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A Model Predictive Controller for The Water Level of Nuclear Steam Generators

Man Gyun Na
Chosun University
375 Seosuk-dong, Dong-gu, Kwangju 501-759, Korea

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Abstract

In this work, the model predictive control method was applied to a linear model and a nonlinear model of steam generators. The parameters of a linear model for steam generators are very different according to the power levels. The model predictive controller was designed for the linear steam generator model at a fixed power level. The proposed controller designed at the fixed power level showed good performance for any other power levels by changing only the input-weighting factor. As the input-weighting factor usually increases, its relative stability does so. The steam generator has some nonlinear characteristics. Therefore, the proposed algorithm has been implemented for a nonlinear model of the nuclear steam generator to verify its real performance and also, showed good performance.

Key Words : model predictive control, nuclear steam generator, water level control

1. Introduction

The water level of a nuclear steam generator must be properly controlled in order to secure the sufficient cooling water of the nuclear reactor and to prevent the damage of turbine blades. The inadequate and insufficient performance of the conventional controller has often resulted in reactor trip (shutdown) and enforced operators to hang on manual operation at low power (mainly, at a startup time of a nuclear power plant). Also, the non-minimum phase effects are significantly greater at low power, which makes more dangerous the use of a high gain of the control loop at a reduced power level. Even to a skilled operator, therefore, it is hard to react effectively in response to the reverse dynamics (swell and shrink phenomena) of the water level, which is induced by the non-minimum phase effects. Also, the steam generator is highly complex, non-linear, and time-varying system. Particularly, its parameters undergo large changes according to changes in operating conditions [1]. The steam generator with narrow stability margin cannot work satisfactorily with fixed P-I gains over all power levels. Therefore, many advanced control methods that include adaptive controllers [1-2], optimal controllers [3-4], and fuzzy logic controllers [5-8], have been suggested to solve the steam generator water level control problem.

The model predictive control methodology has received much attention as a powerful tool for the control of industrial process systems [9-14]. The basic concept of the model predictive control 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. As it were, at the present time k the behavior of the process over a horizon N is considered. Using a model the process response to changes in the manipulated variable is predicted. The moves of the manipulated variables are selected such that the predicted response has certain desirable characteristics. Only the first computed change in the manipulated variable is implemented. The procedure is then repeated at each subsequent instant. This method presents many advantages over the conventional infinite horizon control because it is possible to handle input and state (or output) constraints in a systematic manner during the design and implementation of the control. In particular, it is a suitable control strategy for time varying systems.

The objective of this work is to design a satisfactory automatic controller without any manual operation from start-up to full load transient conditions. In this work, the model predictive control method was applied to a linear model [1] and a nonlinear model [15] of steam generators. The parameters of the steam generator linear model are very different according to the power levels. The model predictive controller was designed for the linear steam generator model at a fixed power level. The steam generator has some nonlinear characteristics. Therefore, the proposed algorithm has to be implemented for a nonlinear model of the nuclear steam generator to verify its real performance.

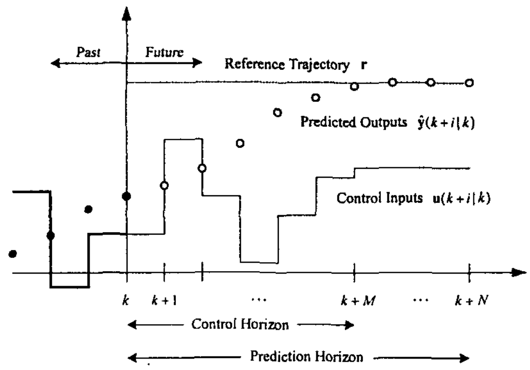


Fig. 1. Model Predictive Control Method

2. Model Predictive Control Method

Model predictive control is a popular technique for the control of slow dynamical systems. At every time instant, model predictive control requires the on-line solution of an optimization problem to compute optimal control inputs over a fixed number of future time instants, known as the time horizon. The on-line optimization can be typically reduced to either a linear program or a quadratic program.

