

[<https://doi.org/10.69646/aob250927>]

[Abstract]

## A Generalization of the PINN Approach for Solving Selected Problems in Astrophysics

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### Abstract:

We apply the methods recent generalizations of the **Physics-Informed Neural Networks (PINNs)**, based on Kolmogorov-Arnold Networks and other interpolations, for the computation of **magnetohydrodynamic (MHD)** equilibria in the solar corona. Equilibrium **curved-magnetic** structures are an important topic in solar physics. They are described by solutions of the Grad-Shafranov (GS) equation, derived in the axisymmetric approximation. For example, the GS equation and its solutions are often used for magnetic-cloud reconstruction (e.g., to determine their geometries from observations, as studied by Isavnin et al. in 2011). GS-like solutions are also important for modelling the **coronal mass ejection (CME)** phenomenon, for which a simple force-free spheromak solution is used, as studied by Shiota & Kataoka in 2016 and Verbeke et al. in 2019. Hence, particular solutions of the GS equation, called **Soloviev solutions**, can also be implemented as **time-dependent** boundary conditions, as done by Linan et al. in 2023, which leads to a better, self-consistent CME evolution model. As another example, we consider the Lane-Emden (LE) equations, which are widely employed in astrophysics and relativistic mechanics.

Our approach is general and may be exploited as an alternative to the standard PINN methodology as developed by Raissi et al. in 2019 and later.

**Keywords:** PINN in Deep Learning, PINN for solution of PDEs, Astrophysics, Computational modelling

### **Acknowledgement**

We acknowledge the support of the projects BG-175467353-2024-07-0008-C01 and BG-175467353-2024-18-0018-C01 with Bulgarian NSF.

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