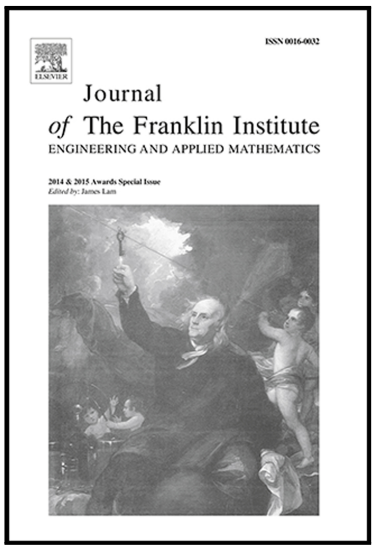


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Bahareh Vatankhah , Mohammad Farrokhi

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# Nonlinear Model-Predictive Control with Disturbance Rejection Property Using Adaptive Neural Networks

**Bahareh Vatankhah, Mohammad Farrokhi**

School of Electrical Engineering, Iran University of Science and Technology, Tehran, 16846-13114, Iran.
Corresponding author e-mail: farrokhi@iust.ac.ir

**Abstract-** In this paper, a method is proposed to reject disturbances in the model predictive control (MPC) strategy. In addition, uncertainties in the system parameters (i.e., internal disturbances) are considered as well. To achieve these goals, adaptive neural networks are designed as the predictor model and as the nonlinear disturbance observer, respectively. The disturbances are rejected via the optimization problem of the MPC. Stability of the closed-loop system is studied based on the input-to-state stability method. The proposed method is applied to the pH neutralization process and CSTR system and its effectiveness in optimal rejection of the disturbances and satisfying the system constrains is compared with the feed-forward control method.

Keywords
Model predictive control, neural network, adaptive model, disturbance observer, process control

## 1. Introduction

Model Predictive Control (MPC) method has been used in different industries due to its effectiveness in the control of the constraint nonlinear systems [1, 2]. This control strategy is a constraint optimal controller, where an on-line optimization problem is solved and an input sequence over a certain time horizon (prediction/control horizon) is generated at every sampling time. Due to the receding horizon policy, only the first input is applied to system and this procedure is repeated during the next sampling instant [3, 4].

Modeling the system is an essential part of the MPC. The model is used to predict the system output based on the past and current information. Accuracy of the model has significant effect on the performance and stability of the closed-loop system. Different modeling approaches (e.g., neural networks and fuzzy systems) are used to model the nonlinear systems in the MPC [5, 6]. Neural Networks (NNs) are known as universal approximators using different learning algorithms. Hence, they are widely used to model nonlinear systems [5, 7, 8]. For MPCs, the NN