Load-following Operation for PWRs Using Fuzzy Model Predictive Control

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1. Introduction

In this study, a fuzzy model predictive control method is applied to design an automatic controller for thermal power and axial shape index (ASI) in pressurized water reactors. The future reactor power and ASI are predicted by using the fuzzy model identified by a subtractive clustering method of a fast and robust algorithm. The genetic algorithm that is useful to accomplish multiple objectives is used to optimize the fuzzy model predictive controller. A 3-dimensional nuclear reactor analysis code is used to verify the proposed controller for a nuclear reactor. From results of numerical simulation to check the performance of the proposed controller at the increase or decrease of a desired load (rapid change, load follow), it was found that the nuclear power level and ASI controlled by the proposed fuzzy model predictive controller could track the desired power level and ASI very well.

2. Fuzzy Model Predictive Control

This study is focused on designing an excellent controller by introducing new methodologies such as a model predictive control method, a fuzzy logic and a genetic algorithm. The model predictive control method is to solve an optimization problem for a finite future at current time and to implement the first optimal control input as the current control input. The procedure is then repeated at each subsequent instant. Fig 1 shows the basic concept of the model predictive control [1].

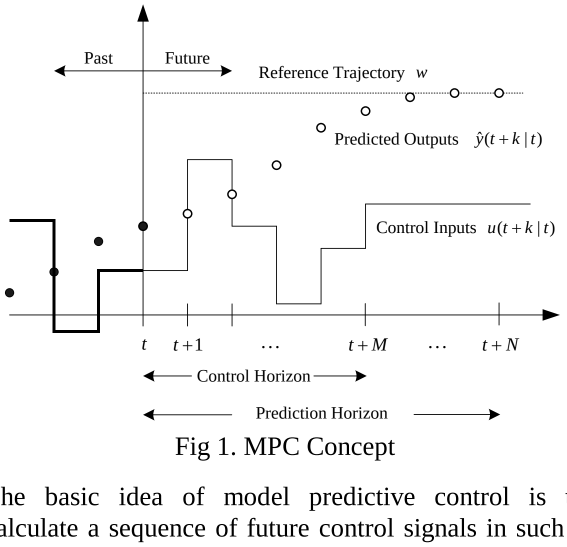


Fig 1. MPC Concept

The basic idea of model predictive control is to calculate a sequence of future control signals in such a way that it minimizes a multistage cost function defined over a prediction horizon. Also, in order to achieve fast responses and prevent excessive control effort, the associated performance index for deriving an optimal control input is represented by the following quadratic function:

$$J=\frac{1}{2}\sum_{k=1}^{L}Q\left[\hat{y}(t+k\,|\,t)-w(t+k)\right]^2+\frac{1}{2}\sum_{k=1}^{M}R\left[\Delta u(t+k-1)\right]^2 \quad (1)$$

subject to constraints

$$\begin{cases}\Delta u(t+k-1)=0 \ \text{ for } \ k>M\,, \\ u_{\min}\le u(t)\le u_{\max}\,, \\ -du_{\max}\le \Delta u(t)\le du_{\max}\,. \end{cases}$$

In order to obtain control inputs, the predicted outputs have to be first calculated as a function of past values of inputs and outputs and of future control signals, which uses the fuzzy model.

2.1 output Prediction

A fuzzy identification model based on the subtractive clustering is used to predict the future output. The inputs and outputs of the fuzzy model are real-valued variables. A Takagi-Sugeno [2] type fuzzy inference system is used where the i -th fuzzy rule for k -th time instant data is described as follows:

$$\begin{aligned}&\text{If } \ y(k-d-1) \text{ is } A_{i,1}(k) \ \ AND\cdots AND \ \ y(k-d-n_y) \text{ is } A_{i,n_y}(k)\\ &\quad AND \ \ u(k-1) \text{ is } A_{i,n_y+1}(k) \ \ AND\cdots AND \ \ u(k-n_u) \text{ is } A_{i,n_y+n_u}(k), \quad (2)\\ &\text{then } \ \hat{y}_i(k) \text{ is } f_i\left(y(k-d-1),\ \cdots,\ y(k-d-n_y),\ u(k-1),\ \cdots,\ u(k-n_u)\right),\end{aligned}$$

