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Multi-agent Model Predictive Control of Nonlinear Interconnected Hydro-Thermal System Load Frequency Control Based on Bat Inspired Algorithm

M. Elsisi
Electrical Power and Machines, Faculty of Engineering (Shoubra), Benha University, Cairo, Egypt
elsisimahmoud22@yahoo.com

M. A. S. Aboelela
Electrical Power and Machines, Faculty of Engineering (Shoubra), Benha University, Cairo, Egypt
magdysafaa@yahoo.com

M. Soliman
Electrical Power and Machines, Faculty of Engineering (Shoubra), Benha University, Cairo, Egypt
msoliman_28@yahoo.com

W. Mansour
Electrical Power and Machines, Faculty of Engineering (Shoubra), Benha University, Cairo, Egypt
wagdy_ibrahim2010@yahoo.com

***Abstract* – Bat Inspired Algorithm (BIA) has recently been explored to develop a novel algorithm for distributed optimization and control. This paper proposes a multi-agent Model Predictive Control (MPC) of Load Frequency Control (LFC) based on BIA to enhance the damping of oscillations in a two-area power system. A two-area hydro-thermal system is considered to be equipped with multi-agent MPC. The proposed power system model considers generation rate constraint (GRC), dead band, and time delay imposed to the power system by governor-turbine, thermodynamic process, and communication channels. BIA is utilized to search for optimal controller parameters by minimizing a time-domain based objective function. The performance of the proposed controller has been evaluated with the performance of the conventional PI controller based integral square error technique , and PI controller tuned by GA in order to demonstrate the superior efficiency of the proposed multi-agent MPC tuned by BIA**

***Keywords* – Bat Inspired Algorithm (BIA), Load Frequency Control (LFC), Multi-agent Model Predictive Control (MPC).**

I. Introduction

Load frequency control represents a very imperative issue in large-scale power systems. It plays an important role in the power system by maintaining the system frequency and tie-line power flow at scheduled values [1-3]. There are two different control loops used to accomplish LFC in the interconnected power system, namely primary and supplementary speed control. Primary control is done by governors of the generators, which provide control action to a sudden change of load. The secondary control adjusts the frequency at its nominal value by controlling the output of selected generators.

Several approaches have been made in the past about the LFC. Among various types of load frequency controllers, Proportional – Integral (PI) controllers. The PI controller is very simple for implementation and gives a better dynamic response, but their performance deteriorates when the system complexity increases [4]. Recent optimal control concept for AGC designs of interconnected power system was firstly presented by Elgerd and Fosha [5-6]. The optimal control faces some difficulties to achieve good performance, such as complex mathematical equations for large systems. A robust LFC via $H\infty$ and $H2/H\infty$ control theories has been applied in [7] with different cases for the norm between load disturbance and frequency deviation output. The main deterioration of these two methods is that they introduce a controller with the same plant order, which in turn doubles the order of the open loop system, and makes the process very complex especially for large-scale interconnected power systems. In practice, different conventional control strategies are being used for LFC. Yet, the limitations of conventional PI and Proportional – Integral – Derivative (PID) controllers are: slow and lack of efficiency and poor handling of system nonlinearities. Artificial Intelligence techniques like Fuzzy Logic, Artificial Neural networks, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and ABC can be applied for LFC, which can overcome the limitations of conventional controls [8-18]. Genetic algorithms have been extensively considered for the design of AGC. Optimal integral gains and optimal PID control parameters have been computed by the GA technique for an interconnected, equal non-reheat and reheat type two generating areas [8-9]. In [10] the Parameters of PID sliding-mode used in LFC of multi-area power systems with nonlinear elements are optimized by GA. In [11], GA is used to compute the decentralized control parameters to achieve an optimum operating point for a realistic system comprising generation rate constraint (GRC), dead band, and time delays. The use of particle swarm optimization (PSO) for optimizing the parameters of AGC, where an integral controller and a proportional-plus-integral controller, is reported in [12]. In [13] the parameters of PI controller are designed by PSO with the new cost function and compared their results with [12]. In [14] Multiple Tabu Search (MTS) algorithm is used in a design of a Fuzzy Logic based Proportional Integral (FLPI) for LFC in two area interconnected power system. In [15], a robust PID controller based on Imperialist Competitive Algorithm (ICA) used for LFC application. The authors of [16, 17] have proposed bacterial foraging optimization algorithm (BFOA) for designing PI and PID-based load frequency controller for a two-area power system with and without GRC. Application of BFOA to optimize several important parameters in AGC of an interconnected three unequal area thermal systems such as the integral controller gains, governor speed regulation, and the frequency bias parameters, has been reported in [18].

Model Predictive Control (MPC) is improved considerably in the last decades in the field of control. It has a lot of advantages such as fast response, and stability against nonlinearities, constraints and parameters uncertainties [19]. In [20-23] some applications of MPC on LFC. In [20] the usage of MPC in a multi-area power system is applied, but, only by economic viewpoint. In [21], a new state contractive constraint-based predictive control scheme was used for LFC of a two-area interconnected power system. This model predictive control algorithm consists of a basic finite horizon MPC technique and an additional state contractive constraint. In [22], feasible cooperation-based MPC method is used in distributed LFC instead of centralized MPC. The paper did not deal with the change of system's parameters and Generation Rate Constraint. A decentralized model predictive control scheme for the LFC of a multi-area interconnected power system is applied in [23]. However, each local area controller is designed alone and does not consider the Generation Rate Constraint that is only imposed on the turbine in the simulation. This solution may effect in poor system-wide control performance of power system with a significantly interacting subsystem.

The large power system problems are such as the large time of computation. With increased number of areas in the cascaded system as a result of that the time of computation increases, and because the time is important. The emergence of the parallel processing system and fast network computation opened new opportunities and challenges to applying these recent technologies to solve power system problems. High efficiency is usually hard to reach because computation and communication take too much time during each calculation, thus for the solution of large-scale power system networks, it is possible to substantially reduce the computation time if special proposed parallel processing hardware and parallel programming were used [24-25]. There are various types of commercially available parallel processing computers: carrier, shared memory, multi-processor computers, and distributed-memory parallel computers, and real-time digital simulator [26]. Control of multi-area power system is often difficult from a single point by a single intelligent control agent; instead control has to be performed using multiple intelligent agents [27]. In this paper, multi-agent control schemes in which each agent employs a model-based predictive control approach is proposed. Communication between the agents is used to improve decision making. This communication can be in the form of parallel.

This paper proposes the BIA for optimal tuning of multi-agent MPC controllers in two area interconnected power system to damp power system oscillations. The multi-agent MPC control design is formulated as an optimization problem and BIA is employed to search for optimal controller parameters by minimizing a candidate time-domain based objective function. The performance of the proposed multi-agent MPC-based on BIA is evaluated by comparison with a conventional PI controller and PI-based on GA. Simulations results on a two-area test system are presented to assure the superiority of the proposed method compared with PI-based on GA and conventional one.

II. BAT INSPIRED ALGORITHM

Bat Algorithm has been built based on the echolocation behaviour of bats. These bats emit a very loud sound pulse (echolocation) and listen for the effect that bounces back from the surrounding objects. Their pulse bandwidth varies depending on the species and increases using harmonics. Some rules building the structure of BAT algorithm and use the echolocation characteristics of bats [28–30].

Step 1 Each bat uses echolocation characteristics to classify between prey and barrier.

Step 2 Each bat flies randomly with velocity v_