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. Figure 1 shows this basic concept [11]. As it were, for any assumed set of present and future control moves, the future behavior of the process outputs can be predicted over a horizon N, and the M present and future control moves ($M \leq N$) are computed to minimize a quadratic objective function. Though M control moves are calculated, only the first control move is implemented. At the next period, new values of the measured output are obtained, the control horizon is shifted forward by one step, and the same calculations are repeated.

The following time invariant discrete system will be considered:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}\mathbf{x}(k)+\mathbf{B}\Delta\mathbf{u}(k)+\mathbf{E}\mathbf{v}(k), \\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k), \end{aligned} \tag{1}$$

where $\mathbf{x}(k)\in R^n$, $\Delta\mathbf{u}\in R^m$, $\mathbf{v}(k)\in R^l$, and $\mathbf{y}(k)\in R^p$ are the state vector, control input (feedwater flowrate), measurable disturbance (steam flowrate), and process output (steam generator water level), respectively. In Eq. (1), the control input $\Delta\mathbf{u}$ was used to remove the offset error. The associated performance index is the following quadratic function:

$$\begin{aligned} J =& \frac{1}{2}\sum_{j=0}^{M}\left\{(\mathbf{y}(k+j)-\mathbf{r}(k+j))^T\mathbf{Q}(\mathbf{y}(k+j)-\mathbf{r}(k+j))+\Delta\mathbf{u}(k+j)^T\mathbf{R}\Delta\mathbf{u}(k+j)\right\} \\ &+\frac{1}{2}\sum_{j=M+1}^{N}(\mathbf{y}(k+j)-\mathbf{r}(k+j))^T\mathbf{Q}_F(\mathbf{y}(k+j)-\mathbf{r}(k+j)), \end{aligned} \tag{2}$$

where $\mathbf{Q}$ (positive semi-definite), $\mathbf{Q}_F$ (positive semi-definite) and $\mathbf{R}$ (positive definite) are weighting matrices to penalize particular components of $(\mathbf{y}-\mathbf{r})$ or $\Delta\mathbf{u}$ at certain future time intervals and also, they are symmetric matrices, and is a reference input (target).

The objective is to find the control sequence $\Delta\mathbf{u}(k)$, $\Delta\mathbf{u}(k+1)$, $\cdots$ $\Delta\mathbf{u}(M)$ (assuming $\Delta\mathbf{u}(M+1) = \cdots = \Delta\mathbf{u}(N)=0$) to minimize the quadratic function. Using the powerful Lagrange-multiplier approach, since there is a constraint function $\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k)+\mathbf{B}\Delta\mathbf{u}(k) + \mathbf{E}\mathbf{v}(k)$, specified at each time k in the interval of interest $[k, k + N]$, we shall require a Lagrange multiplier at each time. We append the constraint to the performance index to define an augmented performance index J' by

$$\begin{aligned} J' =& \sum_{j=0}^{M}\Big[L_1^j(\mathbf{x}(k+j),\Delta\mathbf{u}(k+j))+\boldsymbol{\lambda}(k+j+1)^T\big(\mathbf{A}\mathbf{x}(k+j) \\ &\qquad +\mathbf{B}\Delta\mathbf{u}(k+j)+\mathbf{E}\mathbf{v}(k+j)-\mathbf{x}(k+j+1)\big)\Big] \\ &+\sum_{j=M+1}^{N-1}\Big[L_2^j(\mathbf{x}(k+j))+\boldsymbol{\lambda}(k+j+1)^T\big(\mathbf{A}\mathbf{x}(k+j) \\ &\qquad +\mathbf{E}\mathbf{v}(k+j)-\mathbf{x}(k+j+1)\big)\Big]+L_2^N(\mathbf{x}(k+N)), \end{aligned} \tag{3}$$

where

$$\begin{aligned} L_1^j =& (\mathbf{y}(k+j)-\mathbf{r}(k+j))^T\mathbf{Q}(\mathbf{y}(k+j)-\mathbf{r}(k+j)) \\ &+\Delta\mathbf{u}(k+j)^T\mathbf{R}\Delta\mathbf{u}(k+j) \quad \text{for } j=0,\cdots,M, \\ L_2^j =& (\mathbf{y}(k+j)-\mathbf{r}(k+j))^T\mathbf{Q}_F(\mathbf{y}(k+j)-\mathbf{r}(k+j)) \\ &\text{for } j=M+1,\cdots,N. \end{aligned}$$

