authors  • Lionel Cheng and Ekhi Ajuria Illaramendi and Guillaume Bogopolsky and Michael Bauerheim and Benedicte Cuenot  itide  — Using neural networks to solve the 2D Poisson equation for electric field computation in plasma fluid simulations  source    SupportedSources.INTERNET_ARCHIVE	doc_1		doc_2		decision	id
publication dat © 20:1-11-17 00:00:00  source   SupportedSources.INTERNET_ARCHIVE    journal    **ohttps://wwb.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf    urs    **https://wwb.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf    #*ohttps://wwb.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf    #*ohttps://www.semanticscholar.org/paper/2da0491ba38ac18ef03aee950caac3a6f94ab38e    #*ohttps://www.semanticscholar.org/pap		Bauerheim and Benedicte Cuenot  Using neural networks to solve the 2D Poisson equation for electric field computation in plasma fluid	authors	<ul> <li>Ekhi Ajuria Illarramendi</li> <li>Guillaume Bogopolsky</li> <li>M. Bauerheim</li> </ul>		
source journal volume  doi  urls  * https://web.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf  id 6/2805921429682829845  The Poisson equation is critical to get a self-consistent solution in plasma fluid simulations used for Hall effect thrusters and streamer discharges, since the Poisson solution appears as a source term of the unsteady conclinear flow equations. As a first set, posting the 2D Poisson equation in terms of number of branches, depth and receptive field. One key objective is to better understand how neural retworks learn the Poisson solutions and provide guidelines to achieve optimal network configurations, specially when coupled to the time-surjung Falor equations with plasmas solutions with plasmas problem. The performance of the optimal neural network is observed that an unsteady Euler plasma fluid ciguations solver in the context of the electron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. Plasmas the is finally tested on a more complex case of discharge propagation involving chemistry and advection. The guidelines established in previous sections are applied to build the CNN to solve he same Poisson equation in eylindrical coordinates. Which firent boundary conditions, social social plasmas problem. The periodination test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation the electron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation in eylindrical coordinates with deliferant boundary conditions, social consistency of the neural network so			title			
Journal   Volume   SupportedSources.SEMANTIC_SCHOLAR   Journal   ArXiv   Journal   Journal   ArXiv   Journal   Jou	source	SupportedSources.INTERNET_ARCHIVE	publication date			
doi  uris  https://web.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf  id id2805921429682829845  The Poisson equation is critical to get a self-consistent solution in plasma fluid simulations used for Hall effect thrusters and streamer discharges, since the Poisson solution appears as a source term of the unsteady nonlinear flow equations. As a first step, solving the 2D Poisson equation in plasma fluid simulations used for Hall effect of thrusters and streamer and network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. One key objective is to better understand how neural networks learn the Poisson solutions and provide guidelines to achieve optimal network configurations, sepecially when coupled to the time-avraing immultiple-scale architectures, losses, and hyperparameters provides an optimal network to solve accurately the steady Poisson problem. The performance of the optimal neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neural network solver, called PlasmaNet, is then proposed using a proper scaling of the neu	journal		source	SupportedSources.SEMANTIC_SCHOLAR		
• https://web.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf  id id2805921429682829845  The Poisson equation is critical to get a self-consistent solution in plasma fluid simulations used for Hall effect thrusters and streamer discharges, since the Poisson equation with zero Dirichle boundary conditions using a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. One key objective is to better understand how neural networks learn the Poisson solutions and provide guidelines to achieve optimal network configurations, especially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimal network to solve accurately the steady Poisson problem. The performance of the optimal neural network to solve accurately the steady Poisson problem. The performance of the optimal neural network solver, called PlasmaNet, is coupled with an unsteady Euler plasma fluid equations solver. The test case corresponds to new resolutions and provide guidelines solver in the context of the electron plasma oscillation with recasing number of nodes, and compared with classical parallel classical plasma solver of the regulaclines established in previous sections are applied to build the CNN to solve the same Poisson equation in cylindrical coordinates with different boundary conditions, and provide guidelines stablished in previous sections are applied to build the CNN to solve the same Poisson equation in cylindrical coordinates with different boundary conditions, and provide guidelines stablished in previous sections are applied to build the CNN to solve the same Poisson equation in cylindrical coordinates with different boundary conditions, and previous sections are applied to build the CNN to solve the same Poisson equ			journal	ArXiv		
id id280592142968289845  The Poisson equation is critical to get a self-consistent solution in plasma fluid simulations used for Hall effect thrusters and streamer discharges, since the Poisson solution appears as a source term of the unsteady nonlinear flow equations. As a first step, solving the 2D Poisson solution appears as a source term of the unsteady nonlinear flow equations suiting a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. One key objective is to better understand how neural networks configurations, especially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimum network to solve accurately the steady Poisson problem. The performance of the optimal network solver, called PlasmaNet, is coupled with an unsteady Euler plasma fluid equations solver in the excessary to produce a stable simulation. PlasmaNet is finally tested on a more complex case of discharge propagation involving chemistry and advection. The guidelines established in previous sections are applied to build the CNN to solve he same Poisson equation in cylindrical coordinates with different boundary conditions. Results reveal good CNN predictions and pave the way to new computational strategies using modern GPU-based hardware to predict unsteady problems involving a Poisson equation.  Versions  id id6967410644607476469  The Poisson equation is critical to get a self-consistent solution in plasma fluid simulations used for Hall effect thrusters and streamers discharges. Solving the 2D Poisson equation with zero Dirichlet boundary conditions using a deep neural network is investigated using multiple-scale architectures, losses, and hyperparameters provides an optimum network to solve accurately the steady Poisson problem. Applyac	doi		volume	abs/2109.13076		
