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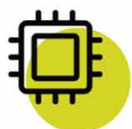
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Investigation of charge and ion drag force dynamics in complex plasma experiments with neon and argon under microgravity

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Abstract

In complex dusty plasmas, micron-sized particles immersed in ionized gas acquire a significant negative charge and experience various forces. One of the primary forces acting on these particles is the ion drag force. The PK-4 facility aboard the International Space Station enables precise studies of such systems under microgravity. During campaigns #17 and #18, we investigated the ion drag force on 3.4 μm melamine-formaldehyde microparticles in argon and neon plasmas across a pressure range of 10–120 Pa. We combined experimental data with advanced machine learning techniques and ion drag force modeling. This allowed us to evaluate and improve theoretical models, including an analytical approach for weak and intermediate ion coupling, as well as a hybrid model that incorporates kinetic simulations. Our results reveal a pronounced enhancement of the ion drag force measured at low pressures (below 30 Pa), especially in neon, where ion collisions and drift velocities significantly affect particle dynamics. These findings emphasize the role of ion-neutral collisions and plasma composition in determining dust-plasma interactions, offering new insight into the limitations of existing theoretical models and the need for gas-specific model refinements.

1. Introduction

Plasma, often referred to as the fourth fundamental state of matter, is characterized by its high electrical conductivity and collective behavior arising from the presence of free-moving charged particles. It forms when neutral gas molecules undergo ionization due to high temperatures, electrical discharges, or other ionizing energy sources, resulting in a system comprising electrons, ions, and neutral particles. The ionized nature of plasma fundamentally differentiates it from the classical states of matter: solid, liquid, and gas. Plasma plays a crucial role in numerous technological applications, including semiconductor processing, environmental monitoring, medical technology, and controlled nuclear fusion. Notably, plasma constitutes approximately 99% of the observable Universe, underscoring its significance in both terrestrial and astrophysical contexts [1].

When micron-sized dust particles are introduced into plasma, they become negatively charged due to electron attachment, forming a system known as dusty or complex plasma. These systems exhibit collective behaviors governed by Coulomb interactions and ion flows. The Plasma Kristall 4 (PK-4) experiment represents the latest in a series of microgravity plasma crystal investigations. It is designed to study fundamental processes at the microscopic level and makes it possible to observe particle dynamics under stable drift conditions in a uniform plasma, allowing for detailed trajectory analysis.

One of the principal forces influencing the motion of dust particles in complex plasmas is the ion drag force. This force originates from the interaction between counter-streaming ions and negatively charged microparticles, driven by the discharge's longitudinal electric field. The resulting ion flow makes

use of a directional force that is partially counteracted by the electrostatic interaction with the dust particles. Since the early stages of complex plasma research, this force has been recognized as a key factor influencing particle transport and structure formation. The theoretical description of the ion drag force was initially developed by Barnes and later refined by Hutchinson and Khrapak. However, significant discrepancies between theoretical predictions and experimental observations have highlighted the limitations of these models. For instance, the formation of voids in radio-frequency (RF) complex plasmas is poorly explained by existing theoretical frameworks [2].

To address the complexities of dust-ion interactions, Khrapak proposed an alternative analytical approach, shifting the focus towards accurately characterizing the interaction cross-section. Rather than seeking a universal solution, this method classifies interactions based on dominant physical mechanisms and provides corresponding descriptions for different regimes [3].

In 2013, Graves and Schwabe introduced a hybrid approach that combines elements of Hutchinson's and Khrapak's theories with results from particle-in-cell (PIC) and Monte Carlo simulations. This model has demonstrated improved predictions, particularly in RF discharges, sheath regions, and multi-particle phenomena observed in plasma crystal experiments [4].

Beyond measuring the ion drag force, this study we aim to evaluate the predictive accuracy of existing theoretical models by comparing them with experimental results obtained from the PK-4 setup. For this purpose, data analysis and the determination of key plasma parameters are optimized using machine learning algorithms. The findings will contribute to refining theoretical descriptions of dust-ion interactions in complex plasmas and improving our understanding of plasma dynamics.

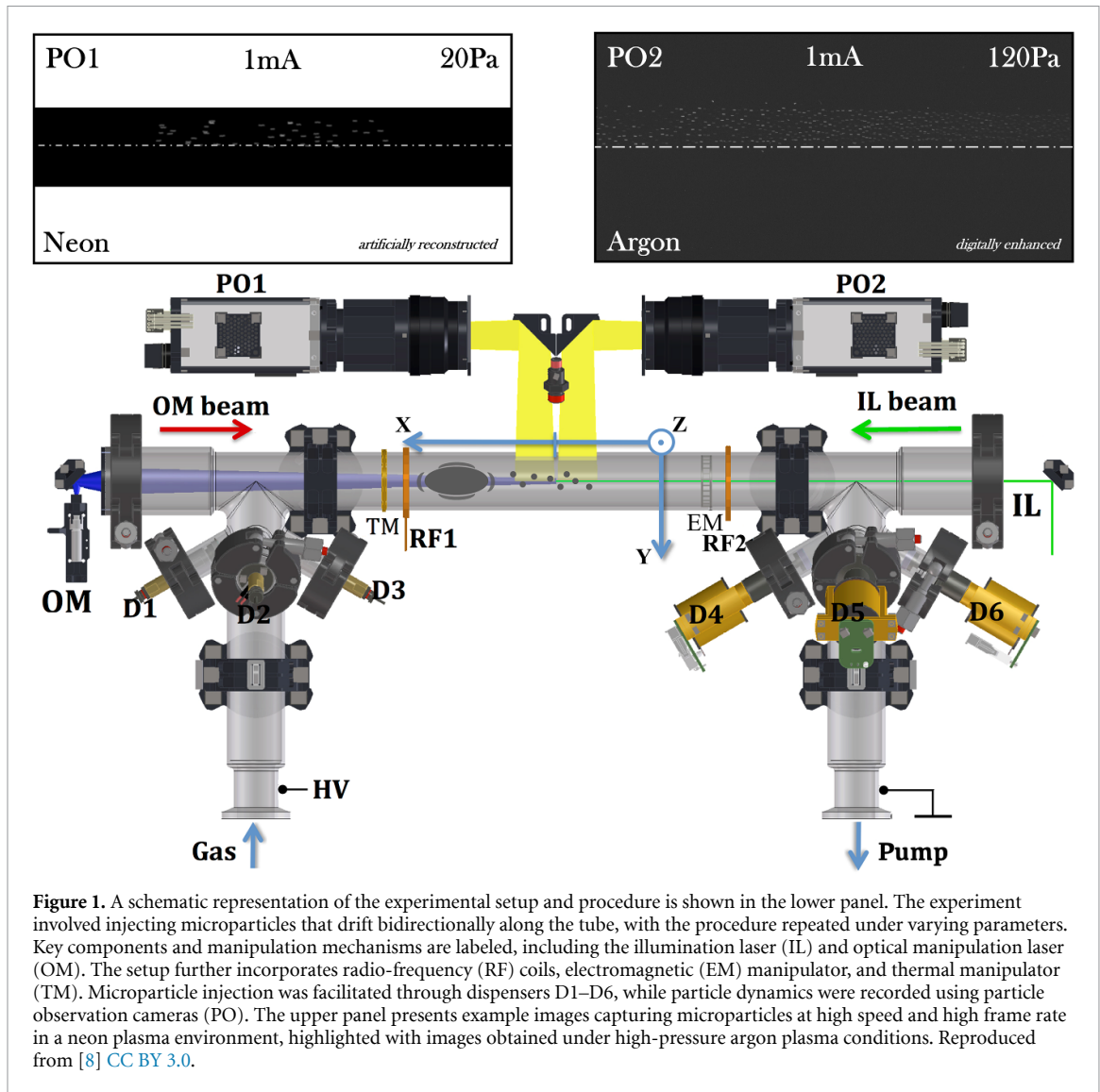
2. Experimental setup and procedure

The experimental investigation began with the confinement of a microparticle cloud within one section of a Π -shaped glass tube using a movable RF coil (RF1), as illustrated in figure 1. The tube, characterized by an inner diameter of $2R = 3$ cm, was filled with either neon or argon gas at pressures ranging from $p = 10 - 120$ Pa. A direct current (DC) discharge was established within the 86 cm-long tube by applying discharge currents of $I_{DC} = 1.0$ mA and 1.5 mA, thereby creating a plasma environment enabling the study of ion drag force. The micro particles were illuminated using an incident green laser system (IL beam), and the microparticle dynamics were recorded using digital imaging systems [5].

