datura stramonium* L. oil with its optimization using combined approaches-Taguchi, grey relational analysis, and response surface methodology. *Environmental science and pollution research international* 31: 23802–23821. <https://doi.org/10.1007/s11356-024-32665-8>.
- Sonthalia, Ankit, Shivam Garg, Rishav Sharma, Thiagarajan Subramanian, and Naveen Kumar. 2019. Effect of electrostatic precipitator on exhaust emissions in biodiesel fuelled CI engine.

Environmental Science and Pollution Research 28: 11850–11859. <https://doi.org/10.1007/s11356-019-07359-1>.

Xu, Luxi, Likun Ma, Pengnian Yang, Kangchun Zhao, Zhixun Xia, and Yunchao Feng. 2024. Drag coefficient for micron-sized particle in high-speed flows. *Physics of Fluids* 36. <https://doi.org/10.1063/5.0201397>.

Yang, Zhengda, Chenghang Zheng, Qianyun Chang, Yi Wan, Yi Wang, Xiang Gao, and Kefa Cen. 2017. Fine particle migration and collection in a wet electrostatic precipitator. *Journal of the Air & Waste Management Association* 67: 498–506. <https://doi.org/10.1080/10962247.2016.1260074>.

Zhai, Yunfei, Xiaowei Liu, Jingkun Han, Yue Zou, Yubo Huang, Huakun Wang, Lei Liu, and Minghou Xu. 2022. Study on the removal characteristics of different air pollution control devices for condensable particulate matter in coal-fired power plants. *Environmental Science and Pollution Research* 29: 34714–34724. <https://doi.org/10.1007/s11356-021-17952-y>.

Zhang, Boxin, Derek Schrock, Fuoad Pavin, Andrey Livchak, Mark Thomas, Sunil Murthy, Dan Singleton, and Stephen B Cronin. 2026. Plasma-enhanced electrostatic precipitation (PE-ESP) of restaurant smoke emissions. *Environmental science and pollution research international*. <https://doi.org/10.1007/s11356-026-37448-x>.

Zheng, Chenghang, Yifan Wang, Xuefeng Zhang, Zhengda Yang, Shaojun Liu, Yishan Guo, Yongxin Zhang, Yi Wang, and Xiang Gao. 2018. Current density distribution and optimization of the collection electrodes of a honeycomb wet electrostatic precipitator. *RSC Advances* 8: 30701–30711. <https://doi.org/10.1039/c8ra04765k>.

Zhu, Li-Tao, Jia-Xun Tang, and Zheng-Hong Luo. 2020. Machine learning to assist filtered two-fluid model development for dense gas–particle flows. *AIChE Journal* 66. <https://doi.org/10.1002/aic.16973>.

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Authors' Contributions

Amogh Sambare contributed to the conceptualization, methodology, software development, validation, formal analysis, investigation, and data curation of the study. He also prepared the original draft of the manuscript and was responsible for writing, reviewing, and editing the final version of the manuscript. The author has read and approved the final manuscript.

Ethical Approval

Not applicable. This study does not involve human or animal subjects.

Consent to Participate

The authors confirm that this study did not involve human participants, human data, or animals. Therefore, formal consent to participate was not required. All procedures performed in this research were in accordance with institutional, national, and international ethical standard.

Consent to Publish

The authors consent to the publication of this manuscript in Environmental Science and Pollution Research.

Competing Interests

The authors declare no conflict of interest.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author.

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