SP-100 우주선 원자로를 위한 고장진단 및 제어 통합 시스템

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A Fault Diagnosis and Control Integrated System for an SP-100 Space Reactor

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Abstract - In this paper, a fault diagnosis and control integrated system (FDCIS) was developed to control the thermoelectric (TE) power in the SP-100 space reactor. The objectives of the proposed model predictive control were to minimize both the difference between the predicted TE power and the desired power, and the variation of control drum angle that adjusts the control reactivity. Also, the objectives were subject to maximum and minimum control drum angle and maximum drum angle variation speed. A genetic algorithm was used to optimize the model predictive controller. The model predictive controller was integrated with a fault detection and diagnostics algorithm so that the controller can work properly even under input and output measurement faults. With the presence of faults, the control law was reconfigured using online estimates of the measurements. Simulation results of the proposed controller showed that the TE generator power level controlled by the proposed controller could track the target power level effectively even under measurement faults, satisfying all control constraints.

1. 서 론

The SP-100 space nuclear reactor was designed to provide a realistic and reliable source of very long-term power for space exploration and exploitation activities. The SP-100 system is a fast spectrum lithium-cooled reactor system with an electric power rating of 100 kW [1]. In order to accomplish a space mission with uncertain environment, rare events, and communication delays, all the control functions must be achieved through a sophisticated control system with a limited degree of human intervention from the earth. Therefore, to preserve the safety and reliability of processes, the presence of faults must be taken into account during the control system design. This paper employs the model predictive control (MPC) method [2], which has received increased attention as a powerful tool for the control of industrial process systems. The dynamics of the SP-100 reactor system are highly non-linear. Therefore, a nonlinear MPC methodology has to be applied to predict the future behavior of the plant based on a nonlinear model of the process. In this paper, the nonlinear model development was carried out by a fuzzy model because fuzzy models are simpler in structure and easier to develop compared to other nonlinear models. Also, regarding the nonlinear optimization problem, conventional optimization techniques cannot be easily applied due to the peculiarity of fuzzy models. Therefore, the on-line optimization problem is solved using a genetic algorithm. In addition, another fuzzy model estimates the input and output of the control system by using other process signals, and the residuals between the estimated signals and the measured signals are used to determine the health of the measurement instruments by using the sequential probability ratio test (SPRT).

2. 본 론

2.1 MPC Combined with a Fuzzy Model

The basic idea of MPC 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. A performance index for deriving an optimal control input is represented by the following quadratic function:

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

$$\text{subject to constraints}\quad\begin{cases}\Delta u(t+k-1)=0 \ \text{ for } k>M\\ u_{\min}\le u(t)\le u_{\max}\\ \left|\Delta u(t)\right|\le \Delta u_{\max}\end{cases}$$

For any assumed set of present and future control moves, the future behavior of the process outputs can be predicted over a prediction horizon L, and the M present and future control moves ($M\le L$) are calculated to minimize the quadratic objective function of (1). Although M control moves are calculated, only the first control move is implemented. At the next time step, new values of the measured output are obtained, the control horizon is shifted forward by one step, and the same calculations are repeated. The purpose of taking new measurements at each time step is to compensate for unmeasured disturbances and model inaccuracies, both of which make the measured system output to be different from the one predicted by the fuzzy model.

In this paper, a fuzzy model based on subtractive clustering (SC) [3] was used to predict the future output of the model predictive controller. The i-th fuzzy rule for t-th time instant data is described as follows:

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

The fuzzy model consists of a total of n fuzzy rules. The input vector to the fuzzy model consists of y and Δu which are past values of output and control input move, respectively:

$$\mathbf{x}(t)=\left[y(t-d-1)\cdots y(t-d-n_y)\ \ \Delta u(t-1)\cdots\Delta u(t-n_u)\right]. \tag{3}$$

When the SC method is applied to a collection of input/output data, each cluster center is in essence a prototypical data point that exemplifies a characteristic behavior of the system and each cluster center can be used as the basis of a fuzzy rule that describes the system behavior. Therefore, a fuzzy model can be developed based on the results of the SC technique. The number of n fuzzy rules can be generated, where the premise parts are fuzzy sets, defined by the cluster centers that are obtained by the SC algorithm. The membership function value $A_i(x(t))$ of an input data vector $x(t)$ to a cluster center $x^*(i)$ can be defined as follows:

$$A_i\left(\mathbf{x}(t)\right)=e^{-4\left\|\mathbf{x}(t)-\mathbf{x}^*(i)\right\|^2/r_a^2},\ i=1,\ 2,\cdots,n. \tag{4}$$

The fuzzy model output $\hat{y}(t)$ is calculated by the weighted average of the consequent parts of the fuzzy rules as follows:

$$\hat{y}(t)=\frac{\sum_{i=1}^{n}A_i\left(\mathbf{x}(t)\right)f_i\left(\mathbf{x}(t)\right)}{\sum_{i=1}^{n}A_i\left(\mathbf{x}(t)\right)} \tag{5}$$

where the function $f_i(x(t))$ is a polynomial in the input variables and represented by the first-order polynomial of inputs as follow:

$$f_i\left(\mathbf{x}(t)\right)=\sum_{j=1}^{m}q_{i,j}x_j(t)+r_i \tag{6}$$

The parameters, $q_{i,j}$ and r_i, are calculated with the N training input/output data pairs. Conventional optimization techniques for solving the cost functions of (1) cannot be easily applied due to the peculiarity of a fuzzy model that is basically a nonlinear model. Therefore, the on-line nonlinear optimization problem is solved using a genetic algorithm, which guarantees the feasibility of all the generated potential solutions. A chromosome which is a candidate solution of the optimization problem is represented by s_g, whose elements consist of present and future control inputs and has the following structure:

$$s_g = \left[u_g(t)\quad u_g(t+1)\quad \cdots \quad u_g(t+M-1)\right]\ ,\ g=1,\cdots,G \tag{7}$$

The genetic algorithm proceeds according to the six steps: initial population generation, fitness function evaluation, selection operation, crossover operation, mutation operation, and repeat or stop (refer to references [4]).

