An advanced multiple model based control of an industrial steam turbine using fast version of GPC

Mojtaba Kordestani (IEEE member)
Power and Control Engineering
Dept. Shiraz University
Shiraz, Iran
mojtaba.kordestani@ shirazu.ac.ir

Ali Akbar Safavi
Power and Control Engineering
Dept. Shiraz University
Shiraz, Iran
safavi@shirazu.ac.ir

Abstract— **A non-linear controller based on multiple linear models is proposed to regulate the output power of an industrial steam turbine. First, the operating regimes of the system are divided into 3 linear regions. Then, a controller auto-regressive integrated moving average (CARIMA) model is developed for each region and the general predictive control (GPC) law of its region is obtained. The linear models are used to capture the process dynamics at different operating points. The suggested 3 local linear GPC laws are utilized within a framework using the concept of non-linear multiple models. For this purpose, the nonlinear control law is built by a weighted combination of the outputs of the linear controllers. The nonlinear controller consists of three linear GPC laws which may takes too much time to be updated at each sampling time. This is not suitable for online applications. Because of this fact, a fast version of GPC is considered. The fast nonlinear GPC is acted like a weighed discrete PID controller which is updated and retuned according to set point at each sampling time. Simulated industrial steam turbine is invoked for this study under the set point tracking and load disturbance. Simulation results show the performance and effectiveness of the proposed non-linear GPC controller.**

Keywords- **non-linear systems; predictive control; steam turbine**

I. INTRODUCTION

The demand for producing electricity with higher qualification and competition between power suppliers has urged companies to look for automatic techniques to give better power delivery and assure reliability of the system. A sudden loss of load or disturbances in the distributed power system may cause electricity loss or even instability and power shutdown in the system [1].

The load/frequency control is widely used in steam turbines for power system stability. Low frequency oscillations in the turbines are appeared because of changes in power balance between the mechanical power and the load demand. Speed governors have been considered for many years to eliminate these frequency oscillations [2]. To increase the reliability in the system and to reduce response time, fast actuating control valves are used instead of the conventional mechanical governors. Unfortunately, these changes are not enough to guarantee stability due to high interaction of dynamics between boiler and turbine and more modifications are needed. For this purpose, fast adaptive control is necessary to come up with new situations in the system [3].

Recently, many different methods are used for the control of steam turbines. Paper [4] obtains a control law based on gain scheduling method. In this method, the controller is selected from a look up table. Indeed, the control gain is set to pre-obtained values for certain conditions. However, to apply the gain-scheduling controller, prefect knowledge of the system is necessary which makes this method to be impractical in most applications [5]. Robust controllers are considered in systems with high degree of uncertainty when other methods are failed to control the systems. These controllers are designed in the way to compensate the uncertainty in the wide range of operating regions [6]. When a mathematical nonlinear model of the system is available, it is straightforward to use nonlinear method like feedback linearization method for designing controller of the steam turbine. However, a completed model with explicit mathematical formula is not available for large scale systems [4, 7].

Model predictive control has been considered in different fields [8, 9]. The aim of model predictive control is to predict the future system behavior by using a model to minimize an objective function. The idea of MPC came back to the 1960's[10]. It gained attention after publishing a paper on IDCOM [11] and Dynamic Matrix Control (DMC) [12, 13], then, Generalized Predictive Control (GPC) was introduced in [14, 15]. GPC is widely used in industries [16-19]. This method does not need the exact mathematical model of the system, neither much information about different components so that it can be applied to large scale systems. In this method, first, a linear model of the system is identified. Then, the control law is predicted such that the desired performance is determined over a finite time horizon [20].