The microparticles utilized in this study consisted of melamine-formaldehyde (MF) with a diameter of $2a_p = 3.4 \mu\text{m}$, a density of $\rho_d = 1.5 \text{ g cm}^{-3}$, and a mass of $m_d = 3.24 \times 10^{-11}$ g. These particles acquired an approximate charge of $1500 - 5000e$ through electron and ion collection from the plasma. A longitudinal electric field of approximately $2 - 5 \text{ V cm}^{-1}$ in the positive polarization of the discharge facilitated the directed drift of the particles through the plasma chamber [5]. Parameters, such as the actual electric field strength E (V m^{-1}), electron number density n_e , and electron temperature T_e , have been precisely measured in the PK-4 neon configuration but remain incompletely characterized in argon. Significant diagnostic work by Pustilnik and Zobnin [5, 6] has provided key plasma parameters for neon within the parameter space of interest in this study. These parameters were obtained using Langmuir probe diagnostics in the PK-4 setup, increasing the accuracy of analytical findings. In contrast, for argon, the available data are less accurate and incomplete for the parameter space relevant to our study [7]. However, these measurements were conducted only within a limited pressure range of $p = 20 - 60$ Pa, which does not cover the full range of interest. Additionally, no measurements exist for a discharge current of 1.5 mA. To address the absence of experimental data for argon, we employed mathematical inter- and extrapolation techniques to estimate plasma parameters while ensuring physical plausibility. This was achieved by incorporating the measured data points obtained via Langmuir probe diagnostics to guide the inter- and extrapolation process. The results are presented in section 4.2.

The experimental studies were conducted as part of the 17th and 18th International Space Station (ISS) campaigns, employing two particle observation (PO) cameras, PO1 (Camera 1) and PO2 (Camera 2). Both cameras were capable of full-field-of-view (FOV) recording, covering an area of $22.7 \times 17.0 \text{ mm}^2$ with a resolution of $14.2 \mu\text{m}$. To optimize data acquisition, PO1 operated with a reduced FOV of $22.7 \times 3.8 \text{ mm}^2$, thereby minimizing readout time and achieving a maximum frame rate of 100 frames per second (fps). PO2 recorded with an FOV of $22.7 \times 10.9 \text{ mm}^2$ reaching a frame rate of 50 fps.

During the experimental runs, the suspended particles exhibited bidirectional drift along the tube, induced by periodic polarity switching of the electric field at a frequency of $0.25 - 0.5$ Hz. This procedure was repeated under varying experimental conditions. A minor but significant discharge anomaly was detected during the campaign, which was observed to influence microparticle velocity. This anomaly was linked to variations in the longitudinal electric field strength and electron temperature, with noticeable deviations observed for different field polarities. Additionally, particle trajectories exhibited a slight



off-axis displacement across all experimental runs, as shown in figure 1, which was attributed to a weak thermal gradient induced by the heat of the experimental base plate.

Image data acquired during the experiments were processed using a machine learning algorithm developed by Dormagen *et al* [9], enabling the extraction of microparticle velocities. This analysis provided a comprehensive investigation of microparticle dynamics by tracking particle coordinates over multiple frames under varying discharge conditions and electric field configurations.

The primary limiting factors were the brightness of the scattered light and the signal-to-noise ratio. High-speed microparticles required capture by a high-speed camera to prevent drift line overlay. An example image is shown in figure 1 (top-left panel), which was necessarily artificially reconstructed, as no first-order enhancement produces a visually useful image for the naked eye.

3. Theoretical framework

3.1. Force balance

The analysis strategy aims to solve the force equation governing the system. The primary driving force is the electric field force, counteracted by both the neutral drag force and the ion drag force, expressed as:

$$F_E = F_{id} + F_n, \quad (1)$$

where F_E denotes the electric force, F_{id} represents the ion drag force, and F_n corresponds to the neutral drag force.

The electric force follows the classical formulation $F_E = Z_d e E_0$, while the neutral drag force is given by:

$$F_n = v_d \delta_{\text{epstein}} \frac{4}{3} \pi a_p^2 m_n v_{\text{tn}} \left(\frac{p}{T_n k_B} \right), \quad (2)$$

with v_d being the microparticle velocity, the neutral thermal velocity v_{tn} for the plasma at room temperature from $T_n = 300$ K. Furthermore the Epstein damping rate is given by $\delta_{\text{epstein}} = 1.44$ for both neon and argon [10]. The neutral mass is m_n , and k_B denotes the Boltzmann constant. The ion drag force, F_{id} , is of particular interest due to the inherent complexity of ion-dust interactions, which poses significant challenges in deriving a general analytical solution. To refine our understanding of ion drag phenomena in plasma environments, we incorporate an analytical approach proposed by Khrapak *et al* [3], focused on the expression of the interaction cross section between microparticles and ions. Furthermore a hybrid model combining first-principles derivations with analytic results and findings from PIC and Monte Carlo simulations [4] is used. Finally, we compare the results with the most recent theoretical framework derived from first principles by Hutchinson and Khrapak [11]. The integration of these models enhances the accuracy and predictive capability of our analysis, providing a more comprehensive description of ion drag effects in complex plasmas. The individual theories on ion drag are described in subsection 3.3 in more detail.

3.2. Charge and charge depletion

The charge of a microparticle, denoted as Z_d , is a fundamental parameter in complex plasma studies. However, its precise determination remains challenging due to multiple influencing factors. The orbital motion limited (OML) theory provides a useful first-order approximation of the charge state, yet it is inherently limited. Notably, OML theory assumes a collisionless environment and does not account for charge modifications arising from interparticle interactions or plasma-mediated effects in dense microparticle suspensions [12].

Numerous studies have experimentally investigated microparticle charging mechanisms [7, 13]. These investigations demonstrate that microparticle charge potential is significantly influenced by collisional effects, and the particle charge can be expressed as:

$$Z_d = (4\pi \epsilon_0 k_B) \frac{z a_p T_e}{e^2} \quad (3)$$

where z is the reduced charge potential, characterizing the electrostatic potential of a microparticle in a neon or argon plasma, ϵ_0 is the vacuum permittivity, T_e is the electron temperature, and e denotes the elementary charge. Experimental measurements indicate that the reduced charge potential assumes values of 0.3 ± 0.1 in neon plasma and 0.4 ± 0.1 in argon plasma [7]. These values serve as reference parameters for charge estimations based on equation (3).