2.2 FDCIS

In this paper, a fault detection and diagnostics algorithm was developed to estimate the input and output measurements using a fuzzy model based on the subtractive clustering method and to check the operability of existing hardware sensors using a SPRT [5] so that the FDCIS can handle the fault situations of the input and output measurements or partial loss of actuators. In this paper, a fuzzy model was used to estimate the input and output measurement signals. This fuzzy model is another fuzzy model which is different from the fuzzy model that predicts the system output, which is needed to minimize the control objective function. In this paper, the control input signal is the control drum angle to regulate the reactivity and the output signal to be controlled is the TE power. These input and output signals are basically measured. Also, to handle the sensor faults, the input and output signals of the control system are estimated by using a fuzzy model for signal estimation from the measurements of the SP-100 reactor system. The residuals between the estimated signals and the measured signals are used to detect the sensor faults by applying the SPRT. If the input or output sensors are normal, the measured values are used to predict the future control system output. But if they are determined to be degraded or faulty, the faulty sensors are isolated and the estimated sensor signals instead of the measured values are used to predict the future system output. That is, with the presence of faults, the control law is reconfigured using online estimates of the measurements. Although the control structure is not completely changed, it is suitably reconfigured to use estimates rather than measurements. This means that the measured values of (3) to be used in the output prediction, $x(t)$, are replaced by the estimated values after the measurement faults are detected and isolated. The schematic block diagram of the proposed FTC is illustrated in Fig. 1.

2.3 Application to the SP-100 Space Reactor

The SP-100 space reactor system is a fast spectrum lithium-cooled reactor system that can generate electric power of 100 kW for space exploration and exploitation activities. The reactor system is made up of a reactor core, a primary heat transport loop, a TE generator, and a secondary heat transport loop to reject waste heat into space through radiators. The reactor core is composed of small disks of highly enriched (93%) uranium nitride fuel contained in sealed tubes. The heat generated in the reactor core is transported by liquid lithium and is circulated by electromagnetic (EM)pumps. The energy conversion system uses the direct TE conversion mechanism. A temperature drop of about 500 K is maintained across the TE elements by the cooling effect of a second liquid lithium loop that transfers the waste heat from the converter to a heat-pipe radiator. Figure 2 shows the performance of the proposed FTC for normal transients such as the setpoint change of TE power. It is shown that the TE generator power follows its desired setpoint change very well. Figure 3 shows the performance of the proposed FTC against output measurement fault (drift type fault). The output measurement is assumed to start to be gradually degraded on purpose from 300 sec and the fault detection and diagnostics algorithm detects the output measurement degradation at 241 sec since the beginning of the gradual degradation. After detecting the fault, the FTC uses the estimated output signals instead of the measured output signal. It is shown that the TE generator power follows its desired setpoint change very well.

3. 결 론

In this paper, a FDCIS was developed to control the nuclear power in the SP-100 space reactor system. Based on a fuzzy model consisting of the control drum angle change and the TE power, the future TE power is predicted by using the fuzzy model identified with a subtractive clustering method of a fast and robust algorithm. Another fuzzy model combined with the sequential probability ratio test estimates the input and output measurement signals and diagnoses the health of input and output measurements. The genetic algorithm was used to optimize the model predictive controller and both the fuzzy models. With the presence of faults, the control law is reconfigured using online estimates of the measurements. The performance of the new proposed controller was proved to be efficient even under constraint changes and gradual sensor degradation (fault).

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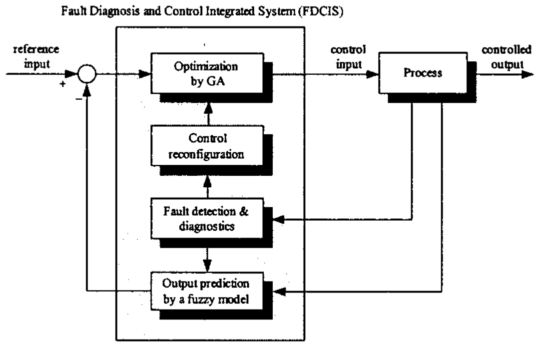

Fig. 1. Block diagram of the proposed FDCIS.

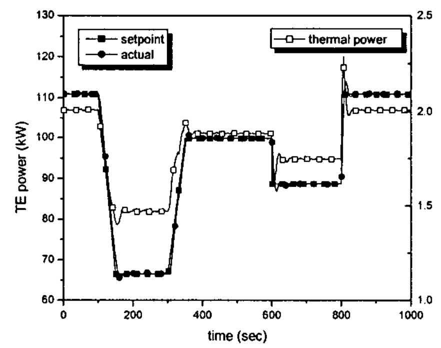

Fig. 2. Performance of the proposed FDCIS for normal transients.

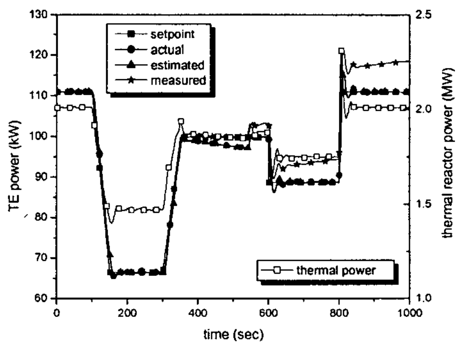

Fig. 3. Performance of the proposed FDCIS against output measurement fault (drift type fault).