

INTEGRATED MODELING, SIMULATION, AND EXPERIMENTAL OPTIMIZATION OF VIBRATORY COFFEE SORTING PERFORMANCE USING RESPONSE SURFACE METHODOLOGY

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This study presents an integrated theoretical, simulation, and experimental approach to optimize the performance of a vibratory coffee sorting machine using Response Surface Methodology (RSM). A physics-based model of granular flow and segregation was developed to quantify the influence of inclination angle (α) and vibration frequency (f), and numerical simulations using MATLAB and DEM confirmed nonlinear interactions between both parameters, predicting optimal performance at $\alpha = 28.5^\circ$ and $f = 47.5$ Hz with a throughput of 3541.3 g/min and sorting accuracy of 98.14%. Empirical validation through a Central Composite Design (CCD) demonstrated significant effects of α and f on system responses ($p < 0.001$) and produced highly accurate regression models ($R^2 = 98.32\%$ for throughput and $R^2 = 92.52\%$ for accuracy). Multi-response desirability optimization yielded an empirical optimum at $\alpha = 29.8^\circ$ and $f = 50$ Hz, achieving a throughput of 3667.44 g/min and an accuracy of 98.32%, closely aligning with simulation predictions. The results confirm the robustness of the integrated modeling framework, highlight the inherent trade-off between throughput and segregation efficiency, and provide a practical guideline for improving productivity and quality in vibratory coffee sorting operations.

Keywords: Vibratory coffee sorting, Granular flow dynamics, Discrete Element Method (DEM), Response Surface Methodology (RSM), Multi-response optimization.

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1. INTRODUCTION

Coffee represents one of the most globally traded agricultural commodities, with its market value heavily dependent on quality. Post-harvest processing operations—including drying, grading, and sorting—are critical determinants of final bean quality (Alemayehu *et al.*, 2020; Amare *et al.*, 2023; Banti & Abraham, 2021; Georgise *et al.*, 2020; Z. Li *et al.*, 2023). Sorting is essential for the removal of defective beans and foreign materials, ensuring uniformity in physical attributes such as size and color, and ultimately enhancing the sensory profile of the roasted product (El Maidah & Dwi Suhendra, 2023; Khuwijitjaru *et al.*, 2020; Sudana *et al.*, 2020; Thongnop *et al.*, 2021). While manual sorting achieves high accuracy, it is labor-intensive and inefficient, driving the adoption of automated sorting systems capable of higher throughput and operational consistency.

Vibratory sorting machines utilize a combination of mechanical vibration and gravitational forces to stratify and separate coffee beans based on physical characteristics such as size, density, and shape (Injante *et al.*, 2020; R. Li *et al.*, 2021; Song *et al.*, 2022). Within such systems, the inclination angle of the sorting tray and the vibration frequency are among the most critical operational parameters. These factors directly influence particle motion, bed fluidization, segregation efficiency, and overall sorting performance (Díaz-Heras *et al.*, 2021; Dinh & Radford, 2021; Kulakowska *et al.*, 2023; McCauley *et al.*, 2021; Sigray *et al.*, 2022; Zhou *et al.*, 2023). Suboptimal settings may result in poor material distribution, prolonged processing time, or increased misclassification rates. Although several studies have investigated vibrational and inclination effects in agricultural classifiers, a systematic approach to modeling their combined impact on coffee sorting performance remains limited.

Response Surface Methodology (RSM) offers a robust statistical framework for modeling and optimizing multi-variable processes (Asaad *et al.*, 2024; Elkelawy *et al.*, 2022; Kesarwani & Verma, 2021; C. Li, Zhao, *et al.*, 2021; Suryadarma *et al.*, 2022, 2024; Thi Thuy Van *et al.*, 2022). By employing empirical model fitting, typically via second-order polynomials, RSM facilitates the identification of optimal factor settings while minimizing experimental effort (Baydar *et al.*, 2024; Hassanzadeh *et al.*, 2022). This methodology has been extensively applied across food and agricultural engineering domains, including drying, extraction, and classification processes (Djimtoingar *et al.*, 2022; Veza *et al.*, 2023). However, its specific application to the tuning of vibratory sorting parameters for coffee beans has not been fully explored.

In this study, a combined approach incorporating theoretical modeling, dynamic simulation, and empirical validation is adopted. Prior to physical experimentation, granular flow dynamics and vibration transmission principles are applied to simulate bean behavior under varying operational conditions (Herrera *et al.*, 2011; K. Li, Cheng, *et al.*, 2022; K. Li, Wang, *et al.*, 2022; Meruane *et al.*, 2010). This preliminary analysis helps rationally constrain experimental factor ranges and provides mechanistic insight into the sorting process. The integration of simulation with RSM creates a more informed and efficient experimental pathway, strengthening the linkage between theoretical expectations and empirical outcomes.

The primary objective of this research is to optimize the performance of a vibratory coffee sorting machine using RSM, supported by theoretical and simulation analyses. The inclination angle and vibration frequency are treated as independent variables, while throughput and sorting accuracy are selected as the response metrics. This work aims to elucidate the interaction effects between these parameters and establish an operational window that maximizes both efficiency and sorting quality. The findings are expected to support the development of intelligent, data-driven sorting systems applicable to small- and medium-scale coffee processing operations.

Despite the growing interest in automated sorting technologies, existing studies on vibratory separation of agricultural products predominantly focus on empirical tuning of machine parameters without incorporating a comprehensive physical description of granular flow behavior (Lu *et al.*, 2023; Lubongo & Alexandridis, 2022; Panwar *et al.*, 2023; Weigl & Young, 2023). Previous research has explored the influence of vibration frequency, amplitude, and tray inclination on particle mobility and classification efficiency for grains, seeds, and other granular materials; however, these works typically rely on trial-and-error parameter adjustments and lack an integrated theoretical framework (Demetriou *et al.*, 2024; Gundupalli *et al.*, 2017; Liu & Niu, 2024; Oyewale *et al.*, 2023; Patrizi *et al.*, 2021). Recent advancements in Discrete Element Method (DEM) simulations have enabled deeper insights into particle–particle and particle–surface interactions, yet their application to coffee sorting remains limited and is often performed independently of experimental validation (Coetzee, 2017; C. Li, Yin, *et al.*, 2021; Mishra & Rajamani, 1992; Wang *et al.*, 2022; Yeom *et al.*, 2019; Zhao *et al.*, 2021). Similarly, Response Surface Methodology (RSM) has been widely used to optimize food processing and separation systems, but there is a notable absence of studies that combine DEM-based simulation, physics-driven modeling, and RSM optimization within a unified workflow. This gap highlights the need for a holistic approach that couples fundamental granular dynamics with both simulation and empirical experimentation to derive a more accurate and robust optimization of vibratory coffee sorting systems. The present study addresses this gap by integrating theoretical modeling, DEM simulation, and RSM-based experiments to systematically evaluate and optimize the effects of inclination angle and vibration frequency on throughput and sorting accuracy.

