Application of an Artificial Neural Network to Non-Linear Process Control

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ABSTRACT

Model predictive control (MPC) is one of the most frequently used process control strategies. The principle of MPC is to have a process model, which is able to predict the process response, in the MPC controller. The manipulated variable is tuned in order to minimize the deviation between the set point and the predicted response for a period of time in the feature. The goal of process control can therefore be achieved by regulating the manipulated variable. The MPC often uses a linear model to simulate the process. Hence, some modeling errors must exist. Some researchers have used an artificial neural network (ANN) to replace the linear model in the MPC control for a complex process, owing to the nonlinear mapping capability owned by an ANN. Usually, the neural predictive control is trained based on the autoregressive model with exogenous (ARX) form and/or autoregressive moving average model with exogenous (ARMAX) form. The ANN model uses the output value as input data iteratively. The drawback of the training pattern includes the induction of inaccuracy and time-consuming. To overcome the drawback, the process convolution model has been used to train the ANN. The proposed model has been named the neural network predictive control (NNPC) in this study. For the training proposes, the pseudo random binary sequence (PRBS) signal patterns are used to identify the process. Once the ANN has been trained, the MPC strategy determines a desired value for the manipulated variable by using the Levenberg-Marquardt method. A CSTR with a nonlinear reaction has been chosen as an example to test the performance of the proposed control strategy. In this example, a temperature loop and a concentration loop and controlled simultaneously. Simulation results have shown that no matter the change of the set point or a load, the NNPC demonstrates a good control performance. When a process possesses a slow response (large time constant), e.g. a bioreactor, the ANN model in the NNPC has to increase the node number in the hidden layer, and therefore increase the training time. To overcome this disadvantage, a simplified neural network predictive control (SNNPC) has been proposed. In this simplified model, the node member of the output layer has been reduced to 3, and the training time has also been reduced substantially. In general, the control performance is still satisfactory, but the offset has been slightly increased.

Keywords : neural network ; model predictive control ; simplified neural network model predictive control

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