The Poisson equation is critical to get a self-consistent solution in plasma fluid simulations used for Hall effect thrusters and streamer discharges, since the Poisson solution appears as a source term of the unsteady nonlinear flow equations. As a first step, solving the 2D Poisson equation in the possion such possion solution and provide guidelines to achieve optimal network configurations, esepecially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of branches, depth and receptive field. One key objective is to better understand how neural networks learn the Poisson solutions and provide guidelines to achieve optimal network configurations, esepecially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimum neutron of on meshes with increasing number of nodes, and compared with classical parallel linear solvers. Next, PlasmaNet is coupled with an unsteady Euler plasma fluid equations solver. The test case corresponds to electron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is finally tested on a more complex case of discharge propagation involving solve the same Poisson equation in cylindrical coordinates with different boundary conditions, estable simulation. This time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is finally tested on a more complex case of discharge propagation involving solve the same Poisson equation in cylindrical coordinates with different boundary conditions, and compared with an existing solver based on a standard linear system algorithm for the Poisson equation in the context of a time-dependent simulation. In this time	urls	<ul> <li>https://web.archive.org/web/20211122194449/https://arxiv.org/pdf/2109.13076v3.pdf</li> </ul>	doi			
effect thrusters and streamer discharges, since the Poisson solution appears as a source term of the unsteady nonlinear flow equations. As a first step, solving the 2D Poisson equation with zero Dirichlet boundary conditions using a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. One key objective is to better understand how neural networks learn the Poisson solutions and provide guidelines to achieve optimal eventwork configurations, especially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimular estady Poisson problem. The performance of the optimal neural network to solve accurately the steady Poisson problem. The performance of the optimal neural network to solve accurately the electron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is then benchmarked on meshes with increasing number of nodes, and compared with an unsteady Euler plasma fluid equations solver in the context of the electron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is then benchmarked on meshes with increasing number of nodes, and compared with an existing solver based on a standard linear system algorithm for the Poisson equation. Results reveal that effect thrusters and streamers discharges. Solving the 2D Poisson equation with zero Dirichlet boundary conditions using a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. The investigation of multiple architectures, defined in terms of number of branches, depth and receptive field. The investigation of multiple architecture	id	id2805921429682829845	urls	https://www.semanticscholar.org/paper/2da0491ba38ac18ef03aee950caac3a6f94ab38e		
nonlinear flow equations. As a first step, solving the 2D Poisson equation with zero Dirichlet boundary conditions using a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. One key objective is to better understand how neural networks learn the Poisson solutions and provide guidelines to achieve optimal network configurations, especially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimal network to solve accurately the steady Poisson problem. The performance of the optimal neural network solver, called PlasmaNet, is then monitored on meshes with increasing number of nodes, and compared with classical parallel linear solvers. Next, PlasmaNet is coupled with an unsteady Euler plasma fluid equations solver in the context of the celetron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is finally tested on a more complex case of discharge propagation involving reveal good CNN predictions and pave the way to new computational strategies using modern GPU-based hardware to predict unsteady problems involving a Poisson equation.  versions			id	id6967410644607476469	DUDITOATE	2
		nonlinear flow equations. As a first step, solving the 2D Poisson equation with zero Dirichlet boundary conditions using a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field. One key objective is to better understand how neural networks learn the Poisson solutions and provide guidelines to achieve optimal network configurations, especially when coupled to the time-varying Euler equations with plasma source terms. Here, the Receptive Field is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimal network to solve accurately the steady Poisson problem. The performance of the optimal neural network solver, called PlasmaNet, is then monitored on meshes with increasing number of nodes, and compared with classical parallel linear solvers. Next, PlasmaNet is coupled with an unsteady Euler plasma fluid equations solver in the context of the electron plasma oscillation test case. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is finally tested on a more complex case of discharge propagation involving chemistry and advection. The guidelines established in previous sections are applied to build the CNN to solve the same Poisson equation in cylindrical coordinates with different boundary conditions. Results reveal good CNN predictions and pave the way to new computational strategies using modern GPU-based		thrusters and streamers discharges. Solving the 2D Poisson equation with zero Dirichlet boundary conditions using a deep neural network is investigated using multiple-scale architectures, defined in terms of number of branches, depth and receptive field 1. The latter is found critical to correctly capture large topological structures of the field. The investigation of multiple architectures, losses, and hyperparameters provides an optimum network to solve accurately the steady Poisson problem. Generalization to new resolutions and domain sizes is then proposed using a proper scaling of the network. Finally, found neural network solver, called PlasmaNet, is coupled with an unsteady Euler plasma fluid equations solver. The test case corresponds to electron plasma oscillations which is used to assess the accuracy of the neural network solution in the context of a time-dependent simulation. In this time-evolving problem, a physical loss is necessary to produce a stable simulation. PlasmaNet is then benchmarked on meshes with increasing number of nodes, and compared with an existing solver based on a standard linear system algorithm for the Poisson equation. Results reveal that PlasmaNet outperforms the classical plasma solver, up to speedups 700 times faster on large meshes containing millions of nodes. PlasmaNet is finally tested on a more complex case of discharge propagation involving chemistry and advection. The guidelines established in previous sections are applied to build the CNN to solve the same Poisson equation but in cylindrical coordinates. Results reveal good CNN predictions with significant speedup. These results pave the way to new computational strategies to predict unsteady problems involving a		•
	701010		versions	Poisson equation, including configurations with coupled multiphysics interactions such as in plasma flows.		