Defining the Hamiltonian function as

$$\begin{aligned} &H^j(\mathbf{x}(k+j),\Delta\mathbf{u}(k+j),\mathbf{v}(k+j)) \\ &= \begin{cases} L_1^j(\mathbf{x}(k+j),\Delta\mathbf{u}(k+j))+\boldsymbol{\lambda}(k+j+1)^T \\ \big(\mathbf{A}\mathbf{x}(k+j)+\mathbf{B}\Delta\mathbf{u}(k+j)+\mathbf{E}\mathbf{v}(k+j)\big) \\ \quad \text{for } j=0,\cdots,M, \\ L_2^j(\mathbf{x}(k+j))+\boldsymbol{\lambda}(k+j+1)^T \\ \big(\mathbf{A}\mathbf{x}(k+j)+\mathbf{E}\mathbf{v}(k+j)\big) \\ \quad \text{for } j=M+1,\cdots,N-1, \end{cases} \end{aligned} \tag{4}$$

we can rewrite the augmented performance index as follows:

$$\begin{aligned} J' =& L_2^N(\mathbf{x}(k+N))-\boldsymbol{\lambda}(k+N)^T\mathbf{x}(k+N)+H^0(\mathbf{x}(k),\Delta\mathbf{u}(k),\mathbf{v}(k)) \\ &+\sum_{j=0}^{N-1}\Big[H^j(\mathbf{x}(k+j),\Delta\mathbf{u}(k+j),\mathbf{v}(k+j))-\boldsymbol{\lambda}(k+j)^T\mathbf{x}(k+j)\Big]. \end{aligned} \tag{5}$$

We now examine the increment in J' due to increments in all the variables $\mathbf{x}(k+j)$, $\Delta\mathbf{u}(k+j)$, and $\lambda(k+j)$. According to the Lagrange-multiplier theory, at a constrained minimum this increment dJ' should be zero. Therefore,

$$\begin{aligned} dJ' =& \left(L^N_{2\,\mathbf{x}(k+N)}-\boldsymbol{\lambda}(k+N)\right)^T d\mathbf{x}(k+N)+\left(H^0_{\mathbf{x}(k)}\right)^T d\mathbf{x}(k)+\left(H^0_{\mathbf{u}(k)}\right)^T d\mathbf{u}(k) \\ &+\sum_{j=1}^{N-1}\Big[\left(H^j_{\mathbf{x}(k+j)}-\boldsymbol{\lambda}(k+j)\right)^T d\mathbf{x}(k+j)+\left(H^j_{\mathbf{u}(k+j)}\right)^T d\mathbf{u}(k+j)\Big] \\ &+\sum_{j=1}^{N}\left(H^{j-1}_{\boldsymbol{\lambda}(k+j)}-\mathbf{x}(k+j)\right)^T d\boldsymbol{\lambda}(k+j), \end{aligned} \tag{6}$$

where

$$H^j_{\mathbf{x}(k+j)} \equiv \frac{\partial H^j}{\partial \mathbf{x}(k+j)} \quad \text{and so on.}$$

Necessary conditions for a constrained minimum are thus given by

$$\mathbf{x}(k+j+1)=\frac{\partial H^j}{\partial \boldsymbol{\lambda}(k+j+1)},\ j=0,\cdots,N-1, \tag{7}$$

$$\boldsymbol{\lambda}(k+j)=\frac{\partial H^j}{\partial \mathbf{x}(k+j)},\ j=0,\cdots,N-1, \tag{8}$$

$$0=\frac{\partial H^j}{\partial \mathbf{u}(k+j)},\ j=0,\cdots,N-1. \tag{9}$$

which arise from the terms inside the summations and the coefficients of du(k), and

$$\left(\frac{\partial L_2^N}{\partial \mathbf{x}(k+N)}-\boldsymbol{\lambda}(k+N)\right)^T d\mathbf{x}(k+N)=0, \tag{10}$$

$$\left(\frac{\partial H^0}{\partial \mathbf{x}(k)}\right)^T d\mathbf{x}(k)=0. \tag{11}$$