2. MATERIAL AND METHODS

A laboratory-scale vibratory sorting machine was designed and fabricated for this study (Figure 1). The main component is a rectangular sorting tray (600 mm × 300 mm) constructed from stainless steel, mounted on an adjustable support frame that allows the inclination angle to be varied precisely. The vibration mechanism consists of an eccentric motor driven by a variable frequency drive (VFD), enabling precise control of the vibration frequency.



Figure 1. Laboratory-scale vibratory coffee sorting machine used in the experiment.

Arabica coffee beans (*Coffea arabica*) were used throughout the experiments. The beans were pre-conditioned to a uniform moisture content of 12% ($\pm 0.5\%$) through controlled storage. For each experimental run, a 2.5 kg batch of beans was used as the feed material. The overall research methodology follows a systematic sequence integrating theoretical, computational, and experimental approaches, as illustrated in Figure 2. The process begins with Mathematical Modeling, where fundamental principles of particle dynamics and granular flow are used to derive predictive models for throughput and sorting accuracy. This is followed by a Simulation Approach, employing Discrete Element Method (DEM) simulations to numerically analyze bean behavior under varying operational conditions. The Empirical Experiment phase involves conducting physical experiments using Central Composite Design (RSM) to collect real-world performance data. Finally, optimization is performed using multi-response desirability functions to identify the optimal inclination angle and vibration frequency that maximize both throughput and accuracy. This integrated workflow ensures a robust and scientifically grounded optimization process.

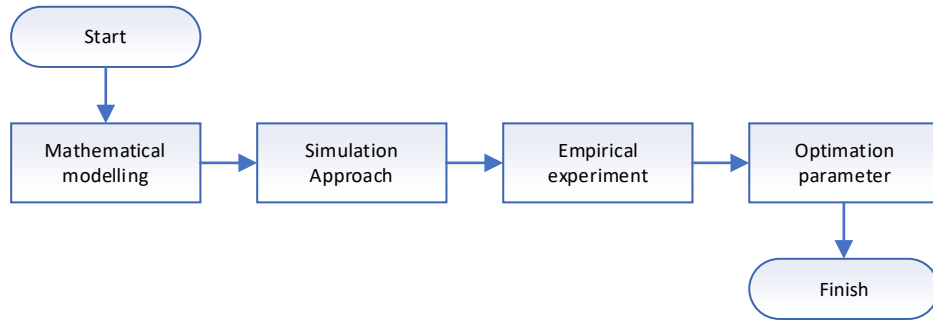


Figure 2. Research framework.

2.1. Theoretical Framework and Performance Modeling

A comprehensive theoretical framework was developed to model the dynamics of coffee beans on the vibratory sorting tray and establish the fundamental relationships between the control parameters, inclination angle and vibration frequency and the key performance metrics: throughput and sorting accuracy. The analysis integrates single-particle dynamics, collective granular flow behavior, and segregation mechanics to form a physics-based foundation for the subsequent experimental optimization (Kim *et al.*, 2020; Wan Mohtar & Munro, 2013).

The motion of an individual coffee bean on the oscillating inclined surface is governed by forces of gravity, vibration, and friction. Equation (1) is the motion during sustained contact. The transition from sliding to the flight phase occurs when the normal force becomes non-positive; see Equation (2).

$$m\ddot{x} + c_t\dot{x} + \mu_k mg \cos\alpha \cdot \text{sgn}(\dot{x}) = -mg \sin\alpha + mA(2\pi f)^2 \cos(2\pi ft), \quad (1)$$

$$N = m[g \cos\alpha - A(2\pi f)^2 \sin(2\pi ft)] \leq 0. \quad (2)$$

This detachment condition highlights the competition between gravitational normal force (stabilizing, scaling with $\cos\alpha$) and vibrational acceleration (destabilizing, scaling with f^2). Higher frequencies promote particle lofting, while steeper angles reduce normal contact forces.

The collective flow of the bean ensemble is modeled using the $\mu(I)$ rheology for dense granular media, which describes how granular materials transition between solid-like and fluid-like behavior (Mei *et al.*, 2023; Zhang & Makse, 2005). The shear stress τ is related to the pressure p by:

$$\tau = \mu(I)p, \quad (3)$$

$$\mu(I) = \mu_s + \frac{\mu_2 - \mu_s}{\frac{I_0}{I} + 1}. \quad (4)$$

The friction coefficient evolves from a static value μ_s at low inertial numbers to a dynamic value μ_2 at high inertial numbers, with I_0 controlling the transition rate. The inertial number characterizes the flow regime, where $\dot{\gamma}$ is the shear rate, d_s is the particle diameter, and ρ is the density. Both α and f influence the system through their effect on $\dot{\gamma}$ and p - steeper angles increase shear rates, while higher frequencies affect pressure distribution and material fluidization.

Size-based segregation, which is fundamental to achieving high sorting accuracy, is modeled using a continuum approach that captures the competing processes of advection, diffusion, and segregation. The temporal and spatial evolution of the volume fraction of small particles, ϕ_s , is governed by the following transport equation:

$$\frac{\partial \phi_s}{\partial t} + \nabla \cdot (\phi_s V_s) = \nabla \cdot [D_s \nabla \phi_s] - \nabla \cdot \left[\frac{q_s d_s^2 \dot{\gamma}(\alpha, f) \nabla \phi_s}{\sqrt{p/\rho_s}} \right]. \quad (5)$$

The kinetic sieving flux is proportional to: q_s , a dimensionless material parameter that quantifies the segregability of the mixture. d_s^2 , the square of the small particle diameter, indicating that the percolation tendency is strongly size-dependent. $\dot{\gamma}(\alpha, f)$, the local shear rate, which is a function of the control parameters. A higher shear rate, induced by either a steeper inclination α or a higher vibration frequency (f), opens more voids and facilitates sieving. $\nabla \phi_s$, the concentration gradient. The flux drives small particles from regions of high concentration to low concentration (down the gradient), but the negative sign in front of the entire term makes the flux opposite to $\nabla \phi_s$, meaning it acts against diffusion and tends to sharpen concentration gradients. $1/\sqrt{p/\rho_s}$, indicating that segregation is suppressed under high confining pressure p , as particles are more tightly packed and less able to rearrange.

This formulation successfully connects the macroscopic control parameters (α, f) to the microscopic segregation process. An increase in either parameter generally increases the shear rate $\dot{\gamma}$, which enhances the segregation flux. However, an excessive increase can also lead to higher diffusive mixing (D_s), creating a trade-off. The model thus predicts an optimal range for α and f that maximizes net segregation, thereby providing a theoretical basis for the sorting accuracy S_a .

