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# Optimization of The Axially Variable Strength Control Rods with Simulation Optimization for The Power Maneuvering for Pressurized Water Reactor

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## Abstract

In this research, the optimization of the axially variable strength control rods (AVSCRs) is performed to provide the AVSCRs with optimal performance for the power maneuvering for PWRs. The optimization objectives are minimizing AO variation and power deviation from target value during the power maneuvering. And the objective functions for the optimization are relationship between AO variation(or power deviation) and worth shape of the AVSCRs. However, in this case, analytic objective function does not exist and the response for input can only be evaluated by computer simulation. Therefore the simulation optimization methodology is used. A typical 100-50-100%, 2-6-2-14h pattern of daily load-follow power maneuvering is adopted in this work based on the demand pattern in Korea. The optimization result shows that the optimized AVSCR has good performance on the AO control and the violation of the AO target boundary during the power maneuvering is minimized, and consequently the AO is regulated well within the AO target band during the power maneuvering.

## I. Introduction

During the power maneuvering of a nuclear power plant, the reactor core is in a transient state induced by transient effects of xenon. The reactivity change makes variation of xenon concentration and axial distribution, and a change in xenon axial distribution causes xenon oscillation, which makes reactor be able to reach uncontrollable state or trip. Therefore, in order to prevent a xenon oscillation, maintaining the axial power distribution within some prescribed range is required during the power maneuvering. However, the reactivity change using the existing mechanisms has difficulties in maintaining this distribution within the prescribed range. In previous study, therefore, lower shifted worth control rods are suggested as a kind of axially variable strength control rods(AVSCRs) to mitigate variation of axial power distribution during the power maneuvering. And through this work, the utilities of the AVSCRs(lower shifted worth control rods) are identified such that these rods have good characteristics for controlling the AO during the power maneuvering of PWRs and the power maneuvering without reactivity compensation by change of boron concentration is accomplished.[1]

In this work, the optimization of the worth shape of the AVSCRs is performed to provide the AVSCRs with optimal performance for the power maneuvering for PWRs. The suggested AVSCRs, in this work, are axially three-sectioned control rods. This control rod is divided into three sections which have different strength each other. The optimization objectives are minimizing AO variation and power deviation from target value during the power maneuvering. And the objective functions for the optimization are relationship between AO variation(or power deviation) and worth shape of the AVSCRs. However, in this case, analytic objective function does not exist and the response for input can only be evaluated by computer simulation using reactor simulation code. Therefore the simulation optimization methodology is used. A simulation optimization problem is an optimization problem where the objective function and/or some constraints are responses that can only be evaluated by computer simulation.

## II. Simulation Optimization

When the mathematical model of a system is studied using simulation, it is called a simulation model. System behavior at specific values of input variables is evaluated by running the simulation model for a fixed period of time. A simulation experiment can be defined as a test or a series of tests in which meaningful changes are made to the input variables of a simulation model so that we may observe and identify the reasons for changes in the output variables. The process of finding the best input variable value from among all possibilities without explicitly evaluating each possibility is simulation optimization.[2] Simply stated, a simulation optimization problem is an optimization problem where the objective function (objective functions, in case of a multi-criteria problem) and/or some constraints are responses that can only be evaluated by computer simulation.

The major issues that simulation optimization addresses are as follows: First, there does not exist an analytical expression of the objective function or the constraints. This eliminates the possibility of differentiation or exact calculation of local gradients. Second, the objective function(s) and constraints are stochastic functions of the deterministic decision variables. This presents a major problem in estimation of even approximate local derivatives. Furthermore, this works against even using complete enumeration because based on just one observation at each point the best decision point cannot be determined. Finally, computer simulation programs are much more expensive to run than evaluating analytical functions. This makes the efficiency of the optimization algorithms more crucial.

And there are advantages in using simulation in optimization that can be exploited. In particular: First, complexity of the system being modeled does not significantly affect the performance of the optimization process. Second, for stochastic systems, the variance of the response is controllable by various output analysis techniques. Finally, where structural optimization of systems are considered, simulation provides an advantage that is often not possible in classical optimization procedures. Here, by employing appropriate techniques, the objective function or constraint can be changed from one iteration to another to reflect alternative design for the system.[3]

The formulation of simulation optimization problems is often done for maximization or minimization of the expected value of the objective function of the system. A general simulation model comprises $n$ input variables $(x_1, x_2, \cdots x_n)$ and $m$ output variables $(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \cdots, f_m(\boldsymbol{x}))$ or $(y_1, y_2, \cdots, y_m)$ as shown in Fig. 1. Simulation optimization entails finding optimal settings of the input variables, i.e. values of $x_1, x_2, \cdots x_n$, which optimize the output variable(s).

