PSO Based Predictive Nonlinear Automatic Generation Control

MUHAMMAD S. YOUSUF   HUSSAIN N. AL-DUWAISH   ZAKARIYA M. AL-HAMOUZ
Department of Electrical Engineering
King Fahd University of Petroleum & Minerals, Dhahran
KINGDOM OF SAUDI ARABIA
zhamouz;hduwaish;zhamouz@kfupm.edu.sa

Abstract: This paper presents a newly proposed Model Predictive (MPC) scheme featuring Particle Swarm Optimization (PSO) technique applied to nonlinear single area Automatic Generation Control (AGC). The proposed scheme formulates the MPC as an optimization problem and PSO is used to find its solution. Single area AGC model is used and it incorporates Generation Rate Constraint (GRC) nonlinearities and constraints on the control input. The simulations results show improvement over previous AGC methods reported in the literature and signify the strengths of the proposed MPC scheme. Furthermore, performance of controller is also explored for varying GRC values and power demands.

Key–Words: Model Predictive Control, Particle Swarm Optimization, Automatic Generation Control, Load Frequency Control, Nonlinear Predictive Control, Optimization Problem.

1 Introduction

Automatic Generation Control (AGC), also known as Load Frequency Control (LFC), has been one of the most important subjects for power systems engineers for decades. Loading in power systems is never constant, and changes in load induce changes in system frequency. This is because imbalance between the real power generated and loading causes the generator shaft speed to change, resulting in the variation of system frequency.

Hence, a controller is needed to keep the frequency of the output electrical power at the nominal value. The input mechanical power to the generator is used to control the load frequency. The main quality risk involved during control is that control area frequencies can undergo prolonged fluctuations due to a sudden change of loading in an interconnected power system as described by Chan [3]. These prolonged fluctuations are mainly the result of system nonlinearities. The purpose of AGC is to track load variations and reduce these fluctuations. In this way, the system frequency is maintained, transient errors are minimized and steady state error is avoided.

Although good linear control of multiarea load frequency has been achieved by several researchers [8], [13], [17], these designs will not work properly in practice due to the real nonlinear nature of AGC systems. Therefore, consideration of nonlinearities in the models of AFC is very important. One of the main type of nonlinearities is the Generation Rate Constraint (GRC) [14]. This is the constraint on the power generation rate of the turbine and due to it the disturbance in one area affects the output frequency in other interconnected areas.

For nonlinear system models of AGC, an important technique used has been Variable Structure Control (VSC) as given in [1] and [2], among others. Additionally, a Ricatti-based optimal VSC technique is proposed by Wang [15] where the controller design is based on optimization of a Ricatti-equation. The results show large variations in frequency and power output and the system states take a long time to settle. Using the proposed technique, these important problems will be tackled. An excellent literature survey on the control of AGC is given in [12].

The previous work on AGC does not incorporate constraints in the controller design process. Model predictive control (MPC) is a well-known control methodology that can easily incorporate and handle nonlinearities and constraints in the controller design. Although it has been extensively used in process control [4], limited applications in power systems have been reported [7]. The proposed approach will handle the nonlinearities and constraints in the AGC system in a structured way in the controller design process. This will give obvious advantages with regards to optimal control and constraints handling.

The paper is organized as follows: First the nonlinear AGC model is presented in Section 2, followed by an introduction to the proposed controller in Section 3. Section 4 gives simulation results and comparisons with previous work on AGC. Finally, conclusions are derived in Section 5.
2 Model of Automatic Generation Control System

The block diagram of an AGC system is given in Figure 1 as in [15] and the states of the system are:

\[ \dot{X} = \begin{bmatrix} \Delta f_i(t) & \Delta \hat{P}_{gi}(t) & \Delta \dot{X}_g(i) & \Delta \dot{P}_c(i) & \Delta \dot{P}_t(i) \end{bmatrix}^T \]  

(1)

The definitions of the symbols used in the model are as follows:

- \( f_i \): area frequency in ith area (Hz)
- \( P_{gi} \): generator output for ith area (p.u. MW)
- \( X_{gi} \): governor valve position for ith area (p.u. MW)
- \( P_{ci} \): integral control value for ith area (p.u. MW)
- \( P_{ti} \): tie line power output for ith area (p.u. MW)
- \( P_{li} \): load disturbance for ith area (p.u. MW)
- \( T_{gi} \): governor time constant for ith area (s)
- \( T_{pi} \): plant model time constant for ith area (s)
- \( T_{ti} \): turbine time constant for ith area (s)
- \( K_{gi} \): plant transfer function gain for ith area
- \( R_i \): speed regulation due to governor action for ith area (Hz p.u. MW \( H z^{-1} \))
- \( R_i \): frequency bias constant for ith area (Hz p.u. MW \( H z^{-1} \))
- \( a_{ij} \): ratio between the base values of areas i and j

The numerical values of these parameters are given in Section 4. The control objective of AGC is to keep the change in frequency, \( \Delta f_i(t) = x_1(t) \) as close to 0 as possible in the presence of load disturbance, \( d_i(t) \) by the manipulation of the input, \( u_i(t) \). The detailed model of the system along with the values of state matrices can be found in [16].

