A Surrogate Neural Network-Based Structure for Process Control

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ABSTRACT

Process control is one of the fundamental pillars of Process Systems Engineering. In particular, Model Predictive Control (MPC) has been widely applied in industrial environments and has established itself as one of the most successful advanced control techniques, due to its predictive capabilities combined with its ability to explicitly handle operational constraints. Among the various nonlinear MPC formulations (NMPC), those employing neural networks as internal process models have gained increasing attention. In this context, alternative approaches have also been proposed in which neural networks are used directly as controllers, rather than solely as dynamic process models. Such approaches lead to significantly simpler and computationally efficient control structures, at the expense of a potential loss of robustness and reduced ability to explicitly enforce constraints. In practice, this trade-off arises from replacing the solution of an optimization problem at each sampling instant with the direct evaluation of a neural network. In this work, a control structure is proposed in which a neural network is used as a surrogate controller, trained from closed-loop operational data generated by an NMPC controller, referred to as Surrogate NMPC (S-NMPC). An additional optimization layer is incorporated to ensure constraint handling and offset-free behavior, acting as a safety layer in the closed loop. The surrogate controller—comprising the trained neural network and the safety layer—is then used to replace the standard NMPC during closed-loop operation. This control structure aims to bridge the gap between computational efficiency and constraint handling in neural network-based control. The proposed approach is evaluated using the van de Vusse CSTR benchmark, a well-known case study due to its challenging static and dynamic characteristics. The results indicate that the surrogate controller presents advantages over conventional NMPC, in terms of structural simplicity and reduced computational cost, while maintaining comparable closed-loop performance. However, it loses some key features of the NMPC framework, such as the ability to directly handle nonlinear dynamics and the flexibility in objective function design, since the trained S-NMPC mimics the NMPC behavior only for a specific set of tuning parameters. As a result, the proposed structure does not allow for online retuning. Furthermore, as observed in most machine learning-based control approaches, the performance of the resulting controller strongly depends on the quality of the training data—generated by the NMPC "teacher"—as well as on design choices in the training procedure, such as the selection of the regression vector used as input to the neural network.

Keywords: Model Predictive Control, Surrogate NMPC, Neural Network Control.

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