Predictive control has been noticed recently in many applications [21-24]. Dieulot et al. [25] develop an predictive controller for supervising a hybrid renewable energy system. The hybrid system integrates a gas micro-turbine, a storage unit and solar panels. The optimal criteria are energy delivery and storage costs. An adaptive fuzzy model predictive control is presented in [26] using the ant colony optimization. The online identification based on the fuzzy method is provided to identify the system parameters. The implementation on two nonlinear processes shows better performance in comparison with proportional integral-ant colony optimization controller and adaptive fuzzy model predictive controller. Cataldo et al. [27] introduce an optimal method for scheduling of a multiple-line production plant consisted of parallel equivalent machines which can be activated at different speeds corresponding to different energ demands. The operating lines may be different in length and the energy consumption. The optimal control actions are computed by model predictive control to minimize energy consumption and to maximize the overall production.

Steam turbines are considered in power plants to produce electricity, they are known as large scale systems with complex structure. The steam turbine explained in this paper is a 440MW power plant with once-through Benson type boiler, comprising high, intermediate and low-pressure sections. This steam turbine is simulated by A. Chaibakhsh and A. Ghaffari [28]. This industrial simulated power plant has been used in different applications [29-32]. This paper presents a new method for control of steam turbine using fast implementation of non-linear GPC. For this purpose, first, a nonlinear input-output diagram of the system is obtained. Then this diagram is divided into three linear sections and for each region, a local linear model is identified and GPC law is formulated. Then, the nonlinear GPC law is obtained by weighed combination of different control laws. The nonlinear GPC consists of three linear GPC and it takes a long time to be computed at each sampling time. To deal with this issue, a fast version of these linear GPC is considered. Indeed the fast nonlinear GPC is acted like a weighed PID controller which is updated and retuned according to set point at each sampling time.

The paper is organized as follows. Section II gives a brief description of the steam turbine. The design methodology of fast nonlinear GPC is presented in Section III. Section IV illustrates simulation study of the purposed method and several simulation tests are carried out to show the performance of the fast nonlinear controller in comparison to fast linear controller. Finally, a summary of the results is given in Section V.

II. AN INDUSTRIAL STEAM TURBINE

Nowadays steam turbines play important roles in producing electricity in the world. Because of this issue they are designed and controlled in the way to increase their performances. To increase steam turbines' thermal efficiencies, they are built to have a complex structure, consisting of multistage steam expansion subsections. This paper uses the steam turbine developed by A. Chaibakhsh and A. Ghaffari [21]. The steam turbine represents an industrial 440MW power plant with once-through Benson type boiler, comprising high, intermediate and low-pressure sections. The system consists of steam extractions (high pressure (HP), intermediate pressure (IP), low pressure (LP)), moisture separators, and the related actuators. Fig.1 shows the steam turbine conditions at extractions.

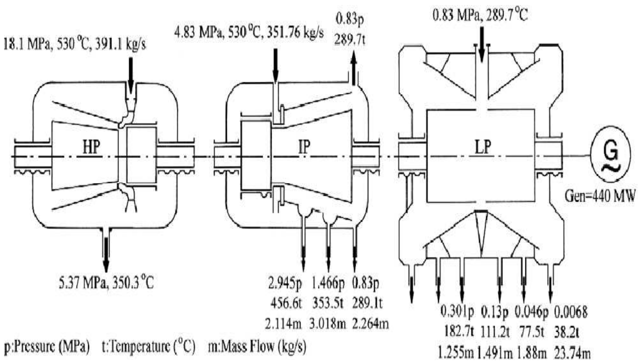

Fig. 1. Steam turbine configuration and extractions.

A nonlinear model is formulated by using energy balance, thermodynamic state conversion and semi-empirical equations. For this purpose, an optimization approach based on genetic algorithm is developed in [21] to estimate the unknown parameters of models. These parameters consists of functions describing specific enthalpy for liquid phase and specific entropy in both liquid and vapor phases as typical example, on the basis of experimental data gathered from a complete set of field experiments. In intermediate and low-pressure turbines where steam variables diverge from prefect gas behavior in sub-cooled regions, the thermodynamic characteristics are dependent on pressure and temperature of each region. Thus, nonlinear functions are constructed in [21] to appraise specific enthalpy and specific entropy at these stages of turbines. Correspondingly, their relevant parameters are set for matching operational range of each subsection by using genetic algorithm. For more details refer to [21].