The impact of collective interactions in a dense dust environment is characterized by the Havnes parameter, P_H , which modifies the plasma quasineutrality condition, expressed as $n_i = n_e + Z_d n_d$. In such a regime, the ion number density, n_i , surpasses the electron number density, n_e , increasing the ion-to-electron flux ratio and consequently reducing the absolute charge of individual microparticles relative to their isolated counterparts [12]. The Havnes parameter is defined as:

$$P_H = \frac{4\pi \epsilon_0 a_p}{e} (k_B T_e / e) (n_d / n_i) \quad (4)$$

The effects of P_H on charge estimation are incorporated via the electron and ion fluxes, determined using the OML approach alongside the quasineutrality condition, yielding the dimensionless relation [12]:

$$\sqrt{\tau} \exp(-z) = \sqrt{\frac{m_e}{m_i}} (1 + z\tau) (1 + P_H) \quad (5)$$

where m_e and m_i denote the masses of electrons and ions, respectively, and $\tau = T_e / T_i$ is the electron-to-ion temperature ratio. This equation provides a comprehensive framework for analyzing the interplay between particle density, the Havnes parameter, and charge dynamics in a plasma environment.

Moreover, at low plasma pressures, ion heating significantly affects charge dynamics. The ion mean free path, governed by neutral gas density, is estimated using the ideal gas equation:

$$l_i = \frac{1}{n_n \sigma_{\text{in}}} \approx \frac{T_n}{p \sigma_{\text{in}}}, \quad (6)$$

where n_n is the neutral number density and σ_{in} represents the ion-neutral collision cross-section, with values of $\sigma_{in}^{Ne} = 10^{-18} \text{ m}^2$ and $\sigma_{in}^{Ar} = 2.3 \times 10^{-18} \text{ m}^2$ [14]. Under reduced pressure conditions, as considered in this study, the ion mean free path approaches or exceeds the system scale, leading to significant ion temperature variations. These variations, in turn, affect charge dynamics according to:

$$\tilde{T}_i = \frac{2}{9} l_i e E_0 \quad (7)$$

where E_0 is the discharge electric field. The total ion temperature is then given by, $T_i = \tilde{T}_i + T_{i, \text{room}}$, with the ion room temperature given by 0.025 eV.

3.3. Ion drag force

The ion drag force arises from the interaction between ions and dust particles. This interaction mechanism can be broadly categorized into two components: (i) Coulomb scattering, which is governed by long-range electrostatic interactions, and (ii) direct ion collection, where ions collide with and are absorbed by the microparticles. While the ion drag force due to direct ion collection can be described straightforwardly, a comprehensive first-principles derivation of the force resulting from field interactions remains unsolved, lacking a general theoretical framework [15].

To address this, an analytical approach has been proposed, incorporating the thermal scattering parameter introduced by Khrapak *et al* [3]

$$\beta_T = \frac{\rho_0}{\lambda_{Di}}. \quad (8)$$

This parameter quantifies the relationship between the Coulomb radius, $\rho_0 = Z_d e^2 / 2\pi \epsilon_0 m_i v_{ti}^2$, of a microparticle and its interaction potential, which is characterized by the ion Debye length, $\lambda_{Di} = \sqrt{\epsilon_0 k_B T_i / (n_i e^2)}$. The ion drift velocity and the electric field are related via the ion mobility coefficient, $u = \mu E = M \cdot v_{ti}$, where M is the mach number of the ions calculated by the modified Frost approximation [16]. The scattering parameter serves as a fundamental descriptor of ion-dust interactions in complex plasma environments and can be categorized into three distinct interaction regimes. When the scattering parameter is significantly less than unity ($\beta \ll 1$), the interaction is classified as weak. Conversely, for $\beta \gg 1$, the interaction is considered strong. An intermediate interaction regime is defined when the scattering parameter is of the order of unity ($\beta \approx 1$) [3].

The theoretical models proposed by Khrapak in 2004 and 2005 [3, 17] provide a comprehensive framework for describing ion-dust interactions across weak, intermediate, and strong coupling regimes. Under the experimental conditions investigated in this study (see section 4.1), which correspond to weak and moderate coupling interactions characterized by $\beta_T \lesssim 5$, the ion drag force is described by [3]:

$$F_{id}^{\text{weak, int}} = \frac{8\sqrt{2\pi}}{3} \cdot n_i \cdot m_i \cdot v_{ti} \cdot u_i \cdot \left(a_p^2 + \frac{a_p \rho_0}{2} + \frac{\rho_0^2 \cdot \Lambda}{4} \right), \quad (9)$$

where the modified Coulomb logarithm is expressed as:

$$\Lambda = 2 \cdot \int_0^\infty e^{-x} \ln \left(\frac{2\lambda_{Di} x + \rho_0}{2a_p x + \rho_0} \right) dx. \quad (10)$$

The ion mass, ion thermal velocity, and ion drift velocity are denoted as m_i , v_{ti} , and u_i , respectively. Furthermore, the effective Debye length is calculated from linear combination of the electron Debye length and the ion Debye length and is assumed to be $\lambda_D \sim \lambda_{Di}$.

In this study, we additionally employ a hybrid model based on kinetic theory, as formulated by Hutchinson [11], incorporating a scattering term as described by Khrapak *et al* [14]. This combined approach enables the development of an analytical framework, which has been previously applied and refined through PIC and Monte Carlo simulations by Schwabe and Graves [4],

$$F_{id}^{\text{hybrid}} = n_i \cdot m_i \cdot v_{ti} \cdot u_i \cdot \left(\sigma_c + \pi \rho_0^2 \left[\Lambda_{0,k}(\tilde{u}_i) + K \left(\frac{\lambda_s(\tilde{u}_i)}{l_i} \right) \right] \right). \quad (11)$$

In the proposed model, the term σ_c denotes the cross-section for ion capture [4]:

$$\sigma_c = \pi a^2 \left(1 + \frac{\rho_0}{a_p} \right). \quad (12)$$

The Coulomb logarithm $\Lambda_{0,k}$ and the collisional function K account for angular momentum loss during ion-neutral collisions [18]:

$$\Lambda_{0,k}(\tilde{u}_i) = \ln \left[\frac{\rho_{0,k}(\tilde{u}_i) + \lambda_s(\tilde{u}_i)}{\rho_{0,k}(\tilde{u}_i) + a_p} \right] \quad (13)$$

and

$$K(x) = x \arctan(x) + \left(\sqrt{\frac{\pi}{2}} - 1 \right) \frac{x^2}{1+x^2} - \sqrt{\frac{\pi}{2}} \ln(1+x^2). \quad (14)$$

These terms are adapted to account for interactions extending beyond the Debye length [11]. Numerical calculations indicate that the evaluation of the Coulomb logarithm, $\Lambda_{0,k}(\tilde{u}_i)$, requires an effective ion velocity, $\tilde{u}_i$, which incorporates both the Coulomb radius, $\rho_{0,k}(\tilde{u}_i)$, and a velocity-dependent screening length, defined as [11]:

$$\lambda_s^2 = \frac{\lambda_{D,e}^2}{1 + \frac{2kT_e}{m_i \tilde{u}_i^2}} + a_p^2. \quad (15)$$

The effective ion velocity $\tilde{u}_i$ is given by [11]:

$$\tilde{u}_i^2 = \frac{8k_B T_n}{\pi m_i} + u_i^2 \left[1 + \left(\frac{|u_i|/u_B}{0.6 + 0.05 \ln(m_\mu) + (\lambda_{D,e}/5a_p) (\sqrt{T_i/T_e} - 0.1)} \right)^3 \right] \quad (16)$$

where m_μ denotes the atomic mass corresponding to the plasma species (argon or neon), u_B represents the Bohm velocity, defined as $u_B = \sqrt{k_B T_e / m_i}$. Since the interaction parameters are defined differently, the scattering parameter is accordingly modified as:

$$\beta_T^{\text{hybrid}} = \frac{\rho_{0,k}(\tilde{u})}{\lambda_s(\tilde{u})}. \quad (17)$$