3 Controller Structure

This section gives the basic structure of the proposed MPC-PSO controller.

3.1 Model Predictive Control

It is recognized that linear control is not able to accurately control nonlinear processes and MPC is one of the most successful nonlinear control methodologies available today. Its main advantages are that it is able to systematically and directly handle process constraints during the controller design and can incorporate any cost function and process model. Its versatility is further enhanced by its ability to integrate with any optimization technique, for example PSO in this case. A good review of MPC can be found in [11].

Consider a discrete-time space with a sampling period \( T \). The input and output of every system in this space will be denoted by \( u[k] := u(kT) \) and \( y[k] := y(kT) \) respectively, where \( k \) is an integer from \(-\infty\) to \(+\infty\). Any nonlinear lumped system in this space can be described by the following sets of equations:

\[
\begin{align*}
\mathbf{x}(k+1) &= \mathbf{h}(\mathbf{x}(k), \mathbf{u}(k), k) \\
\mathbf{y}(k+1) &= \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k), k)
\end{align*}
\]

(2)

(3)

Where \( \mathbf{h} \) and \( \mathbf{f} \) are nonlinear functions of control input, \( u(k) \in \mathcal{U} \in \mathbb{R}^n_u \), system states, \( x(k) \in \mathbb{R}^n_x \), and process output, \( y(k) \in \mathbb{R}^n_y \) which are given at every time instant, \( k \).

The future outputs of the system are determined for a finite period called the Prediction Horizon, \( H_p \). These predicted outputs, denoted by \( \hat{\mathbf{y}} = [\hat{y}(k + 1), \hat{y}(k + 2), ..., \hat{y}(k + H_p)]^T \) are dependent on the future control moves given by \( u = [u(k), u(k + 1), ..., u(k + H_p - 1)]^T \) which are calculated by the optimization of a cost function, \( J \). The objective is to keep the process as close as possible to the reference trajectory, \( w = [w(k + 1), w(k + 2), ..., w(k + H_p)]^T \).

A generalized cost function is given as:

\[
J = \sum_{i=1}^{H_p} e(k+i)^T Q e(k+i) + \sum_{i=1}^{H_u} \Delta u(k+i)^T R \Delta u(k+i)
\]

where \( e(k+i) \) is the tracking error between the predicted and the reference trajectories, \( Q \) is the weighting matrix for the error, and \( R \) is the weighting matrix for the control moves. The optimization problem is solved using a PSO algorithm to find the optimal control moves that minimize the cost function.
\[ H_p = \sum_{i=1}^{H_p} u(k+i)^T S u(k+i) \] (4)

where \( H_p \) is the control horizon and \( e \) is the error between the desired output and the predicted output.

\[ e = u(k) - \hat{y}(k) \] (5)

\( Q, R \) and \( S \) are the weighting matrices and penalize the error \( e \), control effort \( u \), and change in control effort \( \Delta u \) respectively. Their values are assigned according to the process model and constraints.

Figure 2 shows the behavior of predicted output and input over one such horizon.

3. A receding horizon strategy, so that at each instant the horizon is moved towards the future which involves the application of the first control signal of the sequence calculated at each step.

3.2 Particle Swarm Optimization

PSO is one of the best known and widely used optimization methods. It was introduced by Eberhart & Kennedy [6] and incorporates three important properties of human or animal social behavior, which are evaluation, comparison, and imitation. Compared to other Evolutionary Algorithms (EAs), PSO is a more robust and faster algorithm that can solve nonlinear, non-differentiable, multi-modal problems which involve minimization of a objective function. This function will give the optimal control signals to the proposed controller.

Since PSO can generate a high-quality solution quickly with most stable convergence characteristics, it has been effective in solving problems to a wide variety of scientific fields as in and abundant literature is available on it. Kennedy gives details on how to avoid bad practices while using the PSO algorithm for effective use [5]. The details of PSO can be studied in the various sources cited in this paragraph.

3.3 Proposed MPC-PSO Method Summary

3.3.1 Controller Objective

Given a linear or nonlinear plant, the controller objective is to construct the PSO based predictive controller such that it searches for the optimal control signals and minimizes the error in the minimum time using minimum effort in the presence of disturbances and constraints.

3.3.2 Algorithm Implementation

The algorithm is implemented as follows:
1. Initialize particles at the start by assigning them random values.
2. Generate set of inputs for the process and apply to the model.
3. Evaluate cost function based on the model's output.
4. Evaluate fitness function, which is the inverse of cost function: $\text{fitness} = \frac{1}{|J|}$
5. Based on fitness, find optimal input sequence consisting of physical control moves or signals using PSO.
6. Update particles with these values and apply them to the model again, repeating a certain number of times.
7. Apply the first optimal control signal to the system and repeat these steps for next samples.