III. THE DESIGN METHODOLOGY OF FAST NONLINEAR GPC

The elementary theory behind the suggested fast nonlinear GPC is illustrated in this section. For this purpose, it is assumed that the nonlinear model can be available and linearized in several points. In the next subsections, for each local point, a controller based on GPC is developed, then, they are utilized within a unique framework as a nonlinear controller. Finally, a method is presented to convert the local GPC to the fast version.

A. General predictive control (GPC)

In this section, the generalized predictive control (GPC) is considered. GPC is the most popular version of MPC which is introduced by D. W. Clarke, C. Mothadi, P. S. Tuffs [14, 15].

To apply GPC method, first, a local discrete model known controlled auto-regressive integrated moving average (CARIMA) model is applied for output prediction as follows:

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t-1) + \frac{\zeta(t)}{\Delta} \quad (1)$$

Where u(t), y(t) and ζ(t) imply control input, output and noise input sequences of the system, respectively. In Eq. (1), A and B are polynomials in the backward shift operator q-1 as:

$$A(q^{-1}) = 1 + a_1q^{-1} + a_2q^{-2} + \cdots + a_{na}q^{-na}$$
$$B(q^{-1}) = b_0 + b_1q^{-1} + b_2q^{-2} + \cdots + b_{nb}q^{-nb} \quad (2)$$

d and Δ are dead time and the difference operator (1-q-1) , respectively. The GPC cost function can be formulated as follows:

$$J(N_1, N_2, N_u, q, r) = \sum_{j=N_1}^{N_2} q(i)[\hat{y}(t+j) - w(t+j)]^2 + \sum_{j=1}^{N_u} r(j)[\Delta u(t+j-1)]^2 \quad (3)$$

Where N1 and N2 signify minimum and maximum prediction horizons, Nu is control horizon, q(i) and r(j) are weighting sequences and w(t + j) is the future reference trajectory.

The aim of predictive control is to calculate the future control sequence such that the plant output y(t) would be equal to a desired value in the future. Obtaining the future tracking errors can be achieved by using Diophantine approach. To formulate a j-step ahead prediction of model output, y(t+j), the Diophantine equation is considered as follow :

$$1 = E_j(q^{-1})\tilde{A}(q^{-1}) + q^{-j}F_j(q^{-1}) \quad (4)$$

where Ã(q-1)=ΔA(q-1) and Ej and Fj are polynomials uniquely defined, given over the prediction interval j.

According to Eqs. (2) and (4), the best predictions of future outputs are computed in the following:

$$\hat{y}(t+j) = G_j(q^{-1}) + \Delta u(t+j-d-1) + F_j(q^{-1})y(t) \quad (5)$$

Where $G_j(q^{-1}) = E_j(q^{-1})B(q^{-1})$. Here, a complete set of predictions where j runs from a smallest amount to a large value is considered. These values correspond to the minimum and maximum prediction horizons. For j < t the prediction process ŷ(t+j) depends on available data, but for j≥t some assumption needed about future control actions, which are the main key in the GPC. To determine Eq. (5) it is needed to calculate the Diophantine equation recursively.

Then, equation (5) can be written in following form:

$$\hat{y} = G\tilde{u} + f \quad (6)$$

Reference vector is given in the below:

$$w = [w(t+1),\ w(t+2), \ldots, w(t+N)]^T \quad (7)$$

The cost function in equation (3) can be rewritten as follows:

$$J = \left(Gu + \tilde{f} - w\right)^T \left(Gu + \tilde{f} - w\right) + \lambda u^T u, q(i) = 1, r(i) = \lambda \quad (8)$$

In this case, minimization of J, when no constraints are imposed on future controls signals, can be obtained by making the gradient of J equal to zero, as follows:

$$\tilde{u} = (G^T G + \lambda I)^{-1} G^T (w - f) \quad (9)$$

Notice the first element of $\tilde{u}$ is $\Delta u(t)$, so that the control law is determined by the following equation:

$$u(t) = u(t-1) + g^{-T}(w - f) \quad (10)$$

Where g^{-T} is the first row of $(G^T G + \lambda I)^{-1} G^T$.