4. Results and analysis

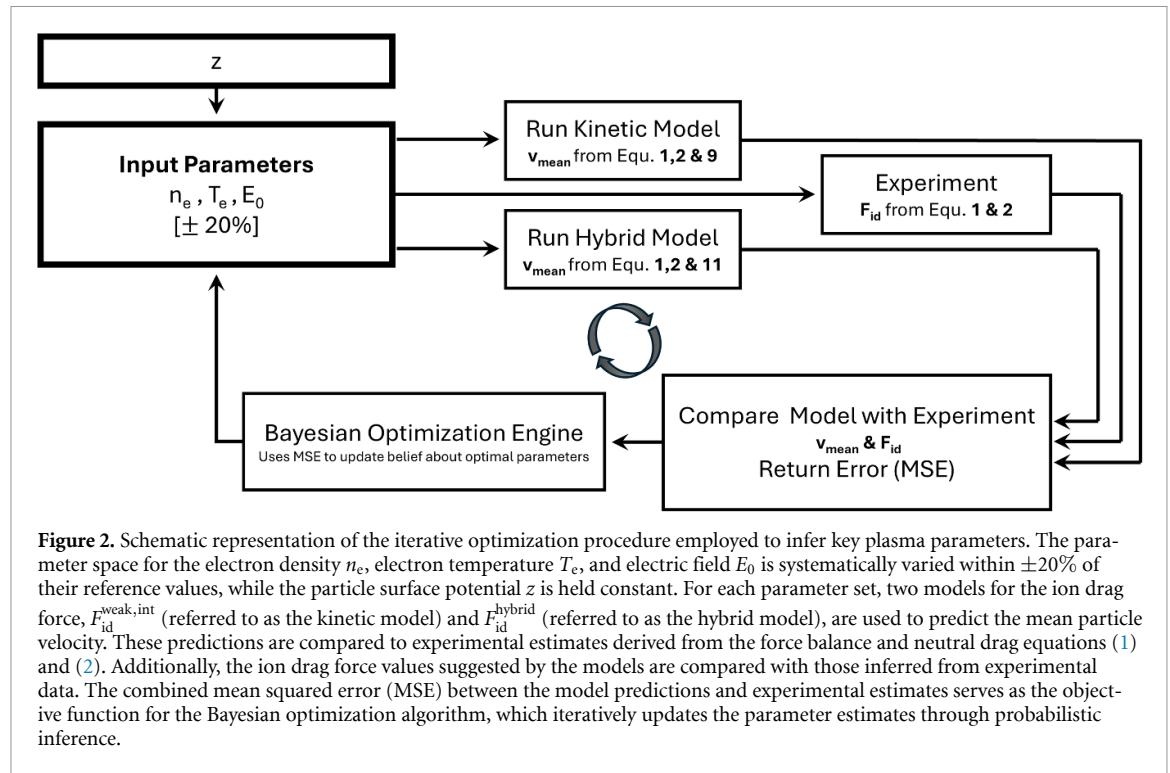
In the following, we present a qualitative analysis of the ion drag force by solving the force balance equation (1) to extract its contribution. However, this equation strongly depends on several key plasma parameters that are not precisely known, including the individual particle charge, the exact electric field, particle number densities, and temperature distributions.

To address existing uncertainties and refine the plasma parameters, we perform a comparative analysis of two theoretical models (see section 4.1). Instead of prioritizing one framework over the other, our objective is to identify a set of plasma parameters that achieves consistency across both models, acknowledging their respective validity and complementary strengths. In this approach, key plasma parameters are treated as free variables constrained within physically motivated bounds and are inferred through reverse modeling to best reproduce the experimental observations. These bounds are grounded in physical plausibility, accounting for measurement uncertainties, and are further constrained by Langmuir probe diagnostics [5, 19].

This inverse problem is addressed using a machine learning approach based on Bayesian optimization [20], which iteratively minimizes a regression error function. The algorithm operates by constructing a probabilistic surrogate model of the objective function, and iteratively refining it based on newly sampled data points. At each step, the algorithm selects the most promising parameter set using an acquisition function that balances exploration of uncertain regions and exploitation of known good candidates.

Specifically, for each set of candidate plasma parameters, both ion drag models are evaluated to compute the resulting mean dust particle velocity, v_{mean} , which is compared with experimentally measured values. Simultaneously, the model-predicted ion drag force, F_{id} , is compared to values inferred via force balance equations (1) and (2). The resulting discrepancy is quantified using the mean squared error (MSE), which serves as the feedback signal for the Bayesian optimization loop used to construct the surrogate model, see figure 2.

Through this iterative process, Bayesian optimization updates its internal model of the objective function based on probabilistic inference, allowing for efficient navigation of the multidimensional parameter space. The final optimized plasma parameters, including the derived individual dust particle



charge, are presented in section 4.2, forming the basis for the analysis of ion drag phenomena discussed in section 4.3.

4.1. Data and models

The individual velocities of microparticles were determined using machine learning techniques, as described by Dormagen *et al* [9]. Specifically, a U-Net [21], a type of convolutional neural network designed for image segmentation, was employed to estimate the weighted center coordinates of particle drift lines. These coordinates were then tracked and linked across multiple images to reconstruct the particle trajectories, thus enabling the calculation of their velocities. The resulting dataset is presented in figure 3 as the mean particle velocity, v_{mean} , measured in both argon and neon plasmas under discharge currents of 1 mA and 1.5 mA. The uncertainty associated with v_{mean} was quantified by calculating the standard deviation, based on the assumption that the data adheres to a Gaussian distribution. This assumption is justified by the high statistical significance of the dataset, which indicates that the velocity distribution is centered around the true value.

Our measurements indicate the presence of both positively and negatively polarized velocity distributions, which correspond to the opposing directions of the applied electric field. This is illustrated in the experimental data (+) and (−) shown in figure 3. As previously reported [5], and supported by our data, a reduction in the electric field strength is observed during the positively polarized cathode phase. This effect may be attributed to slight asymmetries in the cathode geometry, which can introduce artifacts in the field distribution. However, deviations of all the key plasma parameters must be considered, to accurately simulate the behavior using the best-fitting models. The final parameter results are discussed in section 4.2. In the initial stage of the analysis, we focus on the experimental data acquired during the negatively polarized discharge, as this dataset exhibits comparatively smoother trends in the pressure range of 22–40 Pa, see figure 3(c).

In this study, we evaluate the predictive accuracy of theoretical models describing the ion drag force. The analytical model, derived specifically for weak and intermediate ion-particle coupling regimes [3], is denoted as $F_{id}^{weak,int}$ and is given by equation (9). In contrast, the hybrid model, which incorporates simulation data [4], is referred to as F_{id}^{hybrid} and defined in equation (11).

Model predictions for neon and argon discharges are shown in figures 3(a) and (c) (neon) and figures 3(b) and (d) (argon), corresponding to discharge currents of 1 mA and 1.5 mA, respectively. In all cases, both ion drag models demonstrate strong agreement with experimental measurements within the stated uncertainties. This agreement persists up to a critical pressure threshold, below which systematic deviations emerge.