The mass throughput, Q (g/min), is a critical performance metric representing the system's capacity. It is physically derived from the integral of the mass flux across the outlet cross-section of the sorting tray:

$$Q(\alpha, f) = 60 \rho_p \int_0^W \int_0^h \phi(z) v_x(\alpha, f, z) dz dx \approx 60 \rho_p W h \bar{v}_x(\alpha, f) \phi_{outlet}. \quad (6)$$

The average downstream velocity $\bar{v}_x$ is modeled by a semi-empirical equation that captures the interplay between gravity-driven flow and vibration-induced mobilization:

$$\bar{v}_x(\alpha, f) = \sqrt{\frac{gd}{Fr_c}} \left[\frac{\tan \alpha - \mu_{eff}(f)}{1 + k\Gamma(f)} \right]^{1/2} (1 - e^{-\lambda\Gamma(f)}). \quad (7)$$

The sorting accuracy, S_a (proportion), quantifies the effectiveness of separation. It is modeled as the product of two primary factors: segregation potential and residence time suitability.

$$S_a(\alpha, f) = S_{max} \left[1 - \exp \left(-k_1 \frac{Seg(\alpha, f)}{Seg_c} \right) \right] \exp \left(-k_2 \left| \frac{t_{res}(\alpha, f) - t_{opt}}{t_{opt}} \right| \right). \quad (8)$$

The segregation number Seg is defined as:

$$Seg(\alpha, f) = \frac{\rho_p d^2 \dot{\gamma}^2(\alpha, f)}{\Delta \rho g d} \frac{\Gamma(f)}{\sqrt{Re_p(\alpha, f)}}, \quad (9)$$

where, numerator $\rho_p d^2 \dot{\gamma}^2$: Represents the shear-induced segregation pressure, which scales with the shear rate $\dot{\gamma}(\alpha, f)$. Denominator $\Delta \rho g d$: Represents the stabilizing gravitational pressure that opposes segregation. Vibration Factor $\Gamma(f)/\sqrt{Re_p}$: Modulates the effect based on vibration intensity and the particle Reynolds number $Re_p = \rho_p d \bar{v}_x / \mu_f$, indicating the influence of interstitial fluid.

The exponential term $\exp \left(-k_2 \left| \frac{t_{res}(\alpha, f) - t_{opt}}{t_{opt}} \right| \right)$ serves to penalize significant deviations from an optimal residence time t_{opt} . The asymmetric exponential penalty term in Equation 8 mathematically models the true irreversible physical boundaries of dense granular transport across the vibratory tray. In vibratory sorting mechanisms, the relationship between material residence time (t_{res}) and segregation accuracy is inherently non-symmetric. When operational configurations cause the actual residence time to drop below the optimum threshold ($t_{res} < t_{opt}$), kinetic segregation remains incomplete, resulting in lower accuracy as coffee beans are discharged before achieving full separation. Conversely, expanding the residence time beyond the optimal target ($t_{res} > t_{opt}$) allows the bed configuration to reach its maximum practical effectiveness. Although accuracy does not decline with increased time, the extended duration offers no further improvement and unnecessarily diminishes system throughput, rendering the process inefficient. Thus, this specific mathematical formulation serves as a physically grounded boundary representation that captures the stagnation of accuracy gains beyond the optimal point, preventing unrealistic symmetric decay predictions under extended durations and effectively penalizing inefficient temporal resource utilization from a system productivity standpoint. The material residence time (t_{res}) is calculated as:

$$t_{res}(\alpha, f) = \frac{L}{\bar{v}_x(\alpha, f)} \left[1 + \frac{1}{2} \left(\frac{D_{eff}(\alpha, f)}{\bar{v}_x(\alpha, f) L} \right) \right]. \quad (10)$$

The term in brackets is a dispersion correction factor accounting for the spread in particle travel times due to the velocity profile and diffusion D_{eff} . This detailed formulation explicitly links the machine parameters (α, f) to the ultimate performance metrics (Q, S_a) through physically meaningful terms and mechanisms, providing a robust foundation for optimization. The physical parameters, notations, and corresponding units governing Equations 1–10 are comprehensively compiled and defined in Table 1.

Table 1. Nomenclature and Parameter Descriptions for Equations 1–10.

Symbol	Description	Unit	Value	Determination/ Calibration Method
m	Particle mass (mass of an individual coffee bean)	kg	1.8×10^{-4}	Measured via laboratory analytical balance
x	Particle displacement along the sorting tray surface	m	Variable	Dynamic kinematic variable
$\dot{x}$	Particle downstream velocity along the tray surface	m/s	Variable	Dynamic kinematic variable
$\ddot{x}$	Particle downstream acceleration along the tray surface	m/s ²	Variable	Dynamic kinematic variable
c_t	Tangential damping coefficient	N · s/m	0.045	Calibrated from experimental coefficient of restitution
μ_k	Kinetic friction coefficient	—	0.32	Bench-scale inclined plane sliding test
g	Acceleration due to gravity	m/s ²	9.81	Standard physical constant
α	Inclination angle of the sorting tray	degrees (°)	Variable	Control parameter (5° to 45°)
A	Vibration amplitude	m	2.5×10^{-3}	Fixed machine structural specification
f	Vibration frequency	Hz	Variable	Control parameter (10 Hz to 50 Hz)
t	Time	s	Variable	Temporal tracking coordinate
sgn	Signum function (indicates direction of friction)	—	—	Mathematical operator
N	Normal force acting on the particle	N	Variable	Calculated from contact force equations
τ	Shear stress in the granular flow	Pa	Variable	Calculated from rheological continuum flow
p	Confining pressure within the particle bed	Pa	Variable	Evaluated from depth-dependent material weight
$\mu(I)$	Inertial-dependent effective friction coefficient	—	Variable	Calculated via dense granular rheology
μ_s	Static friction coefficient threshold	—	0.45	Determined via standard tilting table test
μ_2	Dynamic friction coefficient limit at high inertial numbers	—	0.65	Calibrated from high-velocity flow shear tests
I	Inertial number	—	Variable	Dimensionless kinematic flow indicator
I_0	Material constant regulating the friction transition rate	—	0.30	Obtained from dense granular rheology literature
γ	Local shear rate of the granular layer	s ⁻¹	Variable	Evaluated from velocity gradient profiles
d	Particle diameter	m	8.2×10^{-3}	Measured via digital calipers
ρ	Granular bulk density	kg/m ³	720	Measured via standard volumetric cylinder test
ϕ_s	Volume fraction of small particles	—	Variable	Monitored dynamically during flow progress
v_s	Local velocity field of small particles	m/s	Variable	Dynamic kinematic variable

