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Reduced-order Neural Network Plant Models for Proton Exchange Membrane Fuel Cells using Principal Component Analysis

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ABSTRACT

High-fidelity physics-based models can represent complex systems with high accuracy but, due to high computational cost, are often ill-suited for real-time applications. Data-driven models such as neural networks can yield competitive accuracy with reduced computation cost, may capture system-specific phenomena not accounted for in physics-based models, and can be further accelerated using parallel computing. For resource-constrained applications such as embedded controllers for automotive platforms, data-driven approaches can enable use of model predictive control where an analytical physics-based model would be computationally prohibitive. A disadvantage can be the memory (static ROM and dynamic RAM) required to store the model parameters which is a key metric for feasibility of use in embedded control systems. Model complexity reduction is therefore highly desirable.

In this work, an ensemble of feedforward neural networks is used to approximate the input-output mapping for a hydrogen proton exchange membrane fuel cell of a typical design used in production light-duty fuel cell vehicles. The baseline models are fully-connected multilayer perceptron networks using rectified linear unit activation functions, trained using scaled conjugate gradient backpropagation. These models achieve mean relative error of <6.6% versus ground truth data over 52 predicted output features. The models are further optimized by pre-conditioning the neural network training data using principal component analysis (PCA) to project the input features onto an orthogonal basis, maximizing the variance per input feature and allowing for reduction of the input dimension by discarding negligible components. The PCA-reduced models achieve an overall reduction of 6-45% in neuron count compared to the baseline models, corresponding to memory reductions of 6-45% in calibration ROM and 8-40% in stack RAM. Aggregate execution time of the ensemble was measured at 146 μs and 107 μs on representative automotive controller hardware for the baseline and PCA-reduced models, respectively, representing a 26.7% reduction. For this improvement in performance (reduction in model size), the PCA-reduced models achieve mean relative error per output variable of 0.3-7.1% versus ground truth data, with absolute differences in mean relative error over the data set, per variable, of between -1.1% to +1.5% versus the baseline models.

In summary, PCA-reduced neural network plant models of PEM hydrogen fuel cells can achieve high accuracy at the computational speeds required for real-time embedded controllers.

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