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Increasing Operational Safety in NPP using Modified Predictive Control

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ABSTRACT

One of the most important decisions for regulatory body is to give a license for increasing or decreasing reactor power or reactor operation. Model predictive control proves its reliability to help the operator and regulatory body to ensure NPP operational safety. This paper introduces a modified model predictive control based on genetic algorithm. It relies on decreasing both the input cost and the difference between real output and optimum output by using a minimizing factor. The results show a reduction in overshoot and settling time of NPP systems parameters, which improve the NPP safety and stability.

Keywords: *Nuclear Power Plant, Predictive Control, Genetic Algorithm.*

1. INTRODUCTION

As NPP is frequently exposed to load change, it should respond quickly and safely. Its controller should maintain the performance of the reactor operating condition while keeping the highest thermal efficiency. Industrial Model Predictive Control (MPC) had gained a significant attraction since it was introduced in 1970's [1], due to the increasing requirement from modern industry. MPC which also known as receding horizon control or moving horizon control starts from applications then expand to theoretical field. The MPC concept starts by Engineers at Shell Oil who developed their own dependent MPC technology [2].

The basic idea for MPC could be summarized as follows:

1. Predict the future behavior of the process state/output over the finite time horizon.
2. Compute the future input signals online at each step by minimizing a cost function under inequality constraints on the manipulated (control) and/or controlled variables
3. Apply on the controlled plant only the first element of vector control variable and repeat the previous step with new measured input/state/output variables.

It means that, at a certain time, the behavior of the process over a prediction horizon is considered, and the process output related to changes in a manipulated variable is predicted by using a mathematical design model. The changes of the manipulated variables are selected such that the predicted output has certain desirable characteristics. However, only the first computed change in the manipulated variable is implemented, and at each subsequent instant, the procedure is repeated.

Many researches had been developed to introduce MPC methods such as self-adaptive long-range predictive control (LRPC) method [3], which focus on robustness with respect to un-modeled dynamics, parameter variations, process noise and varying dead-time. It uses the plant step response or impulse response for the selection of prediction horizon to guarantee the closed-loop stability [4]. In general, the stability of linear plants could be achieved by a constrained receding horizon predictive control optimizes a quadratic function over a costing horizon (the computation is more complex). The other way is to use finite-horizon methods, which are numerically highly sensitive [5-14].

This paper presents a modified model predictive control method that applied to design an automatic controller for the turbine speed and steam pressure of steam generator in the NPP second loop system. The mathematical model had been built. The simulation results show the ability of MMPC to give a significant improvement compared with PID controller.

2. MATHEMATICAL MODEL OF NPP SECOND LOOP

2.1 Mathematical Model of Once-Through Steam Generator

According to properties of the once-through steam generator, it is divided into sub-cooled region, boiling region, and super-heated region. The mathematical description of each region [15-19] is

$$\frac{\partial P}{\partial t} = \mp \frac{\partial g}{\partial z} \text{.............................}(1)$$

$$\frac{\partial (Ph)}{\partial t} = \mp \frac{(gh)}{\partial z} \pm \frac{q}{A} + \frac{\partial p}{\partial t} \text{............}(2)$$

$$\mp \frac{\partial g}{\partial t} = -\frac{\partial}{\partial z}\left(\frac{g2}{P}\right) - \frac{\partial p}{\partial z3} + r \text{..........}(3)$$

Where: Equations (1)-(3) are equations of mass, energy, momentum respectively.
The above symbol represents secondary side, the below symbol represents once side, P is the density with kg/m , g is the mass flux with kg/(m^2·s), h is energy with J, q is the heat flux with J/s, A is the area with m^2, p is the pressure with Pa , r is the pressure drop with Pa.

2.2 Mathematical Model Of Turbine

According to single cylinder steam structural characteristic, process of energy transfer and power conversion [15-19], the mathematical model of turbine is divided into six parts: steam entering flow calculation, pressure calculation of after the steam room of control stage, calculation of expansion doing work, rotor model, moment of inertia calculation, load model. Speed differential equation is

$$\text{..........................}(4) \quad \frac{dn}{dt} = \frac{(P_T - P_s)}{An}$$

Where: n is the speed of propeller or propeller shaft with r/min, P_T is the drive power of turbine rotor with W, P_S is output power of propeller with W, A $=(\pi^2(Jk^2+J_s))/900$ is the changing factor of speed, j is the moment of inertia of turbine rotor with kg / m^3 ᾽ j_s moment of inertia of output axis and propeller with kg / m^3 , k is the ratio of drive.