B. The nonlinear GPCmethod

This section presents the idea of nonlinear GPC based on multiple models. GPC is a linear controller and it is not suitable for system with uncertainty or high nonlinearity. Because of this, in nonlinear system, incorporating GPC causes some problems. For example, divergence of the controller from set point when some large disturbances occur may cause instability. Although, the adaptive inherent of the controller assists the system to be robust in small changes or disturbance and the nonlinear system can work around set point, but the system cannot tolerate for large steps of changes in set points or disturbances. Nonlinear GPC using multiple local models is introduced by S. Townsend and G. W. Irwin [33]. To apply the nonlinear GPC, first, the nonlinear model is converted to several local linear models. Then, for each local linear model, a GPC law is driven. Finally, the nonlinear GPC law for three local models is obtained as follows:

$$u_{\text{nonlinear GPC}} = W_1 \times u_{\text{GPC for local model1}} + W_2 \times u_{\text{GPC for local model2}} + W_3 \times u_{\text{GPC for local model3}} \quad (11)$$

Indeed, the nonlinear control law is a weighted combination of the outputs of the linear GPCs. Fig. 2 shows the block diagram of nonlinear controller for three local linear models. The weighting function Wi is defined in the way when the set point is in the region i, the Wi has the maximum value and other weighting functions have their minimum valves. Besides, $u_{\text{GPC for local model i}}$ is obtained by Eq. (10) where the local model i is used. It should be noticed that the nonlinear GPC is used in the Eq. (11) to capture the process dynamics at different operating points. For more details, refer to [33].

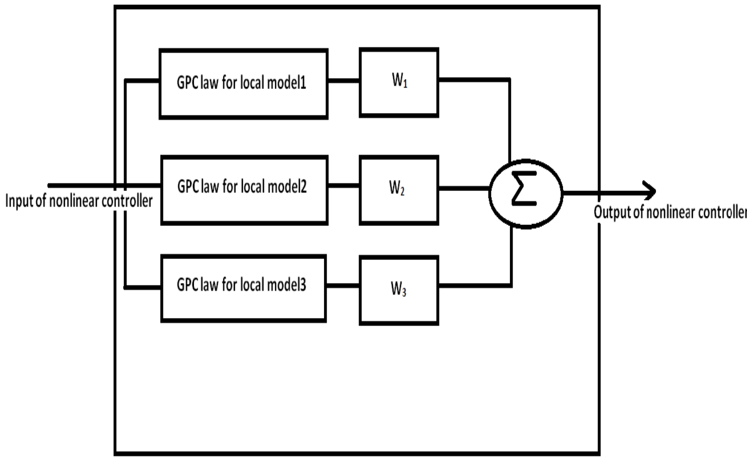

Fig. 2. The structure of nonlinear controller for three local models.

C. The fast version of nonlinear GPC method

The GPC is a linear controller in which the implementation of its algorithm has some difficulties like the problem of existing inverse of matrix $G^T G + \lambda I$ at each iteration or the time of computing the control law especially for a large prediction horizon which may not be suitable in real applications. It becomes worse for nonlinear GPC based on multiple models, because several linear GPC laws are computed together. To deal with these issues, when nonlinear GPC based on multiple models is used, the plant's parameters for each model are fixed, so that the controller's parameters for each model are constant and they need to be determined once for each weighting factors of the controller. This property is used to design the nonlinear GPC controller. To obtain the nonlinear fast GPC, it is enough that the fast version of a linear GPC is considered [34]. Then, the fast version of the nonlinear GPC is obtained by combination of weighted linear GPCs.