From Eqs. (7)-(9)

$$\mathbf{x}(k+j+1)=\begin{cases}\mathbf{A}\mathbf{x}(k+j)+\mathbf{B}\Delta\mathbf{u}(k+j)+\mathbf{E}\mathbf{v}(k+j) \\ \quad \text{for } j=0,\cdots,M, \\ \mathbf{A}\mathbf{x}(k+j)+\mathbf{E}\mathbf{v}(k+j) \\ \quad \text{for } j=M+1,\cdots,N-1,\end{cases} \tag{12}$$

$$\boldsymbol{\lambda}(k+j)=\mathbf{C}^T\mathbf{Q}\mathbf{C}\mathbf{x}(k+j)+\mathbf{A}^T\boldsymbol{\lambda}(k+j+1) - \mathbf{C}^T\mathbf{Q}\mathbf{r}(k+j), \tag{13}$$

$$0=\mathbf{B}^T\boldsymbol{\lambda}(k+j+1)+\mathbf{R}\Delta\mathbf{u}(k+j). \tag{14}$$

From Eq. (10), Boundary conditions are as follows:

$$\boldsymbol{\lambda}(k+N)=\mathbf{C}^T\mathbf{Q}_F\left(\mathbf{C}\mathbf{x}(k+N)-\mathbf{r}(k+N)\right). \tag{15}$$

The stationarity condition, Eq. (14), shows that

$$\mathbf{u}(k+j)=-\mathbf{R}^{-1}\mathbf{B}^T\boldsymbol{\lambda}(k+j+1). \tag{16}$$

The Lagrange multiplier is a variable that is determined by its own dynamical equation. It is called the costate of the system and is called the adjoint system. The coupled state and costate equations can be written as

$$\begin{bmatrix}\mathbf{x}(k+j+1)\\ \boldsymbol{\lambda}(k+j)\end{bmatrix}=\begin{bmatrix}\mathbf{A} & -\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\\ \mathbf{C}^T\mathbf{Q}\mathbf{C} & \mathbf{A}^T\end{bmatrix}\begin{bmatrix}\mathbf{x}(k+j)\\ \boldsymbol{\lambda}(k+j+1)\end{bmatrix} +\begin{bmatrix}\mathbf{E}\\ \mathbf{0}\end{bmatrix}\mathbf{v}(k+j)+\begin{bmatrix}\mathbf{0}\\ -\mathbf{C}^T\mathbf{Q}\end{bmatrix}\mathbf{r}(k+j) \tag{17}$$

for $j=0,\cdots,M$,

$$\begin{bmatrix}\mathbf{x}(k+j+1)\\ \boldsymbol{\lambda}(k+j)\end{bmatrix}=\begin{bmatrix}\mathbf{A} & \mathbf{0}\\ \mathbf{C}^T\mathbf{Q}\mathbf{C} & \mathbf{A}^T\end{bmatrix}\begin{bmatrix}\mathbf{x}(k+j)\\ \boldsymbol{\lambda}(k+j+1)\end{bmatrix} +\begin{bmatrix}\mathbf{E}\\ \mathbf{0}\end{bmatrix}\mathbf{v}(k+j)+\begin{bmatrix}\mathbf{0}\\ -\mathbf{C}^T\mathbf{Q}_F\end{bmatrix}\mathbf{r}(k+j) \tag{18}$$

for $j=M+1,\cdots,N-1$.

This version of the control law cannot be implemented in practice, since the boundary conditions are split between times $j=0$ and $j=N$. From Eq. (15), it seems reasonable to assume that for all $j\le N$, we can write

$$\boldsymbol{\lambda}(k+j)=\mathbf{F}(j)\mathbf{x}(k+j)-\mathbf{g}(k+j). \tag{19}$$