3. MODIFIED MODEL PREDICTIVE CONTROL [MMPC]

The structure of MMPC based on a model of NPP secondary loop system as shown in figure (1).
It consists of multi-step predictor based on integrated model [15], genetic choice making. In figure (1), $Y_{pre}(k+j)$ is the P step predicted value of the predictive model, where 1<j<P and P ts the predictive step, $E_j(k)$is the predictive error, W(k+ j) is the reference trajectory; Y(k) is the output of the secondary loop system, U(k) is the optimum control input of the selected nuclear power plant's secondary system by Genetic choice.
The integrated model [19] has two parts, the non-linear static DLF network and the dynamic linear CARIMA(Controlled Auto Regressive Integrated Moving Average
Model). The DLF network connects the input layer with the output layer, based on the BP network. In another meaning, every nerve cell is connected with the output layer one another. The DLF equation is

$$X(k)= W_f U(k)+N_{Bp}U(k-1)\text{........}(5)$$

Where, W_f is I/O connector, N_{Bp}(.) is mapping relation between multi-layer forward BP neural networks.
The dynamic linear multi-input/multi-output CARIMA model
is

$$A_0(z^{-1})Y(k)=B_0(z^{-1})X(k)+C_0(z^{-1}) \quad \xi \quad (k)/\Delta \text{.....................}(6)$$

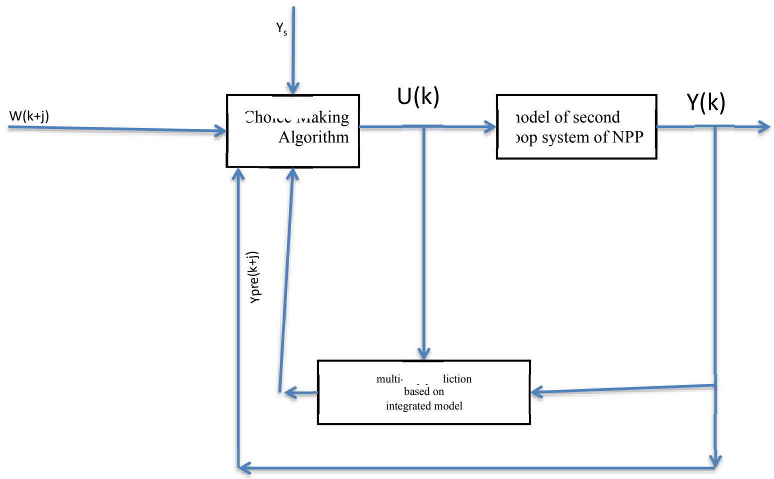

Fig. 1. MMPC Structure.

where $A_0(z^{-1})$,$B_0(z^{-1})$ are n*n polynomial matrix. $Y_{pre}(k)$= f[Y(k-1),U(k-1)].If the predictive step is P, and the predictive output at time k makes recursion by the equation as follows:

$$Y(k+j)=Y_{pre}(k+j)+E(k+j-1)\text{………}(7)$$

$$Y_{pre}(k+j)= f[Y(k+j-1),U(k+j-1)]\text{…….}(8)$$

$$E(k) =Y(k)-Y_{pre}(k)\text{……….}(9)$$

Assume that the error reference trajectory $W_{r,i}(k+j)$ equation is

$$W_{r,i}(k+j)= \alpha_i^{\,j}Y(k)- (1- \alpha_i^{\,j})Y_s\text{…….}(10)$$

Where: Y_s is the steady state output , and $0< \alpha <1$.
The predictive error is

$$E_{i,j}(k+j)=W_{r,i}(k+j)-Y(k+j)\text{…………..}(11)$$

According to Eq. (5,6)

$$X(k+j) =(B_0(z^{-1}))^{-1}(A_0(z^{-1})Y(k+j)=-C_0(z^{-1}) \xi (k)/\Delta)\text{…………}(12)$$

$$U(k+j)= W_f^{-1} (X(k+j)-N_{Bp}U(k+j-1))\text{…………………}(13)$$

In order tto verify an optimum response and minimize the control effort, the optimum control input (objective function) is represented by the quadratic function as follows

$$\boldsymbol{J} = \frac{1}{2}\sum_{j=1}^{j=p} Q\left(Y(k+j)-Y_s\right)^2+\frac{1}{2}\sum_{j=1}^{j=p} R\left(U(k+j)-U(k+j-1)\right)^2 \text{……..}(14)$$

