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# Physics informed neural networks for cybernetics of electric motors

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*This study proposes a physics informed neural networks to predict electromagnetic characteristics of electric motors including a magnetic field, electric field, and magnetic vector potential. In this study, the governing equations correlating the magnetic field vector potential, the electric field, and the magnetic flux density are used for supervising a physics loss term. Maxwell equation is also used to simulate the electromagnetic physics of electric motors. This novel architecture of deep neural network is proposed because conventional physics informed neural networks cannot correctly learn physics for rotational machinery because of their limited capability to capture physics on fixed coordinates. The proposed method would be effective for a rotational machinery in which the coordinates of a rotor are changed, whereas those of a stator are fixed during operations. The proposed method has three key characteristics to deal with the problem aforementioned on the rotational machinery. First, this study proposes physics informed neural networks with the rotational coordinate transformation of a rotor defined in the form of a rotational speed. The rotation coordinate transform is applied to the conventional physics informed neural networks for fixed coordinates so that changes in electromagnetic fields caused by rotation of the rotor can be learned through the proposed physics informed neural networks. Second, separate networks for rotor and stator domains are constructed and trained. Then, prediction results are stitched by addressing an interface loss between two domains to reduce a relatively large error in a rotor-stator interface. Note that significant error in the interface would be also originated from the inherent characteristics of the rotational machinery. In addition, the rotational speed of the rotor and the 3-phase coil current are designated to the input of the rotor domain and the stator domain respectively to apply the same inputs by replicating the actual electric motor system. The proposed physics informed neural networks can be simulated for various conditions through the separate networks and inputs. Third, a learning rate annealing method is adopted to minimize the entire loss by multiplying the adaptive weights for all kinds of different losses including data, physics, and interface losses. This method contributes to effectively train the proposed network because this method solves a problem that different gradient values of each loss term result in a convergence problem. Specifically, a certain loss term only decreases without a learning rate annealing method, resulting in an inaccurate prediction of electromagnetic responses of electric motors even though convergence should be secured for all kinds of loss terms. In a learning rate annealing method, the maximum value of the gradient of the physical loss and the mean value of the gradient of the other losses are calculated for each particular epoch. Then, the adaptive weights are calculated and updated to balance the difference between the gradient values of each loss term by using the learning rate annealing method. Finally, the accuracy and robustness of the proposed physics informed neural networks are validated a high-fidelity finite element model of an electric motor, which aims to design electromagnetic characteristics of electric motors. This high-fidelity model replicates two conditions of steady-state and eccentric failure state of electromagnetic responses. The results clearly reveal that three characteristics of the proposed method significantly improve the accuracy in predicting electromagnetic characteristics of the electric motor. Most importantly, the proposed physics informed neural network is faster than a high fidelity finite element model, suggesting that the proposed neural network can also be used for real-time applications for control enabling solutions as well as design enabling solutions.*

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