This will turn out to be a valid assumption if consistent equations can be found for $\mathbf{F}(j)$ and $\mathbf{g}(k+j)$. We can solve the following control input through very lengthy derivation:

$$\Delta\mathbf{u}(k+j)=-\mathbf{K}(j)\mathbf{x}(k+j)-\mathbf{K}_v(j)\mathbf{v}(k+j) +\mathbf{K}_g(j)\mathbf{g}(k+j+1),\ j=0,1,\cdots,M \tag{20}$$

where

$$\mathbf{K}(j)=[\mathbf{R}+\mathbf{B}^T\mathbf{F}(j+1)\mathbf{B}]^{-1}\mathbf{B}^T\mathbf{F}(j+1)\mathbf{A},$$

$$\mathbf{K}_v(j)=[\mathbf{R}+\mathbf{B}^T\mathbf{F}(j+1)\mathbf{B}]^{-1}\mathbf{B}^T\mathbf{F}(j+1)\mathbf{E},$$

$$\mathbf{K}_g(j)=[\mathbf{R}+\mathbf{B}^T\mathbf{F}(j+1)\mathbf{B}]^{-1}\mathbf{B}^T,$$

$$\mathbf{F}(j)=\mathbf{A}^T\mathbf{F}(j+1)\mathbf{A}-\mathbf{A}^T\mathbf{F}(j+1)\mathbf{B}[\mathbf{R}+\mathbf{B}^T \mathbf{F}(j+1)\mathbf{B}]^{-1}\mathbf{B}^T\mathbf{F}(j+1)\mathbf{A}+\mathbf{C}^T\mathbf{Q}\mathbf{C},$$

$$\mathbf{F}(M)=\sum_{i=0}^{N-M-1}\left(\mathbf{A}^T\right)^i\mathbf{C}^T\mathbf{Q}_F\mathbf{C}^T\mathbf{A}^i,$$

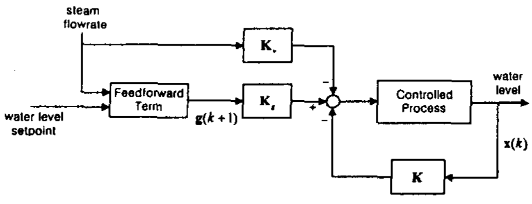


Fig. 2. Structure of the Designed Model Predictive Controller

$$\mathbf{g}(k+j) = \begin{cases} [\mathbf{A}-\mathbf{B}\mathbf{K}(j)]^T \mathbf{g}(k+j+1) - [\mathbf{A}-\mathbf{B}\mathbf{K}(j)]^T \\ \mathbf{F}(j+1)\mathbf{E}\mathbf{v}(k+j) + \mathbf{C}^T\mathbf{Q}\mathbf{r}(k+j) \ \text{ for } j \le M \\ \mathbf{A}^T\mathbf{g}(k+j+1) - \mathbf{A}^T\mathbf{F}(j+1)\mathbf{E}\mathbf{v}(k+j) \\ \quad +\mathbf{C}^T\mathbf{Q}_F\mathbf{r}(k+j) \ \text{ for } M+1 \le j \le N-1 \end{cases}$$

$$\mathbf{g}(k+N) = \mathbf{C}^T\mathbf{Q}_F\mathbf{r}(k+N).$$

Since only the first control input is implemented, the control input (feedwater flowrate) of the model predictive controller is as follows:

$$\Delta\mathbf{u}(k) = -\mathbf{K}(0)\mathbf{x}(k) - \mathbf{K}_v(0)\mathbf{v}(k) + \mathbf{K}_g(0)\mathbf{g}(k+1). \quad (21)$$

In Eq. (21), $\mathbf{K}(0)$, $\mathbf{K}_v(0)$ and $\mathbf{K}_g(0)$ are constant for time-invariant systems. However, $\mathbf{g}(k+1)$ should be solved every time step since the value depends on the reference input (water level setpoint) and the measurable disturbance (steam flowrate). Figure 2 shows the structure of the designed model predictive controller. In this figure, it is shown that the changes of the water level setpoint and steam flowrate drive the control actions.