For this purpose, first, the CARIMA model for each local model of the steam turbine is considered in the following equation:

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t-1) + \frac{\zeta(t)}{\Delta} \quad (12)$$

Where

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2} + a_3 q^{-3}$$
$$B(q^{-1}) = b_0 + b_1 q^{-1} + b_2 q^{-2}$$

Eq. (12) can be converted into the following format:

$$y(t+1) = (1-a_1)y(t) + (a_1 - a_2)y(t-1) + (a_2 - a_3)y(t-2) + (a_3)y(t-3) + b_0\Delta u(t-d) + b_1\Delta u(t-d-1) + b_2\Delta u(t-d-2) + \zeta(t+1) \quad (13)$$

Then, the best expected value for $\hat{y}(t+j|t)$ is obtained as follows:

$$\hat{y}(t+d+j|t) = (1-a_1)\hat{y}(t+d+j-1|t) + (a_1-a_2)\hat{y}(t+d+j-2|t) + (a_2-a_3)\hat{y}\big((t+d+j-3|t)\big) + (a_3)\hat{y}\big((t+d+j-4|t)\big) + b_0\Delta u(t+j-1) + b_1\Delta u(t+j-2) + b_2\Delta u(t+j-3) \quad (14)$$

The control sequence is formulated by minimizing the cost function considered in Eq. (3). Where $N_1 = 1$, $N_2 = N_u = N$. Minimizing Eq. (3) with respect to $\Delta u(t), \Delta u(t+1) \ldots \Delta u(t+N-1)$ results in:

$$Mu = Py + Q\Delta u(t-1) + Rw \quad (15)$$

Where $u = [\Delta u(t), \Delta u(t+1) \ldots \Delta u(t+N-1)]^T$

$y = [\hat{y}(t+d|t)\ \ \hat{y}(t+d-1|t)\ \ \hat{y}(t+d-2|t)\ \hat{y}(t+d-3|t)]^T$
$w = [w(t+1)\ w(t+2)\ \ldots\ w(t+N)]^T$
M and R contain matrices of dimension N×N and P and Q consists of matrices of N×4 and N×3, respectively. Consider q as the first row of matrix M-1. Then, $\Delta u(t)$ is computed in the following:

$$\Delta u(t) = qPy + qQ\Delta u(t-1) + qRw \qquad (16)$$

Then, the control law can be rewritten as follows:

$$\Delta u(t) = l_{y1}\hat{y}(t+d|t) + l_{y2}\hat{y}(t+d-1|t) + l_{y3}\hat{y}(t+d-2|t) + l_{y4}\hat{y}(t+d-3|t) + l_{u1}\Delta u(t-1) + l_{u2}\Delta u(t-2) + l_{u3}\Delta u(t-3) + l_{r1}w(t+1) + \cdots + l_{rN}w(t+N) \qquad (17)$$

The controller parameters are functions of weighting factors, $q(i)$ and $r(j)$. They are calculated by interpolating in a set of previously computed valves. It should be mentioned that the valves of $\hat{y}(t+d|t), \hat{y}(t+d-1|t), \hat{y}(t+d-2|t), \hat{y}(t+d-3|t)$ are given by Eq. (14). Finally, to compute parameters of the controller, a polynomial curve is fitted to each parameter. For this purpose, the following equation is used.

$$p(x) = p_1x^n + p_2x^{n-1} + \cdots + p_nx + p_{n+1} \qquad (18)$$

IV. SIMULATION TESTS AND RESULTS

In this section, first, the structure of the purposed nonlinear GPC controller is presented. Then, a set of tests are simulated to show the performance of the controller.

A. The structure of the nonlinear GPC

This subsection illustrates the structure of the suggested nonlinear GPC controller. The idea of multiple models is used to design the nonlinear GPC. For this purpose, first, the nonlinear response of the system is divided into several linear responses. To do this, the steady state response of the steam turbine from input to output is shown in Fig. 3.