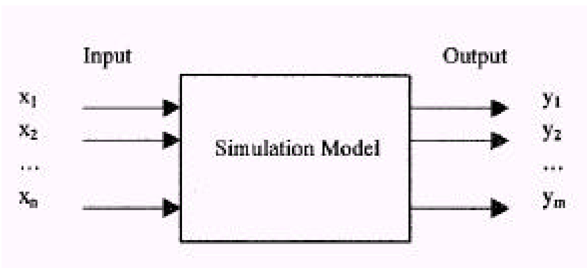



Fig. 1 A general simulation model

A simulation optimization model is displayed in Fig. 2. The output of a simulation model is used by an optimization strategy to provide feedback on progress of the search for the optimal solution. This in turn guides further input to the simulation model.

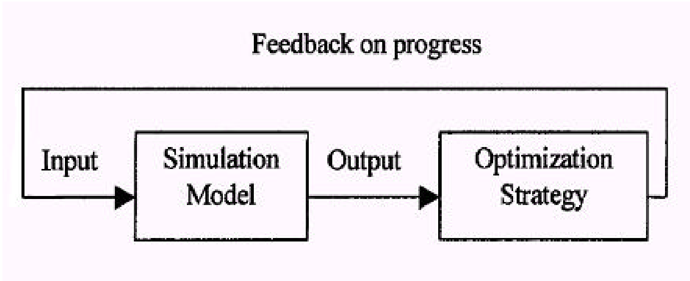



Fig. 2 A simulation optimization model

Simulation optimization methodologies are classified into the six major categories as follows: The first is gradient based search method. The methods in this category estimate the response function gradient to assess the shape of the objective function and employ deterministic mathematical programming technique. The second is stochastic optimization. This is the problem of finding a local optimum for an objective function whose values are not known analytically but can be estimated or measured. The third is response surface methodology(RSM). The RSM is a procedure for fitting a series of regression models to the output variable of a simulation model by evaluating it at several input variable values and optimizing the resulting regression function. The process starts with a first order regression function and the steepest ascent/descent method. After reaching the vicinity, higher degree regression functions are employed. The others are heuristic methods, A-teams, and statistical methods.[2]

Among the six methods, in this work, the response surface methodology is used as the simulation optimization algorithm for the optimization of the worth shape of the AVSCRs.

## III. Optimization of The Worth Shape of The AVSCRs Using RSM

The control rods are classified, in previous study, into two types. The first type is 'multi-purpose control rod', and the other is 'regulating control rod'. Two multi-purpose control rod banks and three regulating control rod banks are suggested. The main tasks of the multi-purpose control rods are controlling the AO and producing the required reactivity instead of a boron concentration change(boration/dilution) during the power maneuvering. And the main purpose of the regulating control rods is producing reactivity change as existing normal control rods.

Two axially variable strength control rods(AVSCRs) are selected as the multi-purpose control rods and existing normal control rods are used as the regulating control rods. The first multi-purpose control rod is the AVSCR1. The AVSCR1 moves mainly in the bottom half of the reactor core, and the AO approaches the upper AO target boundary at initial core state due to this AVSCR1. The requirements of the AVSCR1 are as follows: In respect of AO control, the role of the AVSCR1 is lifting up the AO, therefore the AVSCR1 should mitigate an AO distortion to the negative direction caused by the motion of the other control rods. Also, the AVSCR1 should cause the required reactivity change instead of boron concentration change. The other multi-purpose control rod is the AVSCR2. The AVSCR2 moves in the whole range of the core differently from the AVSCR1. The requirement of the AVSCR2 are as follows: The AVSCR2 controls the AO to the negative and/or the positive direction, and mitigates an AO variation due to the motion of the other control rods. Another important role of the AVSCR2 is to cause the reactivity change needed for maintaining target reactor power instead of boron concentration change, when regulating rods are fully withdrawn.[1]

In this work, the optimization of the AVSCRs is performed to provide the AVSCRs with optimal performance for the power maneuvering for PWRs. The objectives for optimization are minimizing AO variation from target AO boundary and power deviation from target reactor power during the power maneuvering. Therefore the objective functions(optimization indexes) for this optimization are relationship between AO variation(or power deviation) from target and worth shape of the AVSCRs.

