

Learning the Interfacial Area Equation from Data

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The ability for sparse symbolic machine learning techniques to discover governing equations from data [1], [2] has opened up many opportunities in fluid mechanics. The equations solved in fluid mechanics are conservation of mass, momentum, and energy as well as the closure models. Closure models arise from averaging the conservation equations. Averaging introduces additional terms, which require additional equations, termed closure models, to solve. It is in discovering the equations governing the closure models that sparse symbolic machine learning is most useful. Closure models are not based upon strict physical laws, but on experimental data and engineering judgement. This makes them ideal for machine learning techniques. Moreover, sparse symbolic machine learning has an advantage over previous neural network approaches, [3], in that the output can be easily integrated into existing computer codes, with an understanding of how it will extrapolate to untrained conditions. There has already been quite a bit of attention to using sparse symbolic learning for turbulence closure models [4]–[6]. Similar things are possible for two-phase flow.

Two-phase flows are typically modeled using the two fluid model, [7], [8], in which each phase is modeled as a continua and has its own set of conservation equations (mass, momentum, and energy), and the phases are coupled by interfacial transfer terms. The interfacial transfer terms require closure models. The current state of the art for nuclear reactor system codes (RELAP, TRACE, CATHARE) is for the interfacial transfer terms to be correlated in terms of the flow regime. In two phase flow, the flow regime describes the topology of the flow, i.e. whether the gas forms bubbles inside the liquid (bubbly flow) or whether the liquid is confined to the walls and as droplets inside the gas core (annular flow). The flow regime transitions themselves are also empirically correlated. It has been noted that the interfacial transfer closures can be written in terms of a_i , the interfacial area per unit volume, as (Interfacial transfer) = a_i x (Driving Force) [9]. Moreover, the interfacial area changes dramatically with the flow regime, so if one could write an equation for the interfacial area, the empirical flow regime correlations could be dispensed with. Various derivations of an interfacial area equation have been performed [10]–[12], the simplest of which [10] is:

$$\frac{\partial a_i}{\partial t} = \nabla \cdot (a_i v_i) = \sum_{j=1}^4 \phi_j + \phi_{ph}$$

In this equation, ϕ_j represents the interfacial area rate of change due to coalescence or breakup, and ϕ_{ph} represents the rate of change due to phase change. Attempts to validate this equation against high fidelity experimental data using the current state of the art for models of ϕ have noted that there are substantial issues once the flow regime moves beyond bubbly flow [13].

Our aim is to use sparse machine learning to derive the governing equation for the rate of interfacial area change. There are additional challenges when attempting to learn multiphase as opposed to single phase flow closure models. The rate of interfacial area change must be learned from time resolved planar measurements, which is the state of the art for experimental gas liquid measurement techniques [14]. This is because multiphase DNS (direct numerical simulation) and LES (large eddy simulation) methods are not developed enough to apply machine learning techniques directly on numerical data, as was done to learn single phase turbulence closures [4]–[6]. However, the benefit of an accurate interfacial area transport equation is the potential to dramatically improve nuclear reactor system codes and thereby nuclear reactor safety.

[1] M. Schmidt and H. Lipson, “Distilling free-form natural laws from experimental data,” *Science* (80-.), vol. 324, no. 5923, pp. 81–85, 2009, doi: 10.1126/science.1165893.

[2] S. L. Brunton, J. L. Proctor, J. N. Kutz, and W. Bialek, “Discovering governing equations from data by sparse identification of nonlinear dynamical systems,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 113, no. 15, pp. 3932–3937, 2016, doi: 10.1073/pnas.1517384113.

[3] K. Duraisamy, G. Iaccarino, and H. Xiao, “Turbulence Modeling in the Age of Data,” *Annu. Rev. Fluid Mech.*, vol. 51, no. 1, pp. 357–377, 2019, doi: 10.1146/annurev-fluid-010518-040547.

[4] S. Beetham and J. Capecelatro, “Formulating turbulence closures using sparse regression with embedded form invariance,” pp. 1–34, 2020, [Online]. Available: <http://arxiv.org/abs/2003.12884>.

[5] M. Schmelzer, R. P. Dwight, and P. Cinnella, “Machine Learning of Algebraic Stress Models using Deterministic Symbolic Regression,” 2019, [Online]. Available: <http://arxiv.org/abs/1905.07510>.

[6] M. Schmelzer, R. Dwight, and P. Cinnella, “Data-driven deterministic symbolic regression of nonlinear stress-strain relation for RANS turbulence modelling,” 2018 Fluid Dyn. Conf., 2018, doi: 10.2514/6.2018-2900.

[7] J. E. Drew and S. L. Passman, *Theory of Multicomponent Fluids*, vol. 59. 1998.

[8] M. Ishii and T. Hibiki, *Thermo-Fluid Dynamics of Two-Phase Flow*. 2006.

[9] G. Kocamustafaogullari and M. Ishii, “Foundation of the interfacial area transport equation and its closure

- relations,” *Int. J. Heat Mass Transf.*, vol. 38, no. 3, pp. 481–493, 1995, doi: 10.1016/0017-9310(94)00183-V.
- [10] X. Y. Fu and M. Ishii, “Two-group interfacial area transport in vertical air-water flow - I. Mechanistic model,” *Nucl. Eng. Des.*, vol. 219, no. 2, pp. 143–168, 2003, doi: 10.1016/S0029-5493(02)00285-6.
- [11] C. Morel, N. Goreaud, and J. M. Delhaye, “The local volumetric interfacial area transport equation: Derivation and physical significance,” *Int. J. Multiph. Flow*, vol. 25, no. 6–7, pp. 1099–1128, 1999, doi: 10.1016/S0301-9322(99)00040-3.
- [12] D. A. Drew, “Evolution of geometric statistics,” *SIAM J. Appl. Math.*, vol. 50, no. 3, pp. 649–666, 1990, doi: 10.1137/0150038.
- [13] A. J. Dave, A. Manera, M. Beyer, D. Lucas, and M. Bernard, “Evaluation of two-group interfacial area transport equation model for vertical small diameter pipes against high-resolution experimental data,” *Chem. Eng. Sci.*, vol. 162, no. January, pp. 175–191, 2017, doi: 10.1016/j.ces.2017.01.001.
- [14] H. M. Prasser, M. Misawa, and I. Tiseanu, “Comparison between wire-mesh sensor and ultra-fast X-ray tomograph for an air-water flow in a vertical pipe,” *Flow Meas. Instrum.*, vol. 16, no. 2–3, pp. 73–83, 2005, doi: 10.1016/j.flowmeasinst.2005.02.003.

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