Where, the first term is the difference between the future output and the steady state output while the other term represents the change in the future input.
Q is an identity matrix consists of P element, R is a weight diagonal matrix consists of P elements.
The objecFtive function of eq.(14) Is minimized by Choice Making Algorithm [CMA], based on genetic algorithm. In genetic algorithm, the term chromosome refers to a candidate solution that minimizes a cost function. As the generation proceeds, populations of iteratively altered by biological mechanisms inspired by natural evolution mechanisms such as selection, crossover, and mutation. The genetic algorithms require a fitness function that assigns a score to each chromosome (candidate solution) in the current population; additionally, they maximize / minimize the fitness function value. The fitness

function evaluates the extent to which each candidate solution is suitable for the specified objectives. It starts with an initial population of chromosomes, which represent possible solutions of the optimization problem. For each chromosome, the fitness function is computed. New generations produced by the genetic operators known as selections, crossovers and mutations. The algorithm stops after the maximum allowed time has passed.

In CMA, a chromosome will be represented by C_i of which elements consist of present and future errors. The chromosome will have the following structure:

C_i=[Ei,1(k+1)Ei,2(k+2)……………Ei,p(k+p)] ……………(15) $1\leq i \leq p$

A p number of chromosomes with different value of α_i form the initial population. The algorithm proceeds according the following steps+-

step 1# Set the iteration number. Generate an initial population consisting of P chromosome of Eq. (11).

The values are allocated ascendingly, but they should satisfy the following constraints:-

α clanged randomly for each chromosome,

If $E_{i,j}(k+j) > E(k)$ then $E_{i,j}(k+j)=E(k)$,

If $u(k+j) > u_{max}$ then $u(k+j) = u_{max}$,

If $u(k+j) < u_{min}$ then $u(k+j) = u_{min}$.

step #2 Calculate the objective function in Eq.(14) for each chromosome in the population, J_i is the i^{-th} chromosome objective function.

step #3 Organize the chromosomes ascendingly according to their objective function value. Select the last two chromosomes with the highest objective function value.

step #4 Generate a random integer number M from 1 to P-1 . It indicates the position of the crossing point. Two new chromosomes are produced by the interchanging all of the members of the parents (selected chromosomes) Following the crossing point. For example, the crossover operation can be represented as shown below, assuming that the crossover operation to the parent chromosomes C_p , C_{p-1} and M=2:

C_p = [$E_{p,1}(k+1)$ $E_{p,2}(k+2)$ $E_{p,3}(k+3)$ …… …..……$E_{p,p}(k+p)$]

C_{p-1}=[$E_{p-1,1}(k+1)$ $E_{p-1,2}(k+2)$ $E_{p-1,3}(k+3)$ ……………$E_{p-1,p}(k+p)$]

The resulted chromosomes (offspring) are:

C_p = [$E_{p,1}(k+1)$ $E_{p,2}(k+2)$ $E_{p-1,3}(k+3)$ ……………$E_{p-1,p}(k+p)$]

C_{p-1}=[$E_{p-1,1}(k+1)$ $E_{p-1,2}(k+2)$ $E_{p,3}(k+3)$ …… …..……$E_{p,p}(k+p)$]

The crossover at crossing point follows the above constraints.

step #5 If the maximum allowed time has not expired, set iter = iter +1 and return the algorithm to Step 2. Otherwise, stop the algorithm and select the chromosomes that satisfy the following equation ;-

$(u_{min}(k)+u_{av}(k))/2 \leq u(k) - u(k+1) \leq (u_{max}(k)-u_{av}(k))/2$…………..(16)

where,

$u_{av}=(u_{max}(k)-u_{min}(k))/2$ …………………….(17)

From this set of chromosomes, choose one which has the minimum objective function. The input corresponding to the first element in this chromosome is the optimum control input.