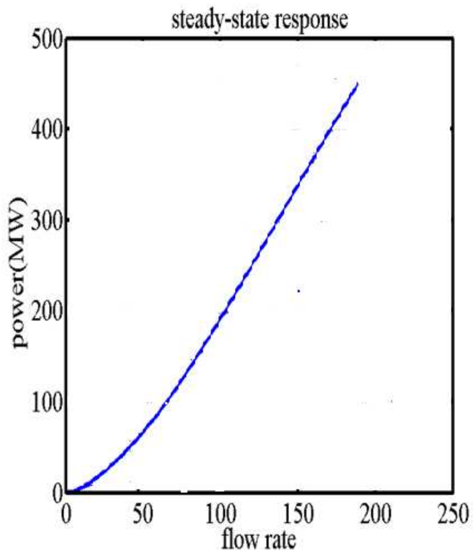

Fig. 3. The steady state response of the steam turbine

The operating point of this steam turbine is between 0 and 500MW. It can be divided into three regions consists of 0-50MW, 50MW-100MW and 100MW-500MW. Then, a CARIMA model considered in Eq. (1) and (2) is identified for the each region. Besides, to have a better sense about the performance of the nonlinear controller and compare it with linear controller, a CARIMA model for the whole region is considered. It should be mentioned to obtain the CARIMA model for the each region, a pseudorandom signal is used in the steam turbine input and the output is computed. After this the CARIMA model is obtained by using these data. Table 1 illustrates the parameters of these local models.

Table 1: The parameters of the local models.

	Parameters of the CARIMA model
local model 1 for region between 0-50MW	$A(q^{-1}) = 1 - 1.761q^{-1} + 1.031q^{-2} - 0.2617q^{-3}$ $B(q^{-1}) = .001912 + 0.01532q^{-1} + 0.002587q^{-2}$
local model 2 for region between 50MW-100MW	$A(q^{-1}) = 1 - 1.667q^{-1} + 0.9436q^{-2} - 0.2656q^{-3}$ $B(q^{-1}) = .001996 + 0.02089q^{-1} + 0.002773q^{-2}$
local model 3 for region between 100MW-500MW	$A(q^{-1}) = 1 - 1.834q^{-1} + 0.8455q^{-2} - .00946q^{-3}$ $B(q^{-1}) = .001153 + 0.01321q^{-1} + 0.009886q^{-2}$
Off line local between 0-500MW	$A(q^{-1}) = 1 - 1.77q^{-1} + 0.968q^{-2} - 0.191q^{-3}$ $B(q^{-1}) = .002199 + 0.01392q^{-1} + 0.0002219q^{-2}$

After this step, the linear GPC law for each local model is obtained by Eq. (10). Then the nonlinear GPC law is computed by Eq. (11). For this purpose, Gaussian functions are used in weighted functions of the local models. Fig. 4 shows the Gaussian weighed functions of the local models.

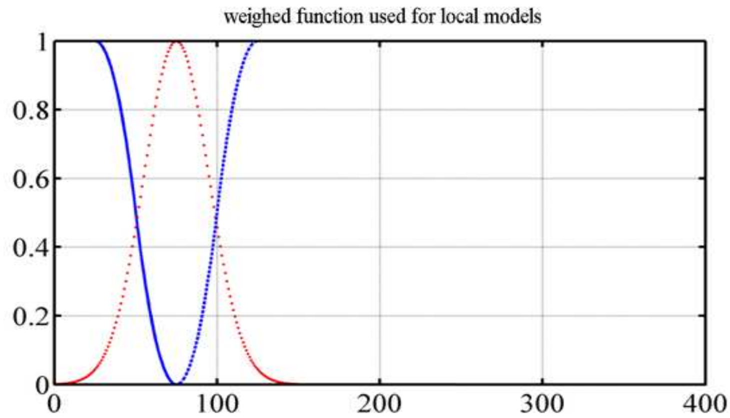

Fig. 4. The Gaussian weighed functions of the local models.