The suggested AVSCRs, in this work, are axially three-sectioned control rods. As shown in Fig. 3, this control rod is divided into three sections which have different strength each other.

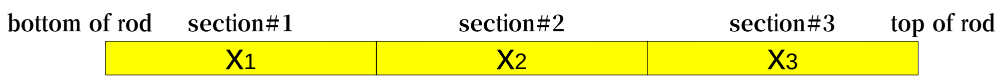



Fig. 3 Three-sectioned AVSCR

However analytic objective function for these objectives does not exist and the response for input can only be evaluated by computer simulation using reactor simulation code. Therefore the simulation optimization methodology is used and the response surface methodology is adopted as the simulation optimization algorithm for the optimization of the worth shape of the AVSCRs.

### III.1 Response Surface Methodology

The response surface methodology(RSM) is a procedure for fitting a series of regression models to the output variable of a simulation model by evaluating it at several input variable values and optimizing the resulting regression function. The RSM is a collection of statistical and mathematical techniques useful for optimizing stochastic functions, not primarily in simulation. It is frequently used for the optimization of stochastic simulation models. This methodology is based on approximation of the stochastic objective function by a low order polynomial on a small subregion of the domain. The coefficients of the polynomial are estimated by ordinary least squares applied to a number of observations of the stochastic objective function. Based on the fitted polynomial, the local best point is derived, which is used as a current estimator of the optimum and as the center point of a new region of interest, where again the stochastic objective function is approximated by a low order polynomial.[4]

RSM provides useful disciplinary models that can be easily combined and manipulated by designer. It also smooths out high frequency noises of an objective function and is thus expected to find a solution near the global optimum. Moreover, it allows various objectives and constraints without additional numerical computations. However, it has a limitation on the number of design variables since the number of data point analysis drastically increase as the number of design variables increases.

Most applications of RSM are sequential in nature. The phase zero is screening experiment. This phase reduces long list of variables to a relatively few so that subsequent experiments will be more efficient and require fewer runs or test. Once the important independent variables are identified. The phase one of RSM begins. In this phase the experimenter’s objective is to determine if the current levels of the independent variables result in a value of the response that is near the optimum or not. If the levels of the independent variables are not consistent with optimum performance, then the experimenter must a set of adjustments to the process variables that will move the process toward the optimum. This phase of RSM makes considerable use of the first-order model and an optimization technique called the method of steepest ascent/descent. The first order model is given as (1).

$$f=\beta_0+\sum_i^k \beta_i x_i \qquad (1)$$

The phase two of RSM begins when the process is near the optimum. Because the true response surface usually exhibits curvature near the optimum, a second(or higher) order model will be used and obtained model is analyzed to determine the optimum conditions for the process. The second order model is given as (2).

$$f=\beta_0+\sum_{j=1}^{k}\beta_j x_j+\sum_{j=1}^{k}\beta_{jj}x_j^2+\sum\sum_{i<j}\beta_{ij}x_i x_j \qquad (2)$$

This sequential process is usually performed within some region of the independent variable space called the operability region.[5]

### III.2 Optimization of The Worth Shape of AVSCRs

The objective functions(optimization indexes) used in this work are the degree of violation of the AO target boundary, power deviation from the reference target power, and initial AO (for AVSCR1). These objective functions are evaluated by computer simulation using ONED94 as follows:

First, an instant AO violation at time $t$, $f_{AOV}(t)$ is calculated as the difference between an instant AO and the AO target boundary shown in Fig. 4.

$$f_{AOV}(t)=\begin{cases} |AO(t)-AO_{upper}|, & (AO(t)>AO_{upper}) \\ |AO(t)-AO_{lower}|, & (AO(t)<AO_{lower}) \end{cases}$$

And an instant power deviation at time $t$, $f_{PWD}(t)$ is calculated as the difference between an instant power and the target power shown in Fig. 4.