The number of particles represent the prediction horizon, $H_p$ and it is taken as 5. Since the control problem involves 2 and 4 areas, the number of particles is increased proportionally to 10 and 20 respectively. The swarm size is 50 and the number of iterations of the swarm per sample is 500, which ensures that the swarm converges to an optimal solution. The PSO parameters, $c_1$ and $c_2$ are both set at 2.04 after several trials. A time varying weighting factor is used that varies from 0.4 to 0.9 as the swarm progresses in the solution space.

4 MPC-PSO for Automatic Generation Control

In this section, the simulation results for the application of the proposed technique on single area nonlinear AGC are given. The PSO parameters are $c_1 = c_2 = 2.04$, and a time varying weight is used. The population is 20 and the prediction horizon, $H_p = 7$.

The AGC parameters are computed using the following values:

- $T_s = 20s$, $K_p = 120$ Hz p.u. $MW^{-1}$, $T_i = 0.3s$, $K = 0.6$ p.u. $MW^{-1}$ rad$^{-1}$, $T_g = 0.08s$, $R = 2.4$ Hz p.u. $MW^{-1}$

The constraint on the control signal is:

$$-0.5 \leq u \leq 0.5$$ (6)

The nonlinearities in the system appear in the form of saturation of states and are illustrated in Figure 1.

4.1 Performance of AGC with GRC=0.0017 p.u. $MW \ sec^{-1}$

The system is tested for a GRC value of 0.1 p.u. $MW \ min^{-1} = 0.0017$ p.u. $MW \ sec^{-1}$, as done in previous work by Al-Musabi [2] and Wang [15]. This means that the generated power output of the system cannot vary by more than 0.0017 p.u. MW in 1 second. A disturbance of 0.01 p.u. is present in the system. The proposed controller is applied to the system with this nonlinearity.

The results of this test can be seen in Figures 4 and 5. It is seen that the proposed technique performs much better than that Riccati-based optimal load frequency controller proposed by [15]. Comparing with the PSO-VSC technique given by [2], the settling time of the system is same, however there is lesser under shoot in frequency deviation. It can be seen in Figure 4, that the maximum frequency deviation of the system using the proposed technique is lesser than the previous work for this value of GRC.

4.2 Performance of AGC with Varying GRC

The system is also tested for a range of GRC values by testing it for three cases. The values of GRC selected to be are 0.0017, 0.005 and 0.01. These GRC
values are practical values and are dependent on the model and specifications of the power generation unit (turbine). All other parameters and control variables are same.

The results are seen in Figures 6 and 7. It is clear that the frequency deviation and the change in generated power is most for the case when the GRC is the smallest. The frequency deviates by as much as 0.152 Hz in this case and becomes 0 only after 19 seconds. The maximum value of the change in generated power is different in each case. It is 0.014, 0.016 and 0.017 for the cases when GRC is 0.01, 0.005 and 0.0017 respectively. When the GRC is smallest at 0.0017 p.u., it takes longest, i.e. 20s for the system to provide the steady demand power of 0.01 p.u. MW. For the cases of GRC 0.01 and 0.005, it took 5 and 8 seconds respectively.

From the behavior of the control inputs, it was observed that they vary till the time it takes for the system to reach the required steady states, after which they take their steady states. It was also observed that the cost is also the most for the case of smallest GRC and least for the case with the largest.

4.3 Performance of AGC with GRC=0.01 p.u. $MW \ sec^{-1}$ and Varying Disturbance

Another challenging test for the AGC system is through varying the load disturbance. A varying load disturbance, as seen in Figure 9, is applied to the single area system with GRC = 0.01 p.u. $MW \ sec^{-1}$. The load disturbance is 0.01 p.u. at the start and then changes to 0.02 and 0.03 p.u., and finally becomes 0.015 p.u. The dynamics of the frequency deviation and change in generated power are seen in Figures 8 and 9 respectively. It is seen that the frequency deviates by 0.033 p.u. every time an incremental disturbance of 0.01 p.u. is given at the load. The frequency deviation is maximum at 0.07 p.u. when the load disturbance changes by 0.015 p.u. at 60s. The generated power from the system fulfills the load demand in all cases as seen from Figure 9.
5 Conclusion

The following conclusions can be drawn from this paper:
1. A new and efficient PSO based MPC scheme is designed. Unlike other control schemes, it can incorporate constraints in the controller design stage, thus giving it the attractive advantages of speed, accuracy and optimal control. Furthermore, application of MPC to the field of power systems extends its applications portfolio.
2. The dynamical behavior of the single nonlinear AGC system is explored with constraints on the control input. Comparison with the previous work using different control schemes shows that MPC-PSO gives reduced settling time and lower overshoots compared to Ricatti-VSC and PSO-VSC.
3. The proposed controller performs well for a range of practical GRC values.
4. The performance of the controller is satisfactory under rapid load variations.

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