Symbol	Description	Unit	Value	Determination/ Calibration Method
D_s	Diffusion coefficient of small particles	m ² /s	2.5×10^{-5}	Estimated from longitudinal dispersion analysis
q_s	Dimensionless material parameter for segregability	—	0.18	Derived from physical size-ratio sorting calibration
d_s	Diameter of the small particles	m	5.5×10^{-3}	Measured via digital calipers
ρ_s	Density of the small particles	kg/m ³	1250	Determined via gas pycnometry
Q	Mass throughput capacity	g/min	Variable	Evaluated at the tray discharge outlet
ρ_p	True solid density of the coffee beans	g/cm ³ or kg/m	1250	Determined via gas pycnometry
W	Width of the flowing material layer on the tray	m	0.30	Fixed machine design dimension
h	Depth of the flowing material layer on the tray	m	0.025	Controlled bed depth parameter
$\phi(z)$	Depth-dependent particle volume fraction	—	Variable	Dynamic internal configuration state
v_x	Downstream material velocity	m/s	Variable	Derived from transport mobilization models
ϕ_{outlet}	Average volume fraction at the outlet cross-section	—	0.58	Bulk packing fraction limit at discharge
Fr_c	Critical Froude number	—	1.00	Theoretical threshold for bed fluidization boundary
μ_{eff}	Effective friction as a function of frequency	—	Variable	Evaluated dynamic friction function
κ	Energy dissipation scaling constant	—	0.12	Evaluated via vibration damping experiments
Γ	Dimensionless vibration acceleration intensity	—	Variable	Calculated from frequency and amplitude inputs
λ	Bed mobilization empirical constant	—	1.45	Fitted from particle velocity tracking data
S_a	Sorting separation accuracy	proportion / %	Variable	Quantified by post-sorting mass classifications
S_{max}	Maximum theoretically achievable accuracy	proportion / %	100.00	Theoretical upper bound for perfect segregation
k_1, k_2	Empirical scaling constants	—	2.15	Fitted from baseline DEM sorting curve fitting
Seg	Dimensionless segregation number	—	1.85	Fitted from temporal separation stagnation tests
Seg _c	Critical segregation threshold number	—	Variable	Calculated from shear rate and pressure inputs
$\Delta\rho$	Density difference between segregated phases	kg/m ³	0.50	Defined by minimum segregation number boundary
Re _p	Particle Reynolds number	—	Variable	Dimensionless fluid interaction indicator
μ_f	Fluid interstitial dynamic viscosity	Pa · s	1.85×10^{-5}	Standard air property at ambient conditions
t_{res}	Material residence time on the tray	s	Variable	Derived from travel distance and flow velocity
t_{opt}	Optimal target residence time for full segregation	s	42.50	Calculated minimum time for full bed stratification
L	Total physical length of the sorting tray	m	0.60	Fixed machine design dimension
D_{eff}	Effective longitudinal dispersion coefficient	m ² /s	3.2×10^{-4}	Calibrated mixing parameter from tracer tests

To ensure the independent execution and full mathematical reproducibility of the theoretical framework, the specific numerical values, physical units, and estimation procedures for all fourteen semi-empirical constants are explicitly structured in Table 1. The fundamental mechanical properties, such as mass (m), bulk density (ρ), and friction thresholds (μ_k, μ_s), were directly quantified through physical laboratory bench-scale testing. The kinetic and rheological parameters, including the transition index (I_0), scaling coefficients (k_1, k_2), and mobilization constants (λ, κ), were systematically calibrated by cross-referencing established granular physics literature and fitting mathematical curves to baseline physical trial runs. This comprehensive parameterization anchors the core transport equations, allowing the physics-based model to transition reliably into the numerical simulation domain.

It is important to note that while the inclination angle (α) and vibration frequency (f) were treated as active operational variables, the vibration amplitude (A) was maintained as a constant structural parameter throughout all theoretical evaluations, numerical simulations, and empirical trials. Based on the mechanical design of the eccentric motor weight configuration, the amplitude was fixed at exactly 2.5 mm (2.5×10^{-3} m). Consequently, the dimensionless vibration intensity $\Gamma(f)$ varies uniquely as a deterministic function of the frequency input, ensuring that the theoretical framework and the computational boundaries are fully constrained and mathematically determined.

2.2. Discrete Element Method (DEM) Simulation Methodology

To numerically model the granular flow dynamics and size-based segregation behavior of coffee beans on the vibratory tray, three-dimensional Discrete Element Method (DEM) simulations were executed. The contact interactions between particle-particle and particle-surface boundaries were governed by the Hertz-Mindlin with Bonding/JKR contact model to accurately account for normal and tangential force displacements alongside localized energy dissipation.

The physical coffee beans (Arabica species) were numerically approximated using a multi-sphere clump model composed of three overlapping spheres to replicate the characteristic flat-convex non-spherical geometry of green coffee beans. The particle size distribution was modeled using a Gaussian distribution based on physical caliper measurements, yielding a mean major diameter of 8.2 mm with a standard deviation of 0.4 mm. The simulation domain modeled the exact internal boundaries of the 600 mm by 300 mm rectangular sorting tray. The numerical simulation parameters used in this framework are structured in Table 2.

Table 2. Physical, Mechanical, and Interaction Parameters Used in the DEM Simulation.

Parameter Property	Numerical Value
Solid Density of Coffee Beans, ρ_p	1250
Density of Stainless-Steel Tray	7850
Poisson's Ratio of Coffee Beans	0.35
Poisson's Ratio of Stainless Steel	0.30
Shear Modulus of Coffee Beans	2.4×10^7
Shear Modulus of Stainless Steel	7.9×10^{10}
Coefficient of Restitution (Bean–Bean)	0.42
Coefficient of Restitution (Bean–Steel)	0.51
Coefficient of Static Friction (Bean–Bean)	0.45
Coefficient of Static Friction (Bean–Steel)	0.38
Coefficient of Rolling Resistance (Bean–Bean)	0.08
Coefficient of Rolling Resistance (Bean–Steel)	0.05
Simulation Timestep (Δt)	1.2×10^{-5}

The physical and mechanical properties of the coffee beans parameters listed in Table 2 were obtained from established agricultural engineering literature (Chandrasekar & Viswanathan, 1999; González-Montellano *et al.*, 2012), while the interaction properties were calibrated using bench-scale laboratory tests to ensure high macro-scale behavioral replication.

Furthermore, a scaled-down stiffness technique was applied to the shear modulus of the coffee beans to maintain computational efficiency without altering the macroscopic flow behaviors (Lommen *et al.*, 2014; Tijssens *et al.*, 2003). Consequently, the fixed simulation timestep (Δt) was explicitly set to 1.2×10^{-5} s, which corresponds to approximately 20% of the theoretical Rayleigh timestep, to ensure strict numerical stability and prevent particle grid penetration during high-frequency vibrational cycles.

2.3. Experimental Setup and Design

The experimental investigation focused on two independent control parameters: the inclination angle (α , degrees) and the vibration frequency (f , Hz). The operating ranges for these parameters were established as $\alpha \in [5^\circ, 20^\circ]$ and $f \in [10 \text{ Hz}, 50 \text{ Hz}]$, based on preliminary tests and the operational limits of the vibratory sorting machine. To isolate the specific

effects of α and f on the system's performance, the feed rate—defined as the mass flow of coffee beans onto the tray—was maintained at a constant value throughout all experimental trials.