$$f_{PWD}(t)=|PW(t)-PW_{tg}|, \qquad \text{where, } PW_{tg}(t): 2-6-2-14 \text{ load pattern}$$

Then index for AO violation and index for power deviation are calculated as the average of instant AO violation and power deviation for $n$ periods.

$$g_{AOV}(x_1,x_2,x_3)=\frac{\sum_{k=1}^{n\ \text{periods}} f_{AOV}(k\Delta t)\Delta t}{n\ \text{periods}}$$

$$g_{PWD}(x_1,x_2,x_3)=\frac{\sum_{k=1}^{n\ \text{periods}} f_{PWD}(k\Delta t)\Delta t}{n\ \text{periods}}$$

where $(x_1,x_2,x_3)$ are the value of strength at each section of AVSCR. And, in above formulas, $AO(t)$ and $PW(t)$ cannot be calculated analytically but can be evaluated by computer simulation.

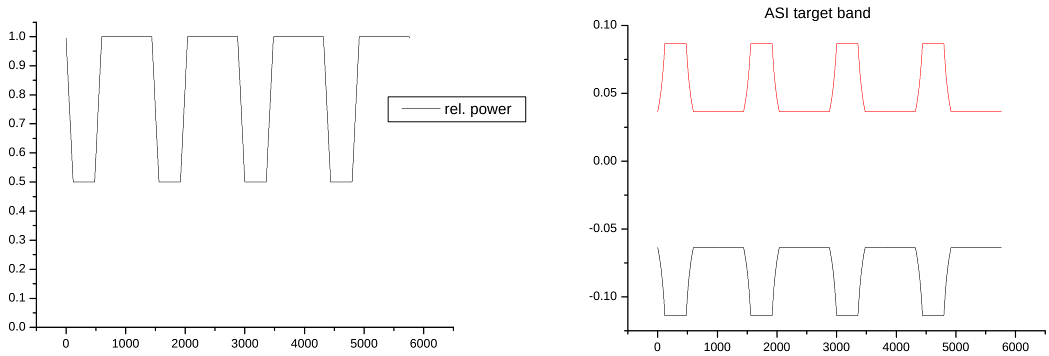



Fig. 4 Target power and AO target band according to power variation

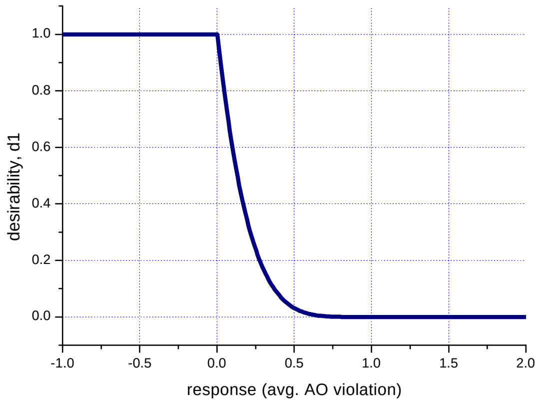
Second, the index for initial AO, $g_{AOi}(x_1, x_2, x_3)$ is evaluated as $AO(0)$ for AVSCR1.

Because there are more than two objective functions, the optimization becomes multiple objective optimization. For solving this problem, a desirability function in which the researcher' s own priorities and desires on the response value are built into the optimization procedure is used. For optimization of AVSCR1, the degree of violation of the AO target boundary and initial AO are considered, and following desirability functions are used:

The first index is the degree of violation of the AO target boundary and the second index is initial AO. For index1, the desirability function is given as Fig. 5(a) because minimizing the degree of violation of the AO target boundary to zero is most desirable. The desirability function for index2 is given as Fig. 5(b) so that the value of initial AO may be greater than 0.0365. And single composite response $D$ is calculated as:

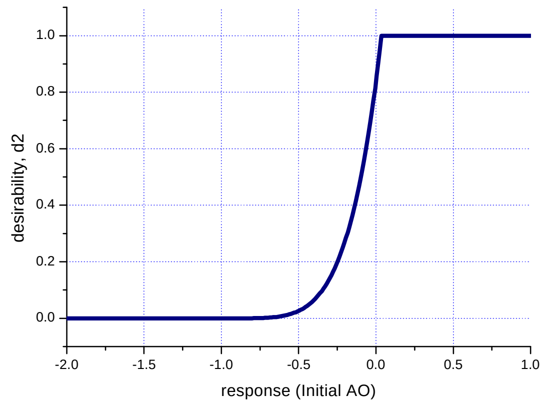
$$D = \sqrt{d_1 \cdot d_2}$$

Taking into account all two responses, clearly one wishes to choose the condition on the design variable(the strength of each section of AVSCR) that maximize $D$. A value of $D$ close to 1.0 implies that all responses are in a desirable range simultaneously.