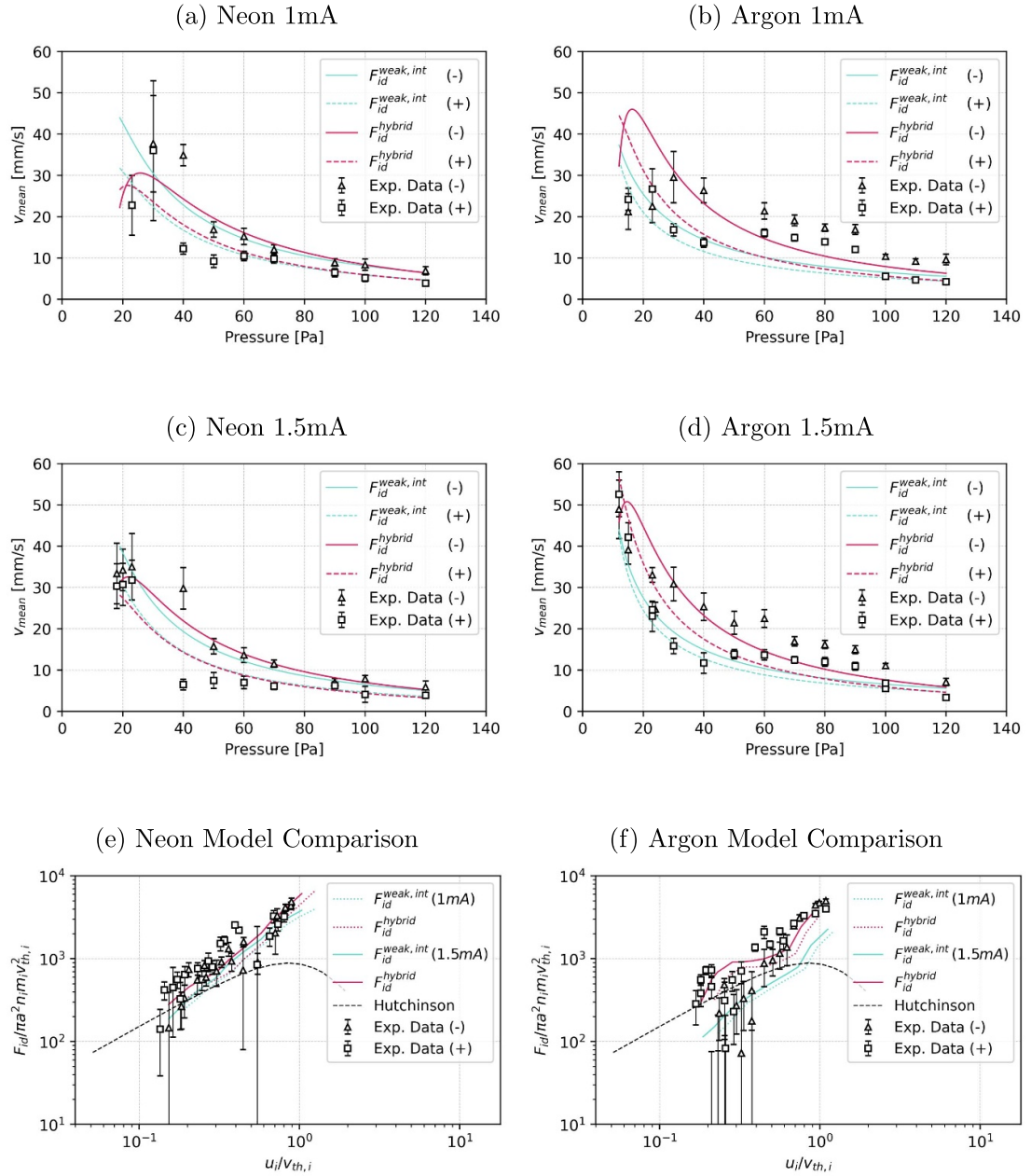
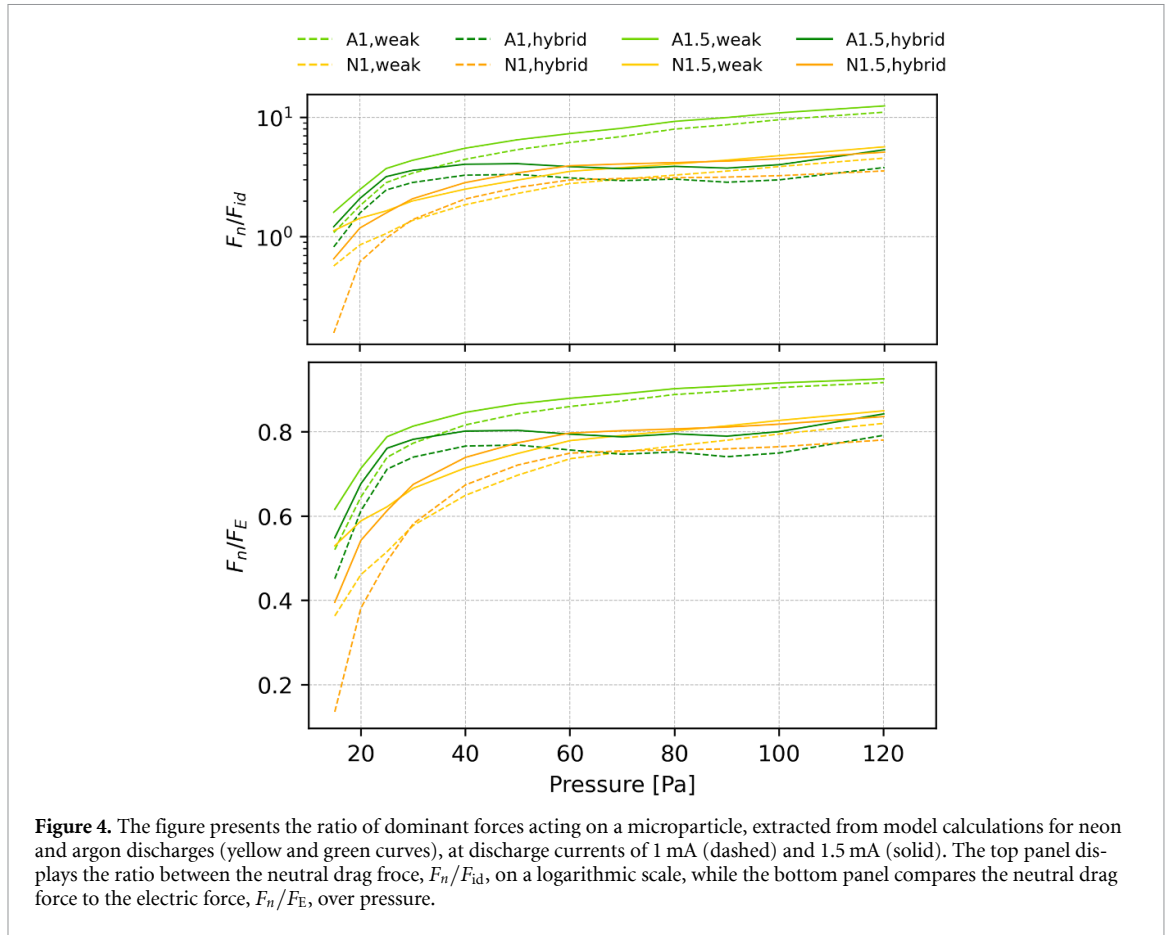


Figure 3. Experimental data from ISS campaigns #17 and #18 are shown as symbols (triangles and squares) indicating discharge polarity (negative and positive, respectively). These are compared with model predictions: the analytical approach for weak and intermediate ion interactions, $F_{id}^{weak,int}$ (blue, equation (9)), and the hybrid model supported by simulations, F_{id}^{hybrid} (red, equation (11)). Model curves corresponding to positive polarity are plotted with dashed lines in the respective colors. The lower panels highlight the comparison of experimental data and models with the theoretical framework by Hutchinson and Khrapak [2], shown as dashed lines, using a logarithmic scale of normalized ion drag force versus ion flow velocity normalized to the thermal velocity.

