# A Fault-Tolerant Controller for an SP-100 Space Nuclear Reactor

Ju Hyun Kim, Dae Seup Kim and Man Gyun Na
*Department of Nuclear Engineering, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju, Korea*

Keywords: Fault Detection and Diagnostics, Fault-Tolerant Control, Fuzzy Model, Model Predictive Control, Space Reactor Power Control, Sequential Probability Ratio Test.

Abstract: The control system is a key element of space reactor design to meet the space mission requirements of safety, reliability, survivability, economics, and autonomous action. The objectives of the proposed model predictive control are 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. A genetic algorithm is used to optimize the model predictive controller. The model predictive controller is integrated with a fault detection and diagnostics algorithm so that the controller can work properly even under input and output measurement faults. Simulation results of the proposed controller show 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 INTRODUCTION

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. The control functions needed for SP-100 can be ensured only by an autonomous control system, which assumes the responsibilities for normal control, abnormal event response and fault tolerance, and provides interface with operators on earth for high-level decision-making.

In order to optimize the reactor power control performance, methods for the optimal power control of nuclear reactors have been presented extensively in the past two decades. But it is very difficult to design optimized controllers for nuclear systems of the SP-100 space reactor. This work employs the model predictive control (MPC) method, 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 work, the nonlinear model development is conducted by a fuzzy model because fuzzy models are simpler in structure and easier to develop compared to other nonlinear models. Thus, the on-line optimization problem is solved using a genetic algorithm, which guarantees the feasibility of all the generated potential solutions.

## 2 MODEL PREDICTIVE CONTROL COMBINED WITH A FUZZY MODEL

In this work, the MPC is combined with the fuzzy model based on the subtractive clustering approach. The model predictive controller combined with a fuzzy model is called a fuzzy model predictive controller. The MPC 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. A performance index for deriving an optimal control input is represented by the following quadratic function:

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

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


Kim J., Kim D. and Na M..
A Fault-Tolerant Controller for an SP-100 Space Nuclear Reactor.
DOI: 10.5220/0004006704520457
In *Proceedings of the 9th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2012), pages 452-457
ISBN: 978-989-8565-21-1

### 2.1 Output Prediction using a Fuzzy Model

In this work, a fuzzy model based on subtractive clustering (SC) is 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:

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

The input vector to the fuzzy model consists of $y$ and $\Delta u$ which are past values of output and control input move, respectively, and can be indicated as a vector consisting of a total of $m$ elements ( $m = n_y + n_u$ , a total number of input variables to the fuzzy model):

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

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. 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 $A_i(\mathbf{x}(t))$ of an input data vector $\mathbf{x}(t)$ to a cluster center $\mathbf{x}^*(i)$ can be defined as follows:

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

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 $f_i\left(\mathbf{x}(t)\right)$ which is an output of a fuzzy rule is a polynomial in the input variables and represented by the first-order polynomial of inputs as follow:

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

### 2.2 Control Input Optimization by a Genetic Algorithm

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.

The fuzzy model is optimized by a genetic algorithm, combined with a least-squares method. That is, the genetic algorithm is used to optimize the cluster radius, $r_\alpha$ , for the subtractive clustering of numerical data, and the least squares algorithm is used to calculate the consequent parameters, $q_{i,j}$ and $r_i$ .

## 3 FAULT-TOLERANT CONTROL USING FAULT DETECTION AND DIAGNOSTICS

Since the human access for fixing the faults is almost impossible in an outer space and also, the maintenance to use robots is very difficult, the SP-100 space nuclear reactor must supply the stable and reliable power source even under the measurement faults related to the control system to support the space exploration and exploitation activities in the outer space. Fault detection and diagnostics is an important module in fault-tolerant control systems and it is desirable to provide diagnostic information as soon as faults develop, so that the controllers are automatically reconfigured and the further deterioration is prevented.

In this work, a fault detection and diagnostics algorithm is 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 sequential probability ratio rest (SPRT) so that the FTC can handle the fault situations of the input and output measurements or partial loss of actuators. In this work, a fuzzy model is 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.