A subtractive clustering (SC) method is used as the basis of a fast and robust algorithm for identifying a fuzzy model and assumes the availability of N input/output training data $\mathbf{z}(k)=\left(\mathbf{x}(k),y(k)\right)$, $k=1,2,...,N$. It is assumed that the data points have been normalized in each dimension. The method starts by generating a number of clusters in the m dimensional input space. The SC method considers each data point as a potential cluster center and uses a measure of the potential of each data point, which is defined as a function of the Euclidean distances to all other input data points [3,4]:

$$P(k)=\sum_{j=1}^{N}e^{-4\|\mathbf{x}(k)-\mathbf{x}(j)\|^2/r_\alpha^2}\ ,\ \ k=1,2,...,N, \quad (3)$$

A complete fuzzy system identification algorithm can be developed based on the results of the SC technique. The number of n Takagi-Sugeno type fuzzy rules can be generated, where the premise parts are fuzzy sets, defined by the cluster centers that are obtained by the SC algorithm.

2.2 Objective Function Optimization by a Genetic Algorithm

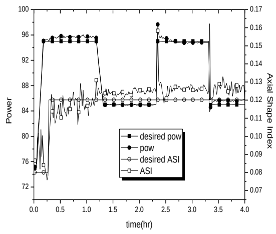
A genetic algorithm is used to minimize the objective function with multiple objectives. The genetic algorithms require a fitness function that assigns a score to each chromosome (candidate solution) in the current population, and maximize the fitness function value. The fitness function evaluates the extent to which each candidate solution is suitable for specified objectives. The genetic algorithm starts with an initial population of chromosomes, which represent possible solutions of the optimization problem. The fitness function is computed for each chromosome. New generations are produced by the genetic operators that are known as selection, crossover and mutation. The algorithm stops after the maximum allowed time has elapsed. A chromosome will be represented by s_g of which elements consist of present and future control inputs and will have the following structure:

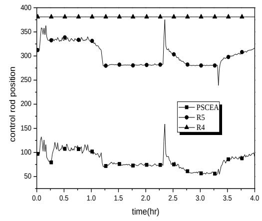
$$s_g = \left[u_g(t) \quad u_g(t+1) \quad \cdots \quad u_g(t+M-1) \right], \; g = 1, \cdots, G, \qquad (4)$$

Assuming we have chosen the number of chromosomes G, which will constitute the initial population, the crossover probability P_c and the mutation probability P_m, the algorithm proceeds according to the following 6 steps (initial population, fitness function evaluation, selection operation, crossover operation, mutation operation, repeat or stop).

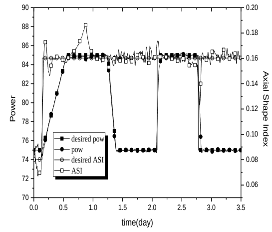
3. Application to Nuclear Reactor Power Control

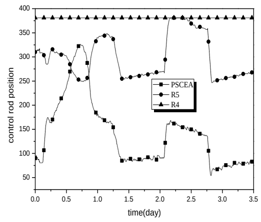
The developed controller was applied to a 3-dimentional reactor analysis code (MASTER code) [5]. The MASTER code is written in FORTRAN and the proposed fuzzy model predictive control algorithm in MATLAB. Fig 2 shows its simulation results of the rapid change and load-follow. Fig 2(a, c) shows the responses of nuclear power level and axial shape index. It is shown that the power level and the axial shape index follow their desired values very well. Fig 2(b, d) shows the positions of the regulating control rod banks that describe their overlapped positions well. In this paper, we proposed a new reactor controller that combines the MPC control methodology which has received much attention as a powerful tool for the control of industrial process systems, and the genetic algorithm and the fuzzy identification which have been widely used in engineering problems. A simple control algorithm is not so important because in these days digital processors are used in control instead of old hardwired circuits. If the control performance can be improved with a new complex control algorithm, it will be better than a simple control algorithm with low performance. As shown in Fig 2(a, b, c, d), the proposed controller provides excellent performance although it is complicated.





(a) Power and ASI (Rapid) (b) Rod Position (Rapid)





(c)Power and ASI (daily load-follow) (d)Rod Position (daily load-follow)

Fig 2. Control perfomance by the proposed fuzzy model predictive controller

4. Conclusions

In this study, the fuzzy model predictive controller optimized by GA has been developed to control the nuclear power and ASI in PWRs. The developed controller has been applied to YGN-3 which was modeled by the MASTER code. Based on a fuzzy model consisting of the control rod position and the reactor power, ASI, the future outputs are predicted by using the fuzzy model identified by a subtractive clustering method of a fast and robust algorithm. The genetic algorithm is used to optimize the fuzzy model predictive controller. It was known that the proposed controller adjusts the control rod position so that the nuclear reactor power and ASI tracks very well its setpoint change according to load.

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