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Towards understanding of boiling conjugate heat transfer using physics informed neural network

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Conjugate heat transfer associated with boiling occurs in multiple industries such as metallurgical processing, power generation, refrigeration, electronics cooling and cryogenics[1]. This work focuses on immersion water quenching, yet the findings may often be extended to any of the above applications. Metallurgical quenching aims to alter microstructural characteristics of metallic materials to tailor their mechanical properties via heat treatment at elevated temperature followed by rapid cooling. The temperature can reach up to thousand of degrees Celsius leading to the appearance of numerous heat transfer regimes. Current simulation techniques rely heavily on empirical and semi-empirical models due to the limited understanding of the underlying boiling physics, while the equations governing the fluid flow are much better understood. In addition, high fidelity experimental data are quite limited, owing to the cost, complexity, accuracy of measurement techniques and data sensitivity. These circumstances make the problem inappropriate for general machine learning algorithms but also challenging for traditional numerical procedures such as the finite volume method. With this in mind, the authors aim to exploit physics informed neural network techniques for this problem. Utilisation of conservation laws and other well-posed mathematical models in machine learning can help circumvent the data shortage, improve generalisation performance, reduce dimensionality and help comprehend unresolved physical phenomena[2]. This work gives guidance on approaching such problems, discusses their feasibility and concludes with benefits and likely limitations.

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