The parameters of fast nonlinear GPC are now computed. Theses parameters are functions of weighting factors of the cost function, $q(i)$ and $r(j)$. Finally, a polynomial curve is fitted to each parameter. The degree of polynomials is considered to be 5.

B. Test scenarios and results

In this subsection different test scenarios such as set point tracking and disturbance rejection are considered to evaluate the performance of the fast nonlinear GPC method. For this purpose, first, set the weighting factors of the cost function on $q(i) = 5$ and $r(j) = 1$. Then, set point jumps up from 0 to 360MW at the beginning and from 360MW to 390MWat 450s. Fig. 5 and 6 show the plant output and controller output, respectively.

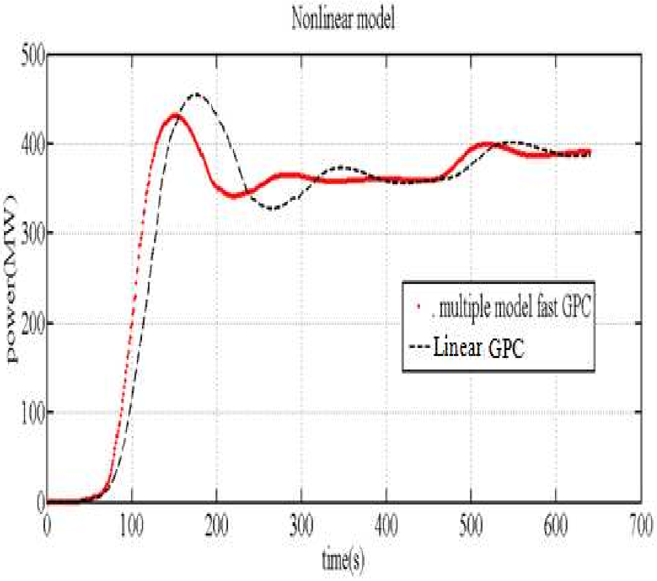

Fig. 5. The steam turbine output for set point tracking

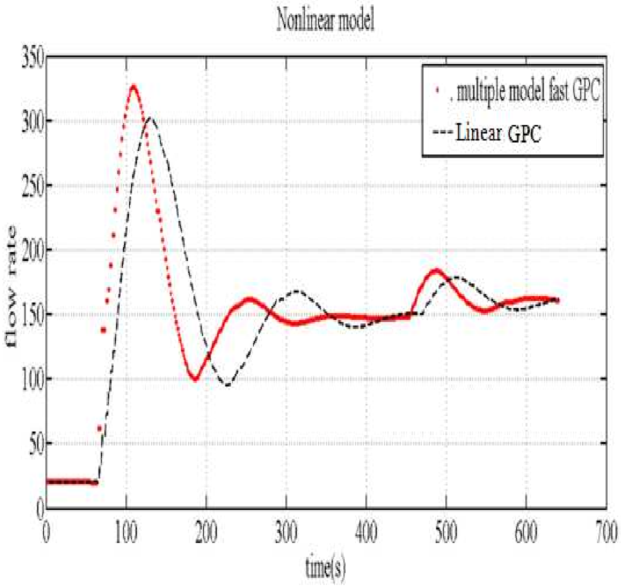

Fig. 6. The controller output for set point tracking

To evaluate the performance of the fast nonlinear GPC, compare it with linear GPC. As it is seen from Fig. 5, the overshoot and settling time of the multiple models fast GPC are less than GPC. It is interesting to note that the settling time of the fast nonlinear GPC method for the first set point tracking is 310S which is much shorter than 380S for the linear GPC. The overshoot for the suggested method is 430MW whereas it is 460MW for the linear GPC. Furthermore, for the second set point tracking the set point of the fast nonlinear GPC is much shorter than the linear GPC. However, it is notice from Fig. 6 that the fast nonlinear GPC needs more attempt to control the situation.