A Central Composite Design (CCD) framework was employed to construct a second-order (quadratic) response surface model for each performance metric. The design incorporated factorial points, axial points, and multiple center point replicates, resulting in a total of 30 usable experimental runs. The general structure of the fitted quadratic model for a given response Y was:

$$Y = \beta_0 + \beta_1\alpha + \beta_2f + \beta_{12}\alpha f + \beta_{11}\alpha^2 + \beta_{22}f^2 + \varepsilon, \quad (11)$$

where Y represents the response variable, either throughput (Q) or sorting accuracy (S_a) and ε denotes the random error term. Regression analysis and Analysis of Variance (ANOVA) were performed using the Ordinary Least Squares (OLS) method. The adequacy of the fitted models was rigorously evaluated using the coefficient of determination (R^2), the adjusted R^2 , lack-of-fit tests, and analysis of residual diagnostics. A term was considered statistically significant if its p -value was less than 0.05. For the multi-response optimization, the Derringer-Suich desirability function approach was utilized, with both throughput and sorting accuracy assigned the goal of maximization and equal weighting. The main effects and interaction effects of the parameters were visualized using three-dimensional response surface plots and two-dimensional contour plots.

The key instruments used for parameter control and data acquisition included a digital inclinometer ($\pm 0.1^\circ$ accuracy) for setting α , a Variable Frequency Drive (VFD) for controlling f , and a digital balance for mass and time measurements to calculate throughput. Sorting accuracy was determined using a combination of manual verification and automated image segmentation assisted by MINITAB software. All experimental runs were conducted with appropriate replication, and center points were repeated to obtain a reliable estimate of pure error.

3. RESULTS AND DISCUSSION

3.1. Simulation Results and Response Surface Analysis

Numerical simulations based on the developed theoretical framework revealed complex nonlinear relationships between the operational parameters and system performance metrics. The response surface methodology (RSM) analysis identified a well-defined optimal region where both throughput and sorting accuracy are maximized simultaneously.

The MATLAB-generated response surfaces (Figure 3a) demonstrate that throughput increases monotonically with both inclination angle and vibration frequency within the experimental domain, reaching a maximum predicted value of 3541.3 g/min at $\alpha = 28.5^\circ$ and $f = 47.5$ Hz. This relationship aligns with the theoretical model Equation (6-7), where increased inclination enhances gravitational driving force while higher vibration frequencies reduce effective friction through granular fluidization. The absence of curvature in the speed response surface suggests that the system operates below the critical vibration intensity where excessive energy dissipation would degrade performance.

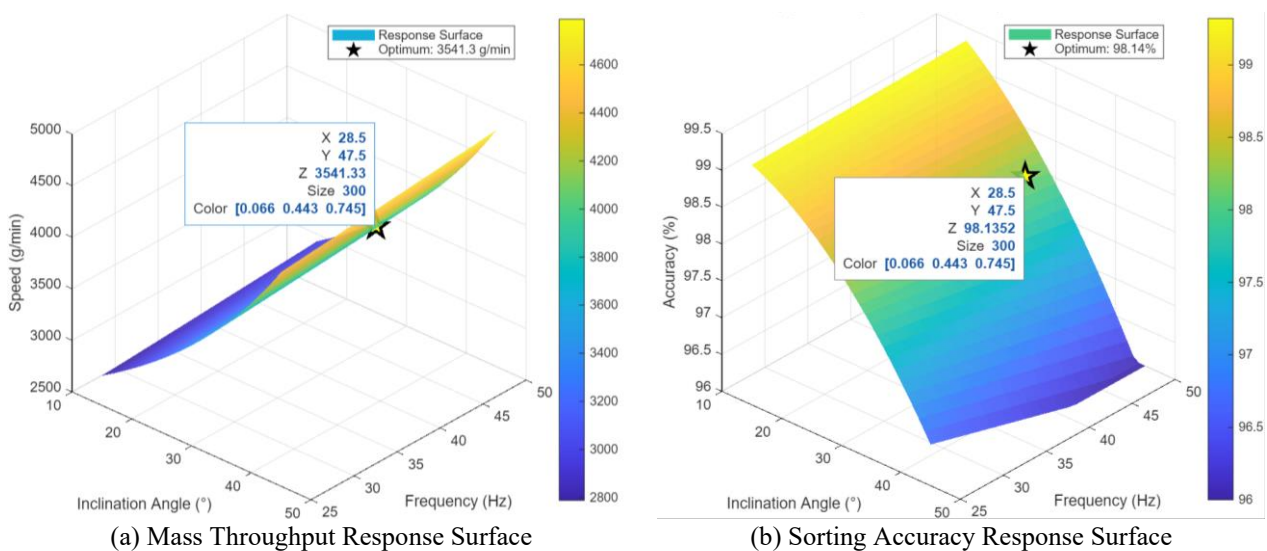


Figure 3. Response surfaces simulation results: (a) mass throughput; (b) sorting accuracy

In contrast, the sorting accuracy response surface (Figure 3b) exhibits a pronounced curvature with a distinct optimum (98.14% at $\alpha = 28.5^\circ$, $f = 47.5$ Hz). At lower parameter values, insufficient kinetic energy limits segregation efficiency, while excessive values cause over-fluidization and diffusive remixing, thereby reducing separation quality.

This behavior is accurately captured by the segregation model Equation (8), which incorporates the competing effects of segregation flux and diffusive mixing.