These deviations are primarily attributed to the diminishing role of neutral gas damping at low plasma pressures ($\lesssim 40$ Pa). As illustrated in figure 4, the ion drag (top panel) and electric field (bottom panel) forces become more dominant at minimum pressure in comparison to the neutral drag force. For pressures above 40 Pa, the ratio of neutral to electric force exceeds $F_n/F_E \gtrsim 0.62$ for neon (yellow curve) and $F_n/F_E \gtrsim 0.77$ for argon (green curve). In this regime, the neutral drag also exceeds the ion drag by a factor of at least $F_n/F_{id} > 2$, indicating that neutral damping is the second most dominant mechanism governing dust particle dynamics at higher pressures, especially for this grain size.

However, the optimization procedure was designed to identify a single set of plasma parameters that yields optimal agreement between model predictions and experimental observations for both ion drag formulations. The consistent predictive performance across both models, within the range of



experimental conditions, underscores the robustness of the approach and the physical relevance of the selected parameters.

4.1.1. Neon model

We observe that the acceleration of microparticles in low-pressure plasma (< 30 Pa) either saturates or decreases. This is evidenced by a reduction in the measured particle velocity despite a continued decrease in pressure, see figure 3, indicating that the ion drag force and the electric field force are of comparable magnitude and in direct competition. This observation, which has not been previously reported [22], suggests a significant enhancement of the ion drag force for microparticles with a diameter of $2a_p = 3.4 \mu\text{m}$. The effect becomes more pronounced at a lower discharge current of 1 mA, which corresponds to a reduced electric field strength.

The F_{id}^{hybrid} model (red) predicts a stronger ion drag force at low pressures (< 30 Pa) compared to the $F_{id}^{\text{weak,int}}$ model (blue) in low-pressure neon discharges, aligning more closely with the trends observed in the experimental data. A key distinction between these models lies in their kinetic treatment of ion dynamics: the hybrid model incorporates an average ion velocity, $\tilde{u}_i$, as defined in equation (16), which accounts for both the thermal motion of ions at room temperature and the ion drift speed. This results in a slightly increased interaction potential of the microparticle.

To further validate our findings, we compare our results with the established kinetic model developed by Hutchinson and Khrapak [2], represented by the dashed line in figure 3(e). The experimental data shown are derived using equation (1) and (2). At low flow-to-thermal ion velocity ratios ($u_i/v_{th,i} < 1$), the fitted model and experimental data show good agreement with the Hutchinson model, although the experimental data exhibit a slight tendency to overestimate the normalized ion drag force. At higher flow-to-thermal velocity ratios ($u_i/v_{th,i} \sim 1$), observed under low-pressure conditions where kinetic effects become significant, a marked increase in the normalized ion drag force is evident, substantially exceeding the predictions of the Hutchinson and Khrapak model. This enhancement indicates that ion collisions play a crucial role in modifying the ion drag force under moderately collisional conditions [15]. This effect is not explicitly captured in Hutchinson's original formulation, which assumes a Maxwellian ion velocity distribution in a collisionless regime. The better agreement with the hybrid model trend F_{id}^{hybrid} supports the idea that the ion drift speed becomes comparable to or even exceeds

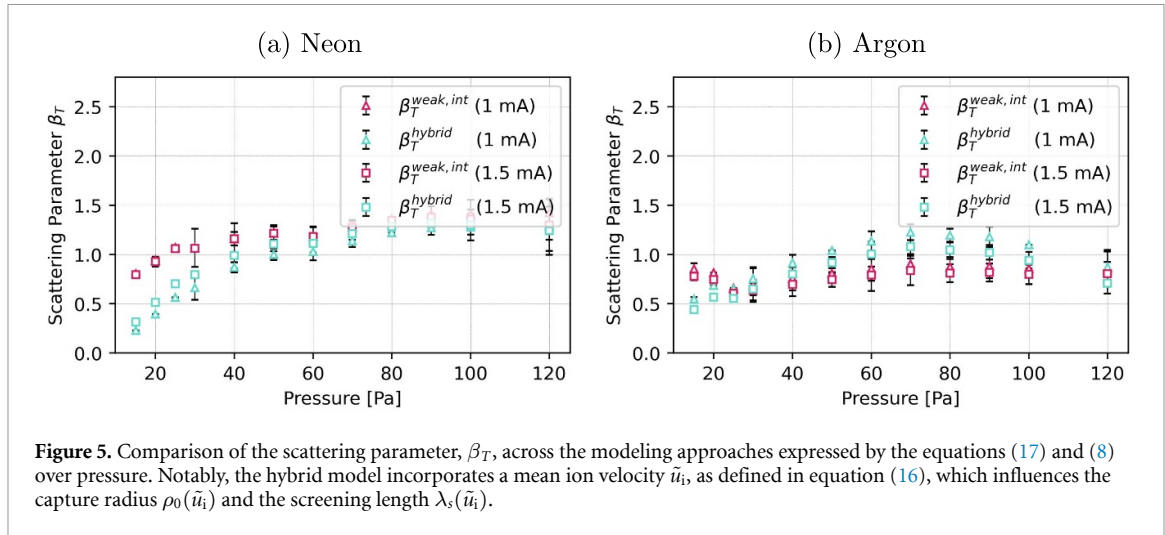


Figure 5. Comparison of the scattering parameter, β_T , across the modeling approaches expressed by the equations (17) and (8) over pressure. Notably, the hybrid model incorporates a mean ion velocity $\tilde{u}_i$, as defined in equation (16), which influences the capture radius $\rho_0(\tilde{u}_i)$ and the screening length $\lambda_s(\tilde{u}_i)$.

the thermal speed. As a result, this has a stronger impact on the calculation of the ion drag force in low-pressure plasmas, leading to improved agreement with experimental data.

The scattering parameter is consistent with our expectations under the conditions we examined. As shown in figure 5(a) [17], the scattering parameter $\beta_T \lesssim 5$, which confirms that our model is a good fit for describing microparticle dynamics in the investigated neon plasma environment [3]. Furthermore, we find a significant difference in the scattering parameter between the considered models. The hybrid model, which incorporates the mean ion velocity into its calculations, results in a lower scattering parameter, particularly at low pressures, due to the increased interaction potential.

4.1.2. Argon model

The ion drag force models also yield reliable results when compared with the experimental data obtained in argon plasma (see figures 3(b) and (d)). However, a more detailed analysis reveals a larger deviation of the hybrid model, F_{id}^{hybrid} , in the low-pressure regime. This suggests that the improved performance of the weak and intermediate coupling model, $F_{id}^{weak,int}$, is dependent on the type of background gas.

The comparative analysis of model performance, shown in figure 3(f), in conjunction with the kinetic framework of Hutchinson and Khrapak [2], provides additional insights. The experimental data presented are calculated using equations (1) and (2). In argon plasma, the flow-to-thermal ion velocity ratio ($u_i/v_{th,i}$) is higher than in neon plasma at elevated pressures, due to the greater mass of argon ions. Moreover, the ion drift speed u_i does not increase as significantly at lower pressures, resulting in a narrower range of $u_i/v_{th,i}$ compared to neon. This allows the conclusion that, in argon, the plasma conditions are more consistently described by a Maxwellian ion velocity distribution across the full pressure range observed, thereby supporting the improved performance of the weak and intermediate coupling model, $F_{id}^{weak,int}$. The significant deviation in the absolute value of the normalized ion drag force observed in figure 3(f) may be attributed to limitations in the plasma model accuracy, as well as the constraint of using a common set of plasma parameters for optimizing both ion drag force models. Nevertheless, this approach allows for a consistent comparison, as both models are evaluated under identical conditions, providing a fair basis for assessing their relative performance.