The objective of sensor fault detection and diagnostics is to diagnose sensor health as soon as possible with a very small probability of making a wrong decision. The SPRT uses the residual (difference between the measured value and the estimated value, $y(t)-\hat{y}(t)$). Normally the residual signals are randomly distributed, so they are nearly uncorrelated and have a Gaussian distribution function $P_i(\varepsilon_t, m_i, \sigma_i)$, where $\varepsilon_t$ is the residual signal at time instant $t$, and $m_i$ and $\sigma_i$ are the mean and the standard deviation under hypothesis $i$, respectively. The sensor degradation or fault can be stated in terms of a change in the mean $m$ or a change in the variance $\sigma^2$. Therefore, the SPRT detects sensor health by sensing the alteration of the probability distribution. If a set of samples, $x_i$, $i=1,2,\cdots,k$, is collected with a density function describing each sample in the set, an overall likelihood ratio is given by

$$\gamma_k = \frac{P_1(\varepsilon_1|H_1)\cdot P_1(\varepsilon_2|H_1)\cdot P_1(\varepsilon_3|H_1)\cdots P_1(\varepsilon_k|H_1)}{P_0(\varepsilon_1|H_0)\cdot P_0(\varepsilon_2|H_0)\cdot P_0(\varepsilon_3|H_0)\cdots P_0(\varepsilon_k|H_0)} \quad (8)$$

where $H_0$ represents a hypothesis that the sensor is normal and $H_1$ represents a hypothesis that the sensor is degraded.

By taking the logarithm of the above equation and replacing the probability density functions in terms of residuals, means and variances, the log likelihood ratio can be written as the following recurrent form:

$$\lambda_k = \lambda_{k-1} + \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \frac{(\varepsilon_k - m_0)^2}{2\sigma_0^2} - \frac{(\varepsilon_k - m_1)^2}{2\sigma_1^2} \quad (9)$$

This ratio is used for deriving the sensor drift detection algorithm. For a normal sensor, the log likelihood ratio would decrease and eventually reach a specified bound $A$, a smaller value than zero. When the ratio reaches this bound, the decision is made that the sensor is normal, and then the ratio is reinitialized by setting it equal to zero. For a degraded sensor, the ratio would increase and eventually reach a specified bound $B$, a larger value than zero. When the ratio is equal to $B$, the decision is made that the sensor is degraded. The specified bounds $A$ and $B$ are important in determining the sensor faults. The decision boundaries $A$ and $B$ are chosen by a false alarm probability $\alpha$ and a missed alarm probability $\beta$; $A=\ln\left(\frac{\beta}{1-\alpha}\right)$ and $B=\ln\left(\frac{1-\beta}{\alpha}\right)$.

The input signal is the control drum angle to regulate the reactivity and the output signal to be controlled is the TE power. 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. 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. The schematic block diagram of the proposed FTC is illustrated in Figure 1.

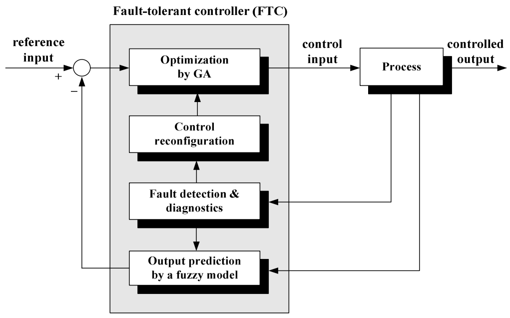



Figure 1: Block diagram of the proposed FTC for an SP-100 space reactor.

## 4 APPLICATION TO THE SP-100 SPACE REACTOR

The reactor system of the SP-100 space reactor 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. Figure 2 shows a schematic of one loop of the reactor system. 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.

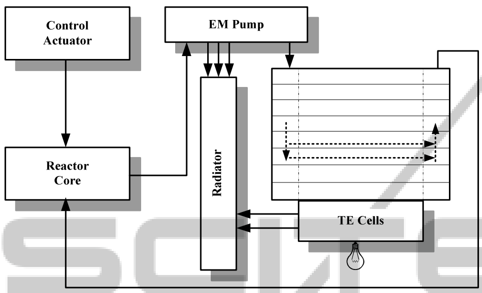



Figure 2: Schematic of TE SP-100 space reactor system.

## 4.1 SP-100 System Description

The individual modules of the integrated model, as shown in Figure 3, include a model of reactor control mechanism, a neutron kinetics model, a reactor core heat transfer model, and a heat exchanger model coupled with the TE conversion model.

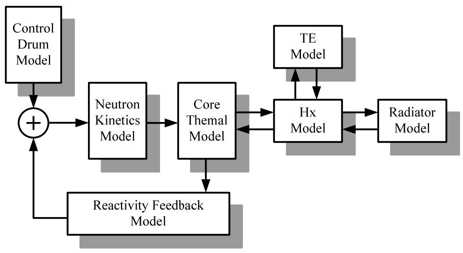



Figure 3: Integrated model of the SP-100 system.