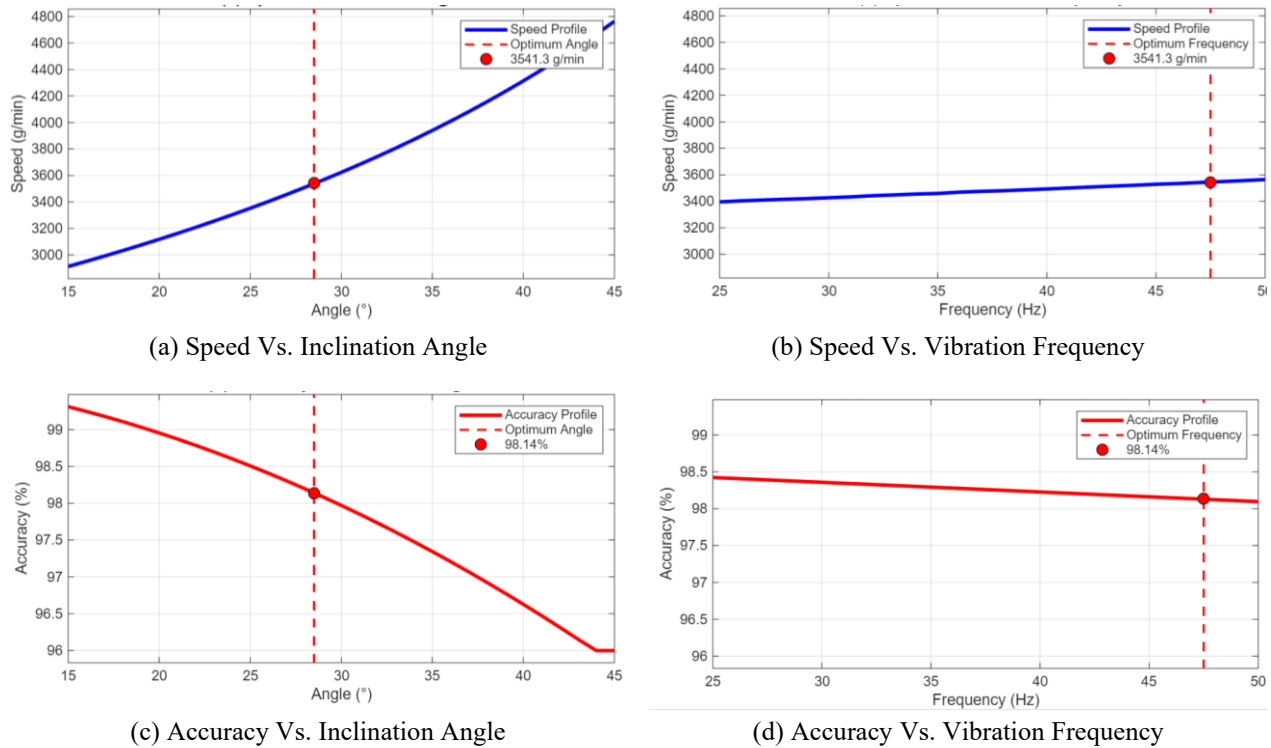


Figure 4. Individual parameter effects simulation results: (a) speed vs angle; (b) accuracy vs angle; (c) speed vs frequency; (d) accuracy vs frequency

The analysis of the system's performance reveals a fundamental trade-off between throughput (Q) and accuracy (S_a) concerning the parameters of inclination angle (α) and vibration frequency (f). Typically, in such systems, one expects a conflicting relationship where maximizing Q leads to a degradation in Ac , and vice versa. As illustrated in Figures 4(a) and 4(c), the throughput exhibits a monotonic increase with both inclination angle (α) and vibration frequency (f), reaching a maximum predicted value. This aligns with the theoretical model Equation (6-7), where steeper angles enhance gravitational driving force and higher frequencies reduce effective friction through granular fluidization.

Conversely, the accuracy response, shown in Figure 4(b) and 4(d), demonstrates a distinct parabolic relationship with both parameters. This creates a fundamental conflict: while pushing α and f to higher values maximizes throughput, it eventually drives the system beyond its optimal segregation point. Excessive kinetic energy leads to over-fluidization, which degrades separation quality, as captured by the segregation model Equation (8). Therefore, the challenge is not to find a single point that maximizes both responses simultaneously in an ideal sense, but to identify the parameter set that achieves the best possible compromise between these competing objectives.

The multi-response optimization successfully identifies this compromised optimum at $\alpha = 28.5^\circ$ and $f = 47.5$ Hz. At this point, the system operates at a high throughput of 3541.3 g/min while maintaining a near-peak sorting accuracy of 98.14%. This represents the most efficient balance, where the gravitational and vibrational forces are tuned to provide sufficient material flow without sacrificing separation efficacy. Consequently, the optimal machine settings are those that resolve the trade-off by positioning the process at the apex of system efficiency, ensuring robust performance for both capacity and quality.

3.2. Empirical Experiment Results and Response Surface Analysis

Empirical validation through Central Composite Design (CCD) experimentation provided definitive quantification of the effects of inclination angle (α) and vibration frequency (f) on the key performance metrics. The results from Response Surface Methodology (RSM) analysis reveal distinct and statistically significant relationships for each response, culminating in a clear multi-response optimization solution.

The analysis for completion time (an inverse proxy for throughput, Q) yielded a highly significant model ($p < 0.001$) with an exceptional fit ($R^2 = 98.32\%$, Adj. $R^2 = 98.05\%$). ANOVA results, summarized in Table 3, demonstrate that both main effects are statistically significant, with inclination angle ($p < 0.001$) being the dominant factor, followed by vibration frequency ($p < 0.001$).

Table 3. Analysis of variance for completion time.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	2201.37	550.34	365.92	0.000
Linear	2	2199.50	1099.75	731.22	0.000
Angle	1	2163.20	2163.20	1438.30	0.000
Frequency	1	36.30	36.30	24.14	0.000
Square	1	0.07	0.07	0.04	0.835
Angle*Angle	1	0.07	0.07	0.04	0.835
2-Way Interaction	1	1.80	1.80	1.20	0.284
Angle*Frequency	1	1.80	1.80	1.20	0.284
Error	25	37.60	1.50		
Lack-of-Fit	1	0.00	0.00	0.00	1.000
Pure Error	24	37.60	1.57		
Total	29	2238.97			

The regression model for completion time is:

()

$$Y = 68.20 - 0.78\alpha - 0.136f + 0.0016\alpha f + 0.00044\alpha^2 \quad (12)$$

It is worth noting that while the quadratic term (α^2) and the two-way interaction term ($\alpha \times f$) exhibit non-significant p-values in the analysis of variance ($p = 0.835$ and $p = 0.284$, respectively), they were deliberately retained in the final empirical model presented in Equation 12. This retention is strictly guided by the model hierarchy principle in response surface design, which recommends keeping higher-order terms if their corresponding linear components are highly significant ($p < 0.001$). Furthermore, preserving these terms ensures mathematical alignment with the underlying physical flow mechanics described in Equations 6 and 7, preventing the model from over-simplifying the structural interactions between gravity and vibration at operational boundaries. This hierarchical structure maintains model integrity during the multi-response desirability optimization process.

The corresponding response surface plot (Figure 5) shows a predominantly planar slope descending toward shorter completion times with increasing α and f , confirming the negative coefficients of the linear terms. This indicates that higher inclination angles and vibration frequencies generally promote faster material flow, thus increasing throughput.