Clearly, the choice making algorithm makes it possible to calculate the optimal control in real time.

4. EXPERIMENTAL RESULTS

The proposed MMPC had been implemented by "MATLAB". The experiment was performed on the secondary loop system of nuclear power plant model by applying MMPC during load change from 100% to 83%. The results shown in fig.(2,3) illustrate the impact of the mentioned disturbance on steam generator pressure and turbine speed in case of using MMPC controller and PID controller. Assuming that the sampling time is 0.1s and iteration number is 100.the curves in figure(2) clarify that the exit steam pressure of steam generator peak overshoot reduces under the application of MMPC controller with respect to PID controller due to the CMA performance. Furthermore, not only the steam generator pressure settling time decreased but also the turbine speed settling time shown in Figure (3) reduced.

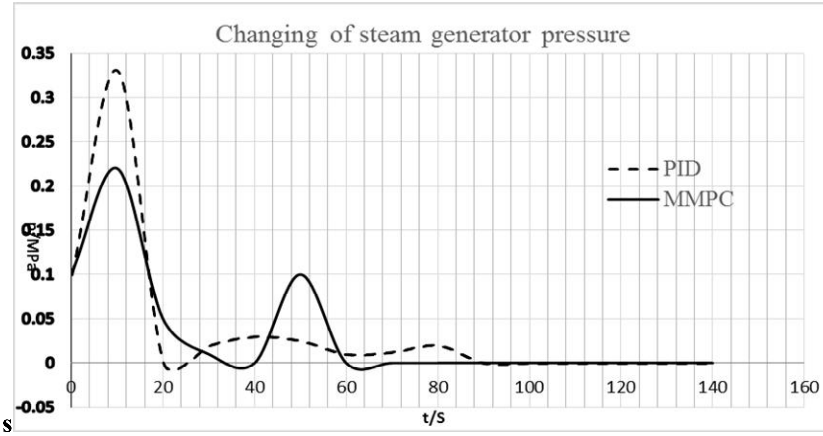

Fig. 2. Steam Pressure Changing.

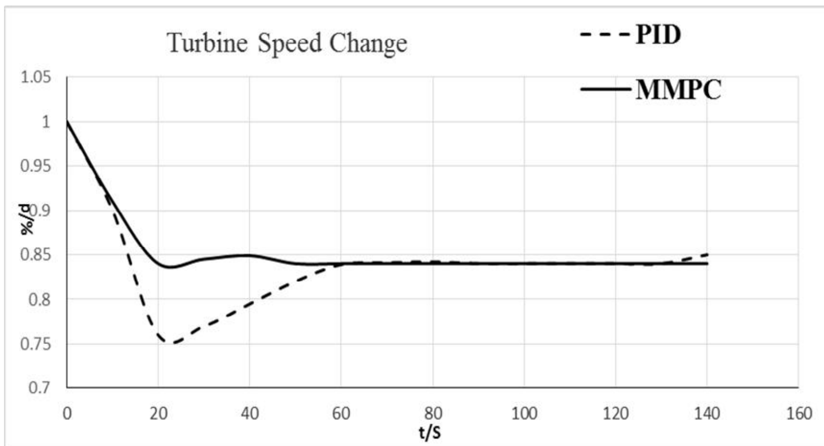

Fig. 3. Turbine speed change

4. CONCLUSION

In this paper, a MMPC controller based on genetic algorithm had been presented. It designed through nonlinear static DLF network model and dynamic linear CARIMA model in addition to CMA algorithm for optimization amd selection.

According to the characteristic of the second loop system of nuclear power plant, the mathematic model of once-through steam generator and turbine are built.The simulations on the secondary loop system of nuclear power plant are processed by applying the Modified Model Predictive Control (MMPC) as mentioned above. Considering the electrical load of nuclear power plant changes , and compared with the simulation results obtained by applying PID controller. The simulation results indicate that the MMPC controller can provide stronger robust performance to nuclear power plant than PID controller, and the varialeness of system main parameters is reduced, which make sure the nuclear power plant safe and stable.

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