$$d_1 = \left( \frac{\hat{y} - 1.0}{0 - 1.0} \right)^5, \quad \text{for index1}$$

Fig. 5(a) The desirability function for index1




$$d_2 = \left( \frac{\hat{y} - (-1.0)}{0.0365 - (-1.0)} \right)^5, \quad \text{for index2}$$

Fig. 5(b) The desirability function for index2

Then the optimization which maximize the value of $D$ is performed in following conditions: The initial value of $\boldsymbol{x}=(x_1, x_2, x_3)$ is set as (2.0, 2.0, 2.0) and the size of the region of interest is 0.005. In phase one of RSM procedure, a $\frac{1}{2}$fraction of a $2^3$ factorial(resolution III) is used with each design point replicated and a method of steepest ascent is used. In phase two, a central composite design(CCD) is used. For experiments, the ONED94 code is used for an application plant. The ONED94 code is an one-dimensional reactor core simulation code. A typical 100-50-100%, 2-6-2-14h pattern of daily load-follow power maneuvering is adopted based on the demand pattern in Korea. The power varies from 100 to 50% in 2h, holds at 50% for 6h, then rise to 100% in 2h. And the burn-up state of the reactor core is BOC. The optimization indexes are evaluated for one-day load cycle. And the optimization results are shown in Fig. 6.

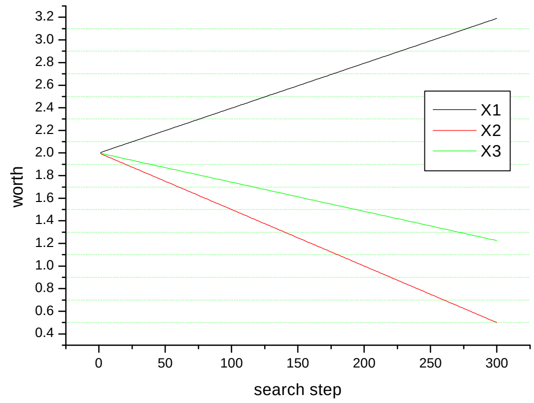



Fig. 6(a) The variation of $(x_1, x_2, x_3)$

Fig. 6(a) shows the variation of $(x_1, x_2, x_3)$ as the optimization is progressed. From the result, it is shown that the shape of AVSCR1 is optimized to (3.1903, 0.5, 1.2255).

Fig. 6(b) indicates the variation of $D$-value and two indexes(the degree of violation of the AO target boundary, initial AO). The $D$-value approaches 1.0 and the degree of violation of the AO target boundary approaches 0.0 as the optimization is progressed.

Finally, the variation of the AO according to time during one-day cycle is shown in Fig. 6(c) and Fig. 6(d). This results shows the effect of this optimization. As shown in Fig. 6(c), the AO is not regulated correctly within the AO target band and the violation of the AO target boundary is relatively large when the initial(before optimization) AVSCR1 is used. However the AO is regulated well within the AO target band during the power maneuvering and the violation of the AO target boundary is minimized after optimization of the worth shape of the AVSCR1 as shown in Fig. 6(d).