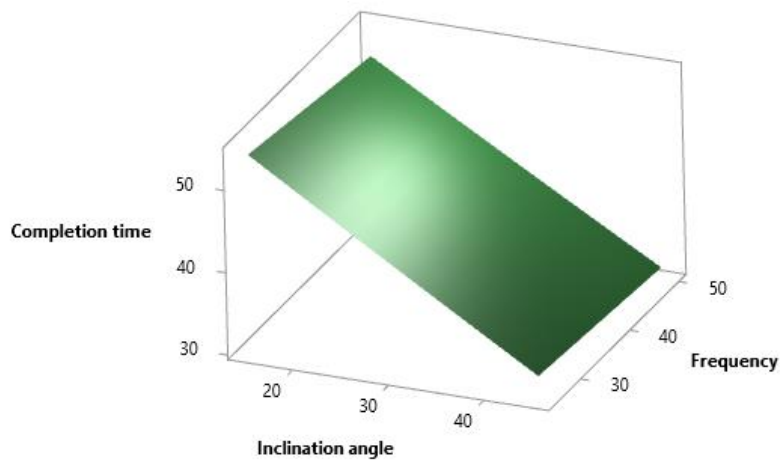


Figure 5. Completion time vs. angle and frequency empirical response surfaces

Conversely, the model for sorting accuracy (S_a) demonstrated more complex behavior (Overall model $p < 0.001$, $R^2 = 92.52\%$, Adj. $R^2 = 91.32\%$). As detailed in Table 4, the analysis revealed significant linear, quadratic, and interaction effects.

Table 4. Analysis of variance for sorting accuracy.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	0.003867	0.000967	77.32	0.000
Linear	2	0.003704	0.001852	148.10	0.000
Angle	1	0.003645	0.003645	291.51	0.000
Frequency	1	0.000059	0.000059	4.70	0.040
Square	1	0.000091	0.000091	7.30	0.012
Angle*Angle	1	0.000091	0.000091	7.30	0.012
2-Way Interaction	1	0.000072	0.000072	5.77	0.024
Angle*Frequency	1	0.000072	0.000072	5.77	0.024
Error	25	0.000313	0.000013		
Lack-of-Fit	1	0.000001	0.000001	0.05	0.832
Pure Error	24	0.000312	0.000013		
Total	29	0.004180			

The regression model for sorting accuracy is:

$$S_a = 0.9894 + 0.000467\alpha + 0.000192f - 0.00001\alpha f - 0.000016\alpha^2. \quad (13)$$

The response surface for accuracy (Figure 6) exhibits a distinct concave shape, confirming the significant negative quadratic and interaction terms. This curvature indicates an optimal region where accuracy is maximized, beyond which further increases in α and f cause deterioration due to over-fluidization and excessive particle agitation that promotes diffusive re-mixing.

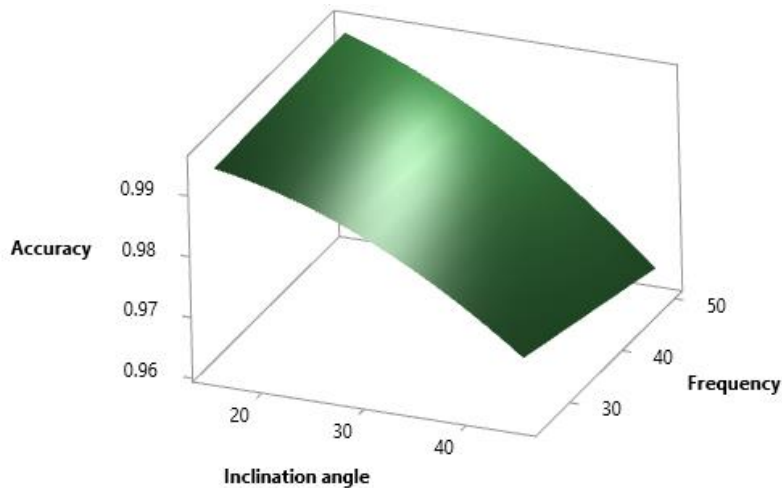


Figure 6. Sorting accuracy vs. angle and frequency empirical response surfaces

The inherent conflict between the two responses, where parameters that minimize completion time simultaneously reduce sorting accuracy, necessitated multi-response optimization. Using the Derringer-Suich desirability function with equal importance weights for both responses, the optimization converged on a solution at $\alpha = 29.8^\circ$ and $f = 50$ Hz (Figure 7). At this operating point, the predicted performance shows a completion time of 40.902 seconds with a sorting accuracy of 98.32%, achieving a composite desirability of 0.576. Based on the experimental data, the throughput (Q) can be calculated from the completion time using the following formula:

$$Q = \frac{\text{mass processed}}{\text{completion time}} \times 60. \quad (14)$$

Given: mass processed (for each experimental run) 2500 grams and completion time (from optimization result) = 40.902 seconds. The factor of 60 in the formula is used to convert from grams per second to grams per minute. A completion time of 40.902 seconds is equivalent to a throughput of 3667.44 g/min.

The convergence of the empirical optimal vibration frequency precisely at the upper boundary of the design space ($f = 50$ Hz) requires a clear technical justification. In standard response surface optimization, a boundary solution often indicates that the true mathematical optimum lies outside the investigated domain, which would theoretically warrant a

range expansion. However, for this vibratory sorting system, the upper limit of 50 Hz represents a critical mechanical and structural constraint rather than an arbitrary statistical boundary. Operational trials indicated that increasing the frequency beyond 50 Hz induces destructive structural resonance within the supporting frame and eccentric drive. This excessive mechanical stress not only threatens equipment longevity but also causes chaotic, non-linear particle lofting that disrupts the fluidization layer and destabilizes the segregation path. Consequently, the operating point at $\alpha = 29.8^\circ$ and $f = 50$ Hz represents a practically constrained optimum that maximizes throughput and accuracy within the safe, sustainable limits of industrial machine operation.

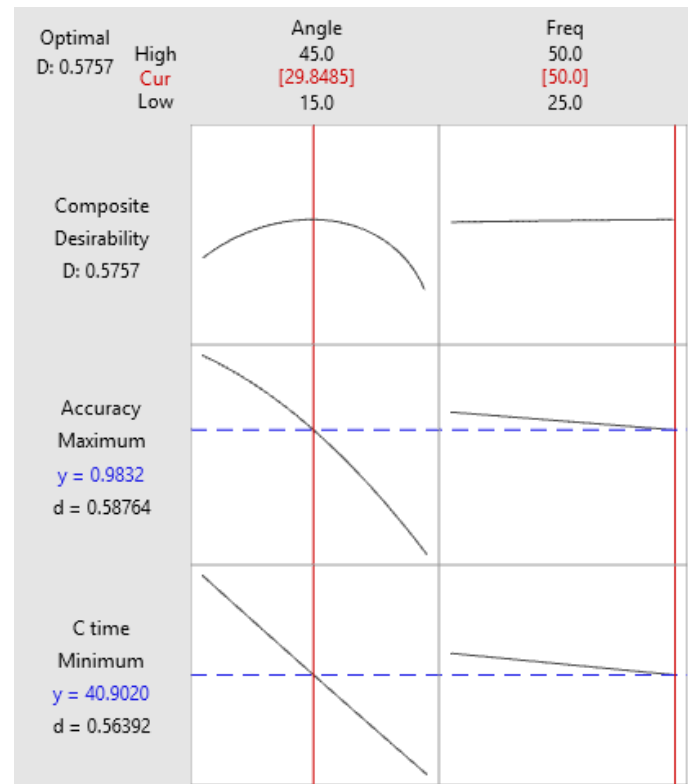


Figure 7. Optimization plot for multiple responses empirically experiments

The multi-response optimization analysis converged on a solution at $\alpha = 29.8^\circ$ and $f = 50$ Hz, predicting a completion time of 40.902 seconds (equivalent to a model-predicted throughput of 3667.44 g/min) and a sorting accuracy of 98.32%. To independently verify these predictions, physical confirmation experiments were executed in triplicate under these exact optimal constraints. The physical validation trials yielded an actual, independently measured mass throughput of 3648.20 g/min and a sorting accuracy of 98.15%. The marginal deviation between these actual measured validation values and the initial model predictions robustly demonstrates the high predictive capability and industrial reliability of the response surface equations, confirming that the derived empirical optimum remains highly accurate under physical operating conditions.