The point reactor kinetics model with six delayed neutron groups is used to describe the dependence of nuclear reactor power on the reactivity change. This is given by the following equations:

$$\begin{aligned}\frac{dP(t)}{dt} &= \frac{\rho(t)-\beta}{\Lambda}P(t)+\sum_{i=1}^{6}\lambda_i C_i(t) \\ \frac{dC_i(t)}{dt} &= \frac{\beta_i}{\Lambda}P(t)-\lambda_i C_i(t)\end{aligned} \tag{10}$$

A simplified reactor core heat transfer model is developed to calculate the fuel temperature, the cladding temperature, and the average core coolant temperature. The fuel temperature $T_f$, the cladding temperature $T_{clad}$ and the average core coolant temperature $T_c$ are described by the following ordinary differential equations:

$$\frac{dT_f(t)}{dt} = \frac{P-\left(T_f-T_{clad}\right)(UA)_f}{C_f} \tag{11}$$

$$\frac{dT_{clad}(t)}{dt} = \frac{\left(T_f-T_{clad}\right)(UA)_f-\left(T_{clad}-T_c\right)(UA)_{clad}}{C_{clad}} \tag{12}$$

$$\frac{dT_c(t)}{dt} = \frac{\left(T_{clad}-T_c\right)(UA)_{clad}-\dot{m}_c C_P\left(T_{ex}-T_{in}\right)}{C_c} \tag{13}$$

where the parameters have their usual meanings.

Electric power is generated by 3 loops × 12 primary heat exchangers × 30 channels × 480 TE cells. Each TE cell consists of two semiconductors, one P-type and one N-type. Because there is a temperature gradient between the hot shoes and the cold shoes of TE cells, when heat is conducted from the hot shoe of a TE cell to its cold shoe, electric power will be generated due to the Seebeck effect.

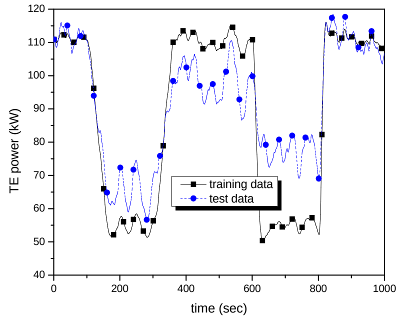
## 4.2 Applications

The FTC for the TE power control is subject to constraints as follows:

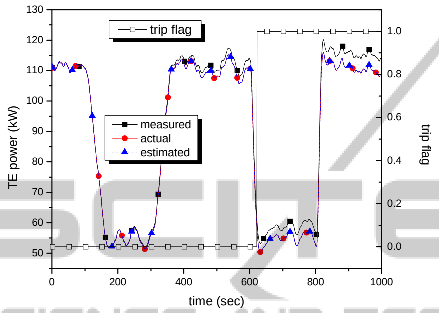
$$\begin{gathered}\Delta u(t+j-1)=0 \ \text{ for } \ j>M \\ 0^o \le u(t) \le 180^o \\ \left|\Delta u(t)\right| \le 1.4^o T\end{gathered}$$

Figure 4 describes the performance of a developed fault detection and diagnostics algorithm. Figure 4(a) shows the training and test data used to design and test the algorithm. Figure 4(b) shows the fault detection and diagnostics performance when the output measurement is assumed to begin to be gradually degraded artificially from 300 sec. The signals used to estimate the output measurement are the reactor core thermal power, control drum angle, core inlet and outlet temperatures, and cold shoe and hot shoe temperatures, which is a total of 6 signals. Since the output signal of the control system is important above all, the output measurement fault was simulated. The gradual degradation of the output measurement is detected at 321 sec since the beginning of the gradual degradation.

Figure 5 shows the performance of the proposed FTC for normal transients such as the setpoint change of TE power. The setpoint starts to change

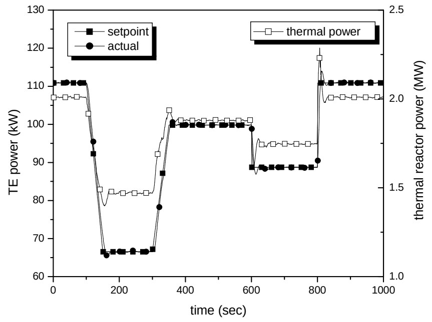



(a) training data and test data

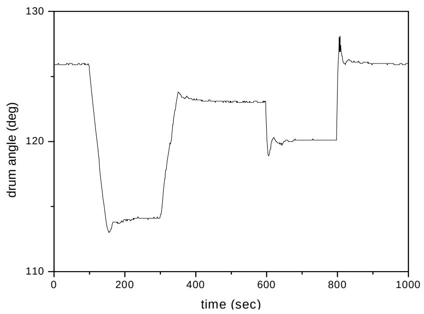



(b) fault detection and diagnostics

Figure 4: Performance of a fault detection and diagnostics algorithm.