In order to guarantee the closed-loop stability for the proposed controller, the following condition of the matrix inequality must be subjected on the terminal weighting matrix $\mathbf{Q}_F$ [14]:

$$\mathbf{C}^T\mathbf{Q}_F\mathbf{C} \ge \mathbf{A}^T\mathbf{C}^T\mathbf{Q}_F\mathbf{C}\left(\mathbf{I}+\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{C}^T\mathbf{Q}_F\mathbf{C}\right)^{-1} \mathbf{A} + \mathbf{C}^T\mathbf{Q}\mathbf{C}. \quad (22)$$

3. Application to the the Steam Generator Water Level Control

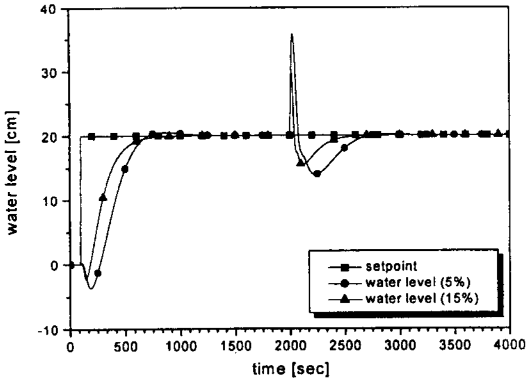
3.1. A Linear Model

Numerical simulations are performed to study the performance of the proposed algorithm. The dynamics of a steam generator is described in terms of input (feedwater flowrate; u), output (water level; y) and measurable disturbance (steam flowrate; V). Based on the step response of the steam generator water level for step changes of the feedwater flowrate and the steam flowrate, Irving [1] derived the following 4-th order Laplace transfer function for steam generators:

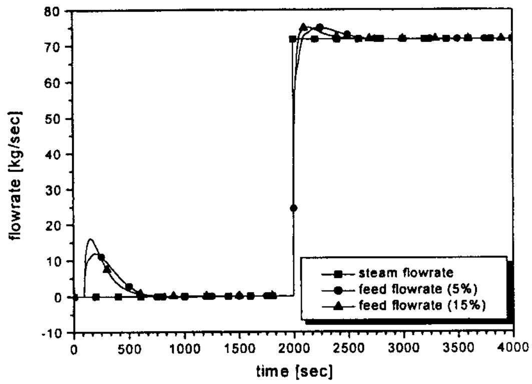
$$y(s) = \frac{G_1}{s}[u(s)-v(s)] - \frac{G_2}{1+\tau_2 s}[u(s)-v(s)] + \frac{G_3 s}{\tau_1^{-2} + 4\pi^2 T^{-2} + 2\tau_1^{-1}s + s^2}u(s), \quad (23)$$

where s is a Laplace variable. This plant is a single input (feedwater) and a single output (water level). The parameter values of a steam generator at several power levels are given in Table 1 and the parameters are very different according to the power levels. Since (G_2 - $G_1\tau_2$) is greater than zero, Eq. (23) has a positive zero that represents a non-minimum phase effect. An unstable zero lowers the control gain to preserve stability. As the load decreases, the zero moves to the right, stability being more critical and the water level of the steam generator being more difficult to control. In these numerical simulations, the sampling time is chosen to be 5 sec.

Figures 3 and 4 show the performances of this proposed controller in case it is applied to the linear model. As shown in Figs. 3 and 4, all conditions are in a steady state during initial 100 sec. Then, the setpoint of the water level was suddenly changed at 100 sec and the steam flowrate (measurable disturbance) was changed at

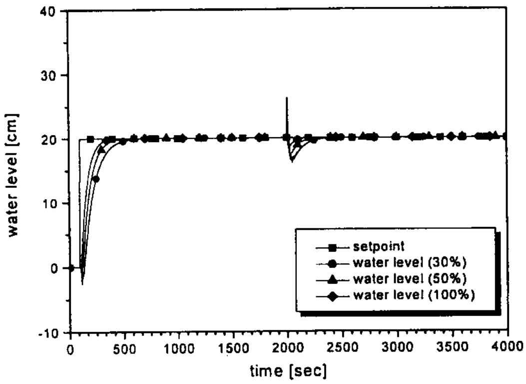


(a) water level

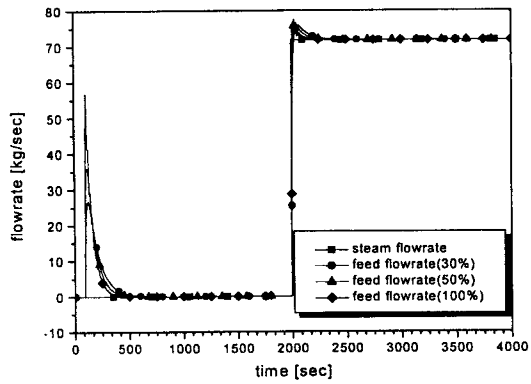


(b) flowrate

Fig. 3. Performance of the Proposed Controller for the Linear Model (Low Powers)