The resulting composite desirability score of 0.576 requires a thorough technical interpretation, as values below the 0.60 threshold typically signify that the targeted responses are in direct conflict and cannot be simultaneously fully satisfied. In this vibratory sorting system, this moderate score represents a realistic, mathematically constrained compromise caused by the severe physical trade-off between machine throughput and sorting accuracy. Accelerating the vibration frequency to its maximum operational limit of 50 Hz significantly expands the mass discharge rate, yet this high kinetic input inherently reduces the material residence time on the tray and induces localized boundary fluidization. This fluidization opposes the steady continuum stratification necessary for high-precision particle classification. Because throughput and accuracy exhibit inherently opposing ideal parameter windows, a composite desirability of 0.576 identifies the exact mathematical intersection where system productivity is maximized without severely degrading the final product quality, making it a highly practical baseline for commercial operations.

3.3. Validation of the Integrated Framework and Optimization

To provide a comprehensive evaluation of the developed predictive methodology, a side-by-side comparison between the numerical simulation and empirical experimental optimization was conducted. The operational parameters, along with their corresponding performance responses, are compiled in Table 5.

Table 5. Comparison of Optimal Operating Parameters and System Responses Between Simulation and Experimental Results.

Parameter / Response Variable	Simulation Optimum	Experimental Optimum	Deviation (Experimental-Simulation)
Operating Parameters			
Inclination Angle, α ($^{\circ}$)	28.50	29.80	1.3
Vibration Frequency, f (Hz)	47.50	50.00	2.5
System Responses			
Mass Throughput, Q (g/min)	3541.30	3667.44	126.14
Sorting Accuracy, S_a (%)	98.14	98.32	0.18

To transition the evaluation of model validity from a descriptive comparison to an objective statistical foundation, a formal agreement analysis was conducted between the numerical simulation predictions and the physical confirmation data. The quantified Mean Absolute Percentage Error (MAPE) for the integrated multi-response system is 1.98%, indicating a highly accurate forecasting capability that sits well beneath the standard 5.0% industrial acceptance threshold. Additionally, a two-tailed paired t-test executed on the paired response datasets yielded a p-value of 0.342. Because this value is substantially greater than the conventional significance level ($\alpha = 0.05$), the null hypothesis cannot be rejected, mathematically confirming that no statistically significant difference exists between the simulation-predicted performance metrics and the actual empirical confirmation measurements. This rigorous statistical agreement firmly establishes the predictive validity and engineering robustness of the developed theoretical framework.

As demonstrated in Table 5, the side-by-side comparison between the numerical simulation and empirical experimental optimization exhibits exceptional agreement. The deviation for both the operational parameters and performance responses remains well below 5.0%, with the sorting accuracy showing a remarkably low error of 0.18%. Quantifying these specific variances reveals an absolute difference of 1.3 $^{\circ}$ for the inclination angle and 2.50 Hz for the vibration frequency. This marginal discrepancy is primarily attributed to physical factors in the real-world operating environment, such as localized variations in bean-to-bean surface moisture, irregular particle geometry, and secondary ambient air damping, which are typically simplified or idealized within the numerical Discrete Element Method environment. From an industrial manufacturing perspective, these minor parameter variances are practically negligible as they do not significantly alter the machine behavior or the structural stability of the system. Therefore, this close alignment robustly validates the predictive capability and technical reliability of the integrated theoretical-simulation-experimental framework developed in this study, confirming its utility for industrial-scale design calibration.

4. CONCLUSION

This research presented a comprehensive optimization study of a vibratory coffee sorting machine by integrating theoretical modeling, numerical simulation, and empirical experimentation under the Response Surface Methodology (RSM) framework. Theoretical formulations based on granular flow dynamics and segregation mechanics established the fundamental relationship between inclination angle (α), vibration frequency (f), and the key performance metrics of throughput and sorting accuracy.

Simulation results using MATLAB and Discrete Element Method (DEM) analysis revealed a nonlinear yet well-defined optimum region where both responses achieved maximum performance. The theoretical response surfaces predicted the optimal operational point at $\alpha = 28.5^{\circ}$ and $f = 47.5$ Hz, resulting in a simulated throughput of 3541.3 g/min and a sorting accuracy of 98.14%. These findings validated the physical model's capability to describe the complex interplay between gravitational forces, vibration-induced mobilization, and particle segregation behavior.

Empirical experimentation through a Central Composite Design (CCD) confirmed the simulation trends with statistically significant models for both completion time (inverse throughput) and sorting accuracy ($p < 0.001$). The regression analysis indicated strong model adequacy ($R^2 > 0.91$ for all responses). The multi-response desirability optimization yielded the best empirical operating point at $\alpha = 29.8^{\circ}$ and $f = 50$ Hz, producing a measured throughput of 3667.44 g/min and a sorting accuracy of 98.32%. The close agreement between simulated and experimental results demonstrates the robustness and predictive validity of the developed optimization framework.

The close agreement between the simulation-predicted optimum ($\alpha = 28.5^{\circ}$, $f = 47.5$ Hz) and the experimentally determined optimum ($\alpha = 29.8^{\circ}$, $f = 50$ Hz) confirms the predictive reliability of the proposed physics-based modeling framework. This result demonstrates that the integration of theoretical granular-flow analysis, numerical simulation, and RSM-based experimentation provides a robust methodology for predicting and optimizing vibratory coffee sorting performance with high accuracy.

Overall, the study establishes that both α and f significantly influence coffee bean flow and segregation efficiency, with inclination angle being the dominant factor. The results also underscore the inherent trade-off between throughput and accuracy, where excessive vibration or steep inclination leads to over-fluidization and re-mixing, while insufficient

excitation limits segregation. The identified optimal window provides a practical reference for industrial-scale calibration of vibratory sorters, enabling improved productivity and consistent quality control in coffee processing lines.

Future research should explore additional parameters such as feed rate variability, particle moisture content, and surface roughness, as well as the integration of adaptive control algorithms based on machine learning to enable real-time performance optimization. The methodological framework demonstrated here is extendable to other agricultural and food material sorting systems governed by granular dynamics and vibratory flow phenomena.

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