The scattering parameter, shown in figure 5(b), does not exhibit a significant increase, with values remaining below $\beta_T \lesssim 5$ across the examined pressure range. However, variations in the adjusted ion velocity, $\tilde{u}_i$, influence the interaction parameter differently than in neon. The hybrid model systematically overestimates the scattering parameter, supporting the conclusion that plasma conditions in argon are less affected by ion collision effects.

4.2. Plasma parameters

The key plasma parameters for the PK-4 experiment have been extensively characterized for neon using Langmuir probe measurements, as documented in reference [5]. In contrast, equivalent data for argon plasmas have not been previously published. Upon request, we employ unpublished Langmuir probe measurements for argon, obtained by the same research team [5]. The triangular and cross markers in figure 6 represent experimental data recorded at discharge currents of 1mA and 2mA, respectively. As these measurements do not fully cover the parameter space explored in this study, interpolation and extrapolation techniques were applied to estimate the complete plasma parameter range in argon, while

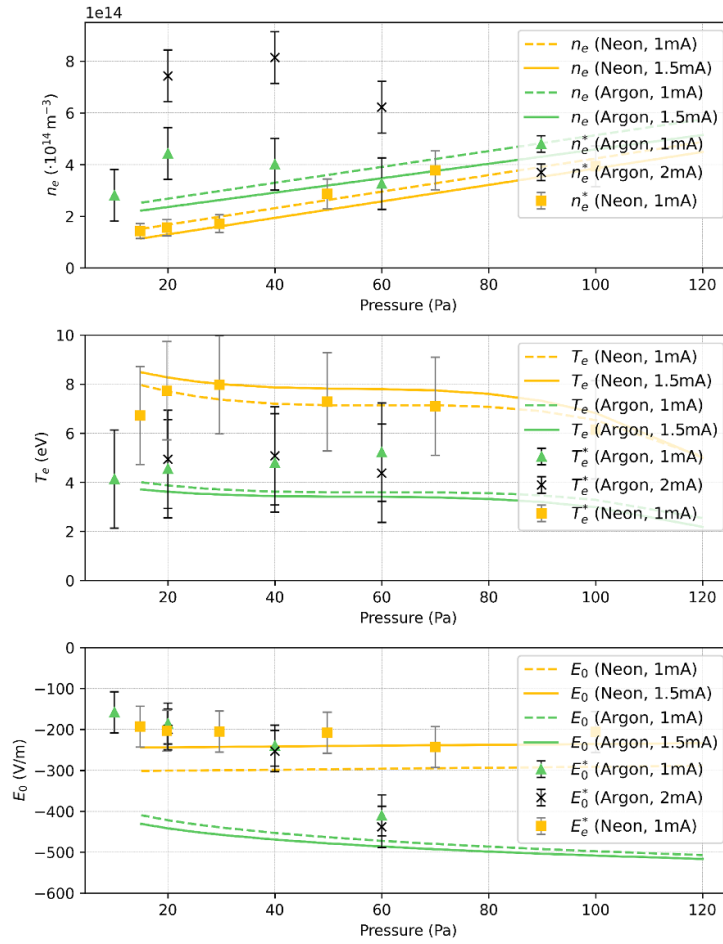


Figure 6. The figure presents key plasma parameters in argon (green), with triangular and cross markers indicating Langmuir probe measurements obtained at discharge currents of 1 mA and 2 mA, respectively. These data serve as reference points for interpolation, extrapolation, and subsequent optimization, and are reported here for the first time. For comparison, the corresponding plasma parameters for neon (yellow) are taken from the literature [5], where measurements were also conducted using Langmuir probe diagnostics (denoted by *). The results are shown as line plots representing the optimized absolute values for negative discharge polarity. The corresponding values for positive polarity can be inferred from table 1.

Table 1. Optimized machine learning parameters. The key plasma parameters, electron density n_e , electric field E_0 , and electron temperature T_e , originally measured via Langmuir probe diagnostics [5], have been refined using Bayesian optimization. The resulting scaling factors, normalized to the reference values, are summarized in this table.

Gas	Current	n_e	E	T_e
Neon	+ 1 mA	0.97	1.05	0.92
	− 1 mA	1.04	1.39	0.96
	+ 1.5 mA	0.60	1.02	0.83
	− 1.5 mA	0.63	1.16	1.02
Argon	+ 1 mA	1.04	1.65	0.8
	− 1 mA	1.04	1.68	1.01
	+ 1.5 mA	0.53	1.47	0.84
	− 1.5 mA	0.57	1.47	1.00

maintaining physical consistency. For comparison, the experimental data for neon (squares) [5] are also shown.

The electron number density in argon, n_e , was modeled to scale linearly with gas pressure, consistent with an empirical trend previously established for neon discharges [5]. This assumption was validated against available experimental data, and the final optimized density profiles are shown in the upper panel of figure 6. Application of Bayesian optimization revealed a systematic reduction of approximately 40% in n_e for both neon and argon at a discharge current of 1.5 mA relative to the values reported in the literature. In contrast, no significant deviation was found at 1.0 mA. The corresponding scaling factors derived from the optimization are listed in table 1, with all variations falling within the range of

reported experimental uncertainties [5]. Additionally, a minor but consistent reduction in electron number density was observed for positive discharge polarity relative to negative polarity. The optimization procedure primarily impacted the low-pressure regime, where the electron number density, n_e , plays a critical role in determining the ion drag force through the quasi-neutrality condition, as well as in modulating interparticle interactions. In this regime, a decrease in n_e results in a corresponding reduction in the ion drag force. A potential limitation of the applied model may emerge at the lowest pressures, where the system becomes increasingly sensitive to the electron drag force not included in our calculations, which may become a dominant contributor to particle dynamics in this parameter regime [23].

Interpolation and extrapolation were employed to estimate the electron temperature in argon, T_e , adopting the pressure-dependent trend observed in neon plasma [5], while adjusting the magnitude within the reported uncertainty bounds of the measurements. The optimization results indicate a reduction in T_e by approximately 5%–15%, with a more pronounced decrease under positive discharge polarity compared to previously published values. This deviation is particularly relevant for interpreting the observed differences in microparticle velocities between positive and negative polarities, as it affects the electric force linearly through the particle charge, which serves as the dominant driving mechanism, especially at higher pressures.

As discussed previously, the observed variations in microparticle velocities indicate that the electric field, E_0 , plays a critical role, as it constitutes the dominant driving force. In neon plasma, an increase of approximately 10%–25% in E_0 was calculated under negative discharge polarity compared to positive polarity, and up to 40% relative to values reported in the literature [5]. Although this increase is substantial, the resulting values remain within the reported measurement uncertainties. The electric field is assumed to vary linearly with pressure, consistent with previous findings [5]. For argon plasma, the electric field was determined through interpolation and extrapolation of the available experimental data. A power-law function was found to best fit the data across the relevant parameter range, yielding the most accurate representation. Based on this fit, an empirical expression was derived to describe the electric field as a function of pressure and discharge current:

$$E_0 (\text{V cm}^{-1}) \approx - (3.015 \cdot I_{\text{DC}}^{0.289}) \cdot P^{(0.1385 - 0.0336 \cdot I_{\text{DC}})} \quad (18)$$

where P is the pressure in pascal (Pa) and I_{DC} is the discharge current in milliamperes (mA). This equation describes the dependence of the electric field on the operating conditions of the discharge plasma, covering a current range from 1 mA to 2 mA.

