

# Learning neural network-based boundary conditions for kinetic plasma sheath dynamics

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## 1 Normalized Vlasov-Fokker-Planck equation

The governing kinetic equation for our study is the 1D1V Vlasov-Dougherty-Fokker-Planck equation in the “flexible plasma normalization” [2]:

$$\partial_t f_s + v \partial_x f_s + (\omega_c \tau) \frac{Z_s}{A_s} E \partial_v f_s = (\nu_p \tau) \sum_s \nu_{ss'} \partial_v \left( \frac{T_{ss'}}{m_s} \partial_v f_s + (v - u_{ss'}) f_s \right). \quad (1)$$

The normalization constants appearing in this equation are as follows:

- $Z_s$  and  $A_s$  are the normalized charge and mass of species  $s$ , expressed in units of the proton charge and mass.
- $\omega_c \tau$  is the normalized reference proton cyclotron frequency in a field  $B_0$  which would give unit plasma beta:  $|B_0|^2 / 2\mu_0 = n_0 T_0$ .
- $\nu_p \tau$  is the normalized proton collision frequency.

For now we can take these normalization constants as given; we will need to concern ourselves with their definitions when we move on to translating a specific physical problem into our equation setup.

Equation (1) is coupled to the normalized Gauss’s law,

$$\partial_x E = \frac{(\omega_p \tau)^2}{\omega_c \tau} \rho_c, \quad (2)$$

where

$$\rho_c = \sum_s Z_s \int f_s dv \quad (3)$$

is the charge density. We will use the elliptic form of Gauss’s law,

$$\partial_x^2 \phi = -\frac{(\omega_p \tau)^2}{\omega_c \tau} \rho_c, \quad (4)$$

with  $E = -\partial_x \phi$ .

### 1.1 Collision operator

Suggest we use the collision parameters derived in [1]

## 2 Domain and boundary conditions

We’ll use a physical domain of length  $L_x$ , which by convention extends from  $-L_x/2$  to  $L_x/2$ .

## 2.1 Absorbing wall

The simplest boundary condition that will produce a Langmuir sheath is the absorbing wall boundary condition. At a spatial boundary  $x_b$  with outward normal vector  $\mathbf{n}(x_b)$ , we have

$$f_s^b(x_b, v) = \mathbf{1}_{\mathbf{n}(x_b) \cdot v < 0} f_s(x_b, v), \quad (5)$$

where  $\mathbf{1}$  is the indicator function.

## 3 Straightforward DLR approximation

Each species distribution function  $f_s$  receives a separate low-rank decomposition:

$$f_s \approx \sum_{ij} X_{si}(x, t) S_{sij}(t) V_{sj}(v, t). \quad (6)$$

In what follows we will omit species subscripts.

Given that we need to apply boundary conditions in  $x$ , which should be applied to  $K_j(x, t)$  rather than  $X_i(x, t)$ , we keep all spatial derivatives applied to  $K$ .

**K step:**

$$\begin{aligned} \partial_t K_j(x, t) + \sum_l \langle V_j, v V_l \rangle_v \partial_x K_l(x, t) + (\omega_c \tau) \frac{Z_s}{A_s} \sum_l \langle V_j, \partial_v V_l \rangle_v E K_l(x, t) \\ = \nu_p \tau \sum_{s'} \nu_{ss'} \sum_l \left[ \frac{T_{ss'}}{m_s} \langle V_j \partial_v^2 V_l \rangle_v + \langle V_j, \partial_v(v V_l) \rangle_v - u_{ss'} \langle V_j, \partial_v V_l \rangle_v \right] K_l(x, t) \end{aligned}$$

**S step:**

$$\begin{aligned} \partial_t S_{ij}(x, t) + \sum_l \langle V_j, v V_l \rangle_v \langle X_i, \partial_x K_l \rangle_x + (\omega_c \tau) \frac{Z_s}{A_s} \sum_{kl} \langle V_j, \partial_v V_l \rangle_v \langle X_i, E X_k \rangle_x S_{kl}(t) \\ = \nu_p \tau \sum_{s'} \nu_{ss'} \sum_{kl} \left[ \frac{1}{m_s} \langle X_i, T_{ss'} X_k \rangle_x \langle V_j, \partial_v^2 V_l \rangle_v + \delta_{ik} \langle V_j, \partial_v(v V_l) \rangle_v - \langle X_i, u_{ss'} X_k \rangle_x \langle V_j, \partial_v V_l \rangle_v \right] S_{kl}(x, t) \end{aligned}$$

**L step:**

$$\begin{aligned} \partial_t L_i(v, t) + \sum_k \langle X_i, \partial_x K_l \rangle_x v V_l(v, t) + (\omega_c \tau) \frac{Z_s}{A_s} \sum_k \langle X_i, E X_k \rangle_x \partial_v L_k(v, t) \\ = \nu_p \tau \sum_{s'} \nu_{ss'} \sum_k \left[ \frac{1}{m_s} \langle X_i, T_{ss'} X_k \rangle_x \partial_v^2 L_k(v, t) + \delta_{ik} \partial_v(v L_k(v, t)) - \langle X_i, u_{ss'} X_k \rangle_x \partial_v L_k(v, t) \right] \end{aligned}$$

The boundary conditions on  $K_j$  are the projection of the full distribution function BCs:

$$K_j^b(x_b) = \langle V_j, \mathbf{1}_{\mathbf{n}(x_b) \cdot v < 0} f_s(x_b, v) \rangle_v \quad (7)$$

$$= \left\langle V_j, \mathbf{1}_{\mathbf{n}(x_b) \cdot v < 0} \left( \sum_{kl} X_k(x_b) S_{kl} V_l(v) \right) \right\rangle_v \quad (8)$$

$$= \sum_l K_l(x_b) \langle V_j, \mathbf{1}_{\mathbf{n}(x_b) \cdot v < 0} V_l(v) \rangle_v \quad (9)$$

### 3.1 Spatial discretization

- I suggest using a finite volume scheme with MUSCL-like slope-limited reconstruction. Such an approach is extremely robust if using a TVD limiter, efficient, and easy to implement.
- For the spatial numerical flux, I suggest we use the kinetic flux vector splitting method applied to the DLR of the Boltzmann equation in [huAdaptiveDynamicalLow2022]
- A similar numerical flux can be applied for the  $E\partial_v f$  terms.

## References

- [1] Evan Habbershaw et al. *A Nonlinear, Conservative, Entropic Fokker-Planck Model for Multi-Species Collisions*. Apr. 2024. arXiv: 2404.11775 [math-ph]. (Visited on 05/22/2024).
- [2] S. T. Miller and U. Shumlak. “A Multi-Species 13-Moment Model for Moderately Collisional Plasmas”. In: *Physics of Plasmas* 23.8 (Aug. 2016), p. 082303. ISSN: 1070-664X, 1089-7674. DOI: 10.1063/1.4960041. (Visited on 02/11/2022).