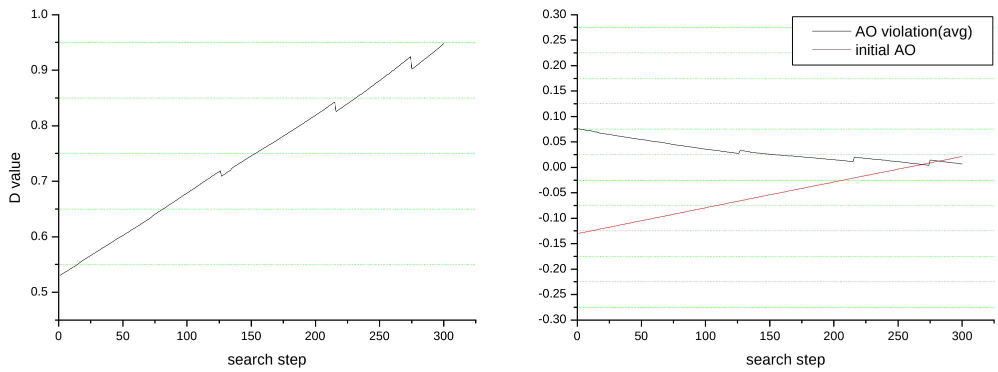



Fig. 6(b) The variation of $D$-value and two indexes

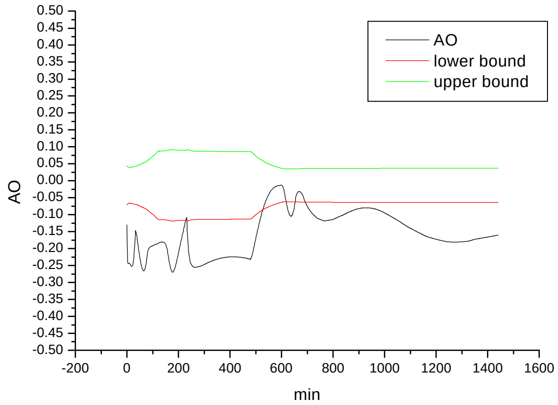



Fig. 6(c) The AO variation with initial AVSCR1 during one-day cycle

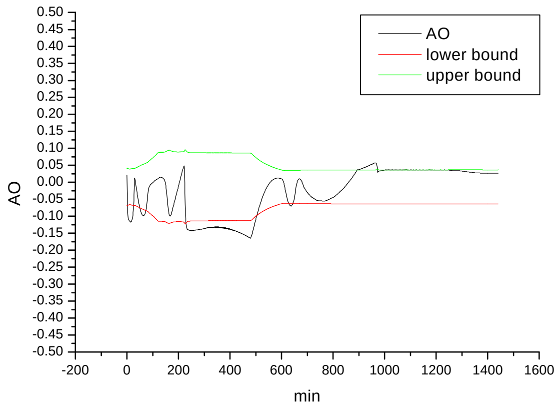



Fig. 6(d) The AO variation with optimized AVSCR1 during one-day cycle

## IV. Conclusions

In this research, the axially variable strength control rods (AVSCRs) are suggested and the optimization of the AVSCRs is performed to provide the AVSCRs with optimal performance for the power maneuvering for PWRs. The suggested AVSCRs are axially three-sectioned control rods. This control rod is divided into three sections which have different strength each other. The optimization objectives are minimizing AO variation and power deviation from target value during the power maneuvering. And the objective functions for the optimization are relationship between AO variation(or power deviation) and worth shape of the AVSCRs. However, in this case, analytic objective function does not exist and the response for input can only be evaluated by computer simulation using reactor simulation code.

Therefore the simulation optimization methodology is used. The process of finding the best input variable value from among all possibilities without explicitly evaluating each possibility is simulation optimization. Simply stated, a simulation optimization problem is an optimization problem where the objective function and/or some constraints, are responses that can only be evaluated by computer simulation. The simulation optimization methodologies are classified into the six major categories and among the six methods, in this work, the RSM is used as the simulation optimization algorithm for the optimization of the worth shape of the AVSCRs. The RSM is a procedure for fitting a series of regression models to the output variable of a simulation model by evaluating it at several input variable values and optimizing the resulting regression function. The process starts with a first order regression function and the steepest ascent/descent method. After reaching the vicinity, higher degree regression functions are employed.

Then the optimization is performed and a typical 100-50-100%, 2-6-2-14h pattern of daily load-follow power maneuvering is adopted based on the demand pattern in Korea. The optimization result shows that the optimized AVSCR has good performance on the AO control and the violation of the AO target boundary during the power maneuvering is minimized, and consequently the AO is regulated well within the AO target band during the power maneuvering.

Through this work, the optimization of the worth shape of axially variable strength control rods, in order to provide these rods with the optimal performance for the power maneuvering, is performed. However, the safety analyses required in order to implement AVSCRs have not been performed yet. Hence, the safety analyses will be performed in further research considering several constraints such as regulation guides, shutdown margin, and etc.

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