Deep Learning with Physics Informed Neural Networks for the Airborne Spread of COVID-19 in Enclosed Spaces

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Most epidemic models studying COVID-19 have focused on the macro scale, evaluating the progression of infected cases across large regions. However, the significant airborne infectivity of the virus has led to important public policy questions about safety measures in enclosed spaces like schools, aircraft, and hospitals. Alarmingly, there is a severe lack of coronavirus-specific literature that models the medium to long term progression of infections in these small spaces. In this work, we introduce a novel framework that combines the Wells-Riley airborne infection model, the SEIR epidemiological model, and an infectious concentration transport model. We apply our integrated framework to a benchmark application of three hospital wards connected by interzonal airflow and perform preliminary computational experiments by varying parameters like ventilation rate and facemask use. We then perform parameter estimation with Physics Informed Neural Networks (PINNs), a novel supervised learning technique that allows us to use our ODE relations as priors to efficiently learn parameters in our system. Our computational results show that PINNs perform well with limited and noisy data.