Then, the steam turbine and controller output are considered in fig. 7 and 8 when a disturbance occur in the high pressure section at 550S.

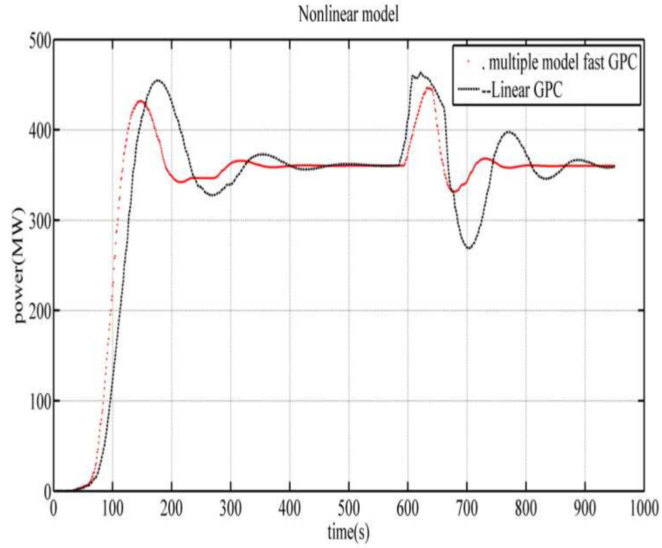

Fig. 7. The steam turbine output for disturbance rejection

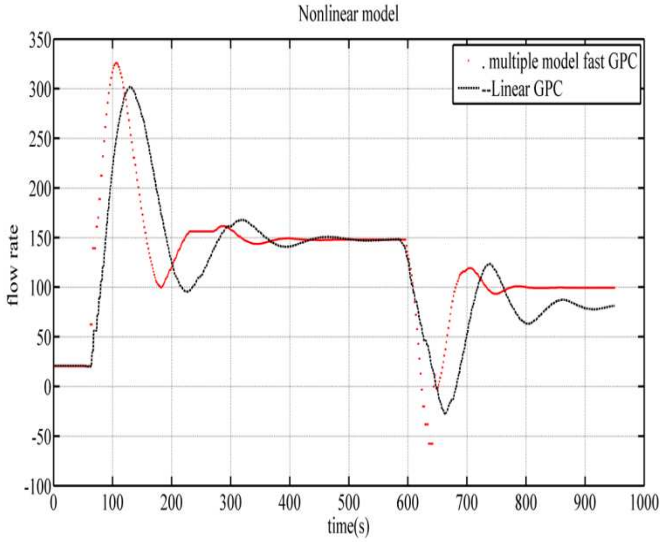

Fig. 8. The controller output for disturbance rejection

As can be indicated from the Fig.7 that the fast nonlinear GPC is much better to cope with this disturbance. The disturbance is vanished at 750S for the fast nonlinear GPC whereas this time for the linear GPC is 950. It is noticeable from Fig. 8 that more attempt is needed from the nonlinear controller.

Finally, it is important to note that the time which takes for computing the nonlinear GPC law for each iteration is 0.93 second. Surprisingly, this time for the fast nonlinear GPC is 0.0045S while it is 0.21 for linear GPC. It is notice that the simulation is done using a three core Sony laptop with 4 GB RAM.

V. CONCLUSION

This paper presented a fast nonlinear GPC method for a simulated industrial steam turbine. The steam turbine represented an industrial power plant with once-through Benson type boiler which consists of high, intermediate and low-pressure sections. To design the purposed nonlinear controller the idea of multiple models was used. The nonlinear controller was made by weighted combination of three local models. The nonlinear GPC was acted like a weighted PID which was retuned according to the current set point. This methodology made the nonlinear GPC to be fast and simple for implementation. Several test scenarios were performed to evaluate the ability of the suggested fast nonlinear controller for set point tracking and disturbance rejection. The performance of the fast nonlinear GPC was much better than linear GPC.

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