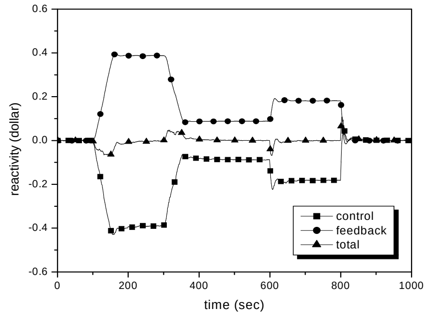



(a) TE power and thermal reactor power.

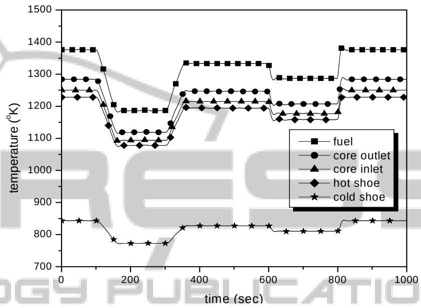



(b) control drum angle

Figure 5: Performance of the proposed FTC for normal transients.




(c) reactivity




(d) temperature

Figure 5: Performance of the proposed FTC for normal transients (cont.).

by ramp at 100 sec and 300 sec, respectively and also changes by step at 600 sec and 800 sec. The performance of the proposed controller was checked with a roughly adjusted factor of $\omega = 1$. It is shown that the TE generator power follows its desired setpoint change very well. It was known that the proposed controller meets several constraints very well and accomplishes the fast and stable responses.

## 5 CONCLUSIONS

In this work, the fault-tolerant controller combining a model predictive controller and the fault detection and diagnostics algorithm 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 by 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 simulation result of the fault-tolerant controller shows that the TE generator power follows its desired setpoint change very well. Also, the proposed controller meets several constraints very well and accomplishes the fast and stable responses.

## REFERENCES


S. F. Demuth, 2003, *SP-100 Space Reactor Design*, Progress in Nuclear Energy, Vol. 42, No. 3, pp. 323-359.

Y. B. Shtessel, 1998, *Sliding Mode Control of the Space Nuclear Reactor System*, IEEE Trans. Aerospace and Electronic Systems, Vol. 34, No. 2, pp. 579-589.

M. G. Na and B. R. Upadhyaya, Aug. 2006, *Model Predictive Control of an SP-100 Space Reactor Using Support Vector Regression and Genetic Optimization*, IEEE Trans. Nucl. Sci., Vol. 53, No. 4, pp. 2318-2327.

M. G. Na and B. R. Upadhyaya, Nov./Dec., 2006, *Application of Model Predictive Control Strategy Based on Fuzzy Identification to an SP-100 Space Reactor*, Annals of Nuclear Energy, Vol. 33, Nos. 17-18, pp. 1467-1478.

M. G. Na, B. R. Upadhyaya, X. Xu, and I. J. Hwang, Nov. 2006, *Design of a Model Predictive Power Controller for an SP-100 Space Reactor*, Nucl. Sci. Eng., Vol. 154, No. 3, pp. 353-366.

S. L. Chiu, 1994, *Fuzzy Model Identification Based on Cluster Estimation*, J. Intell. Fuzzy Systems, Vol. 2, pp. 267-278.

H. Sarimveis and G. Bafas, 2003, *Fuzzy Model Predictive Control of Non-linear Processes Using Genetic Algorithms*, Fuzzy Sets Systems, Vol. 139, pp. 59-80.

M. G. Na and I. J. Hwang, 2006, *Design of a PWR Power Controller Using Model Predictive Control Optimized by a Genetic Algorithm*, Nucl. Eng. Tech., Vol. 38, No. 1, pp. 81-92.

W. H. Kwon and A. E. Pearson, 1977, *A Modified Quadratic Cost Problem and Feedback Stabilization of a Linear System*, IEEE Trans. Automatic Control, Vol.22, No. 5, pp. 838-842.

J. Richalet, A. Rault, J. L. Testud, and J. Papon, 1978, *Model Predictive Heuristic Control: Applications to Industrial Processes*, Automatica, Vol.14, pp. 413-428.

C. E. Garcia, D. M. Prett, and M. Morari, 1989, *Model Predictive Control: Theory and Practice – A Survey*, Automatica, Vol. 25, No. 3, pp. 335-348.