(a) water level



(b) flowrate

Fig. 4. Performance of the Proposed Controller for the Linear Model (High Powers)

2000 sec. In these figures, all values represent the difference from the corresponding steady state values. Therefore, all values are zeros at the steady state. The magnitude of the disturbance at 2000 sec is 5 percent rated steam flowrate [71.75kg/sec = 0.05×1435kg/sec (rated steam flowrate)]. **Q** and $\mathbf{Q}_F$ (these are scalar values because of a single output) were chosen as 0.5 and 1, respectively. The input-weighting factor **R** was differently chosen according to the power level in order to have good performances and, of course, satisfy the stability condition, Eq. (22). The prediction and control horizons are 100 and 3, respectively. The proposed control algorithm tracks well the setpoint and steam flowrate changes. Figure 5 shows the input-weighting factor versus power level. As the power level increases, the factor decreases exponentially. The swell and shrink phenomena are larger at low power levels than those at high power levels. The measured water level tracks its setpoint faster at high powers than at low powers.

3.2. A Nonlinear Model

The steam generator has some nonlinear characteristics. Therefore, the proposed algorithm has to be implemented for a nonlinear model of

Table 1. Parameters of a Steam Generator Model at Several Powers

Power level (%)	G_1	G_2	G_3	τ_1(sec)	τ_2(sec)	T(sec)	(kg/sec)
5	0.058	9.630	0.181	41.9	48.4	119.6	57.4
15	0.058	4.46	0.226	26.3	21.5	60.5	180.8
30	0.058	1.83	0.310	43.4	4.5	17.7	381.7
50	0.058	1.05	0.215	34.8	3.6	14.2	660.0
100	0.058	0.47	0.105	28.6	3.4	11.7	1435.0

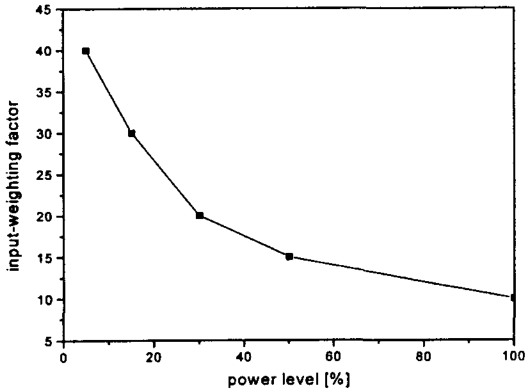


Fig. 5. Input-weighting Factor Versus Power Level

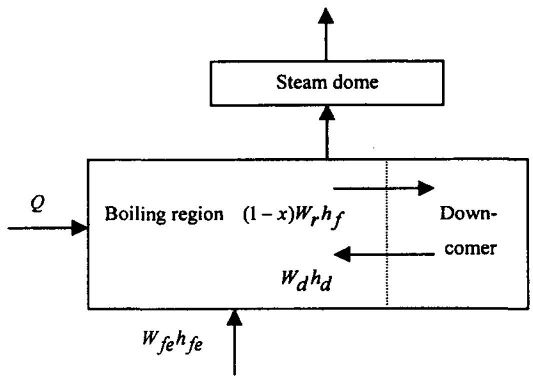
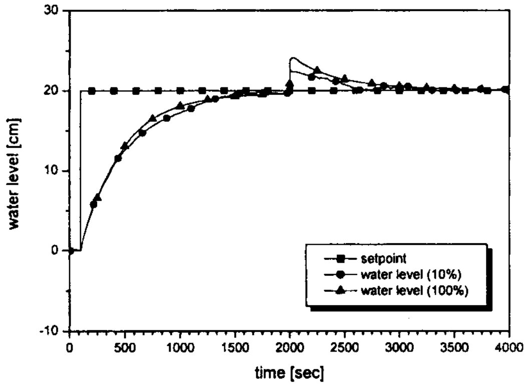