Beyond the direct influence of plasma parameters on the analysis, we additionally accounted for the microparticle density, n_d , which indirectly affects the plasma composition through the quasi-neutrality condition, $n_i = n_e + Z_d n_d$. During experimental investigations, efforts were made to minimize the microparticle density. However, precise control over the injection of microparticles remains challenging, and the complexities associated with multi-particle interactions must also be considered.

A widely used approach for estimating microparticle density is based on the formation of crystalline structures, where the density is inferred from the average interparticle distance. Conversely, in cases where microparticles are randomly distributed while drifting, a broader range of densities can be encountered. Since our experimental setup was not specifically designed to investigate structural variations, density estimates were also derived by referencing prior studies [24]. These studies report interparticle distances consistent with our estimates, corresponding to microparticle densities in the range of 0.08 to $1.01 \times 10^{11} \text{ m}^{-3}$. While this range may appear broad, its impact on the final results remains minimal, as the Havnes parameter varies between 0.1 and 0.7, remaining below unity and thereby indicating a weak influence on the overall plasma system [2, 12].

The optimized model predictions provide valuable insights into specific plasma parameters and enable refined micro-adjustments. Notably, these findings are obtained through parameter optimization, allowing for an estimation of the individual microparticle charge potential, as illustrated in figure 7. The final results are compared with previous studies [7, 24], which suggest a microparticle charge potential of $z = 0.3 \pm 0.1$ in neon and $z = 0.4 \pm 0.1$ in argon.

4.3. Ion drag force

The final experimental results for the ion drag force, extracted using the force balance equations (1) and (2), are presented in figure 8 as a function of pressure for both plasma types. The corresponding model predictions for negative discharge polarity are also shown, along with an uncertainty corridor representing the range of variation in the experimentally determined ion drag force values.

A slight increase in the ion drag force with decreasing discharge current was observed in both neon and argon plasmas. For neon, the model predictions exhibit higher accuracy and consistency, resulting

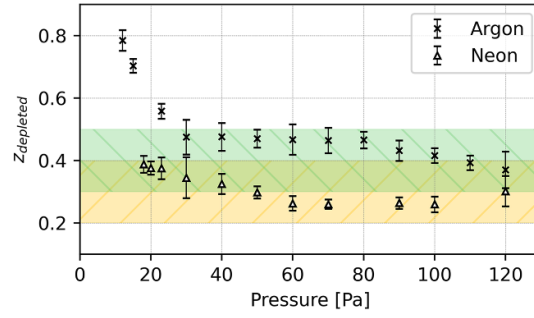


Figure 7. The dimensionless reduced charge potential, z_{depleted} , of an isolated microparticle in both neon and argon plasmas is presented. The term ‘depleted’ reflects the consideration of multiparticle effects in the charge estimation. The results are consistent with previous studies, which suggest a charge potential of $z_{\text{argon}} = 0.4$ and $z_{\text{neon}} = 0.3$, as indicated by the hatched regions (green and yellow).

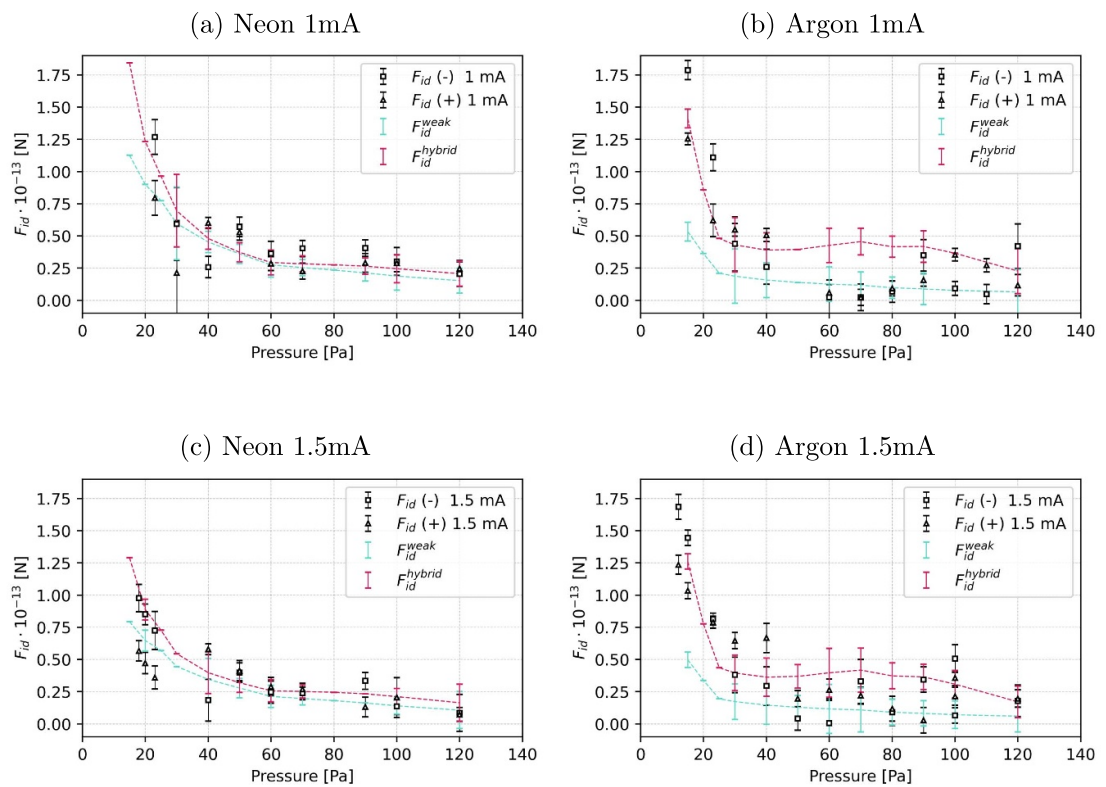


Figure 8. The extracted ion drag force, F_{id} , obtained from equations (1) and (2), represents the experimentally measured data and is compared to the values derived from the best-fitting model (dotted lines) over pressure. The uncertainties are determined based on measurement errors.

in a more pronounced and reliable trend. In contrast, the argon data show greater variability, indicating that additional refinement in the modeling of key plasma parameters is necessary to improve agreement with experimental measurements.

5. Conclusion

This study presents a comprehensive investigation of ion drag force dynamics in low-pressure complex plasmas using data from the PK-4 facility aboard the ISS. By analyzing microparticle motion in both neon and argon plasmas under varying discharge currents and pressures, we extracted the ion drag force and compared the results with two theoretical models. The analytical model for weak and intermediate coupling, and a hybrid model integrating kinetic effects have been tested.

Our results demonstrate that both models reproduce experimental trends well across a broad range of conditions, but notable differences arise at low pressures. In neon plasmas, the hybrid model shows better agreement with experimental data, particularly when the ion drift speed approaches or exceeds

the thermal speed, leading to enhanced scattering and interaction potentials. In contrast, argon plasmas are less sensitive to these effects. As a result, the analytical model provides more accurate predictions, indicating that a Maxwellian ion velocity distribution is more applicable in this regime.

The scattering parameter analysis further supports these findings, as the microparticle–ion interaction behaves differently in argon compared to neon depending on the chosen model. In particular, kinetic effects become less significant and tend to overestimate the ion drag force in argon. This study also highlights the importance of accurately determining plasma parameters, which was achieved here through machine learning-based optimization and extrapolation of Langmuir probe diagnostics.

Overall, this work confirms that ion drag models must be tailored to the specific gas environment to yield accurate predictions. To promote transparency and reproducibility, the models and analysis routines used in this study are openly available on GitHub [25], providing a valuable resource for future modeling and analysis of dust-plasma interactions in microgravity and laboratory settings.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://github.com/luki58/Ion-Drag-Modeling>.

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