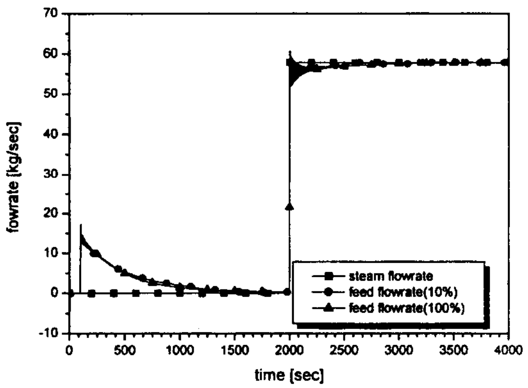
Fig. 6. Two-node Representation of a Steam Generator

the nuclear steam generator to verify its real performance. The 2-region model of a nonlinear model [15] is used in this work and its nodal description is shown in Fig. 6. Table 2 shows the design parameters of a Westinghouse model F steam generator. In this figure, W, h, x, and Q denote flowrate, enthalpy, steam quality, and heat input from the primary side, respectively. The computer code for the nonlinear model is written in Fortran language. In order to perform the numerical simulations, the proposed MATLAB [16] control algorithm is interfaced with the code written in Fortran language.

Since this nonlinear model is inadequate to design the controller, the linear model mentioned above (the linear model at 100 percent power level) was used to design the controller. Figure 7 shows the performance of the proposed algorithm for the nonlinear model. The conditions of the computer simulations for the nonlinear model are the same as those for the linear model. The magnitude of the disturbance at 2000 sec is 5 percent rated steam flowrate [57.85kg/sec = 0.05 $\times$ 1157kg/sec (rated steam flowrate)]. $\mathbf{Q}$ and $\mathbf{Q}_F$ (these are scalar values because of a single output) were chosen as 0.5 and 1, respectively and also, the prediction and control horizons are 100 and 3, respectively. In these simulations of the nonlinear model, the same input-weighting factor ($\mathbf{R}$ = 2) was used irrespective of the power level. Although the linear model was used to design the proposed algorithm, its performance is good. In this nonlinear model, we can see that the swell and shrink phenomena due to the feedwater



(a) water level



(b) flowrate

Fig. 7. Performance of the Proposed Controller for the Nonlinear Model

flowrate change is not described adequately by observing the water level response at about 100 sec when the water level setpoint changes and the feedwater flowrate increase is large. However, it can be seen that the swell and shrink phenomena due to the steam flowrate change is described adequately by observing the water level response at about 2000 sec when the steam flowrate disturbance occurs.

4. Conclusions

In this work, the model predictive control method was developed to control the water level of nuclear steam generators. The developed controller was applied to the linear and nonlinear models for nuclear steam generators. The parameters of the linear model for a steam generator are very different according to the power levels. Although the model predictive controller was designed for the linear steam generator model at a fixed power level, the proposed controller showed good performance for any other power levels by changing only the input-weighting factor. As the power level increases, the input-weighting factor decreases exponentially and the input-weighting factor can be easily selected according to power level change. Since the steam generator has some nonlinear characteristics, the proposed algorithm was implemented for a nonlinear model of the nuclear steam generator to verify its real performance. Also, the proposed controller showed good performance for the water level setpoint and steam flowrate (measurable disturbance) changes.

Table 2. Design Parameters of a Steam Generator Used for the Nonlinear Model (M.K.S. unit)

Name	Size
Cross sectional steam dome area	10.94
Secondary(Primary) heat transfer area	5114(5114)
Cross sectional tube bundle area	2.699
Cross sectional downcomer area	0.7226
Cross sectional riser inlet area	7.760
Cross sectional riser outlet area	3.243
Downcomer volume	33.21
Steam dome volume	43.15
Boiling region volume	39.79
Riser volume	26.45
Lower downcomer length	10.91
Water level in downcomer	13.17
Parallel flow length in tube	6.960
Tube bundle length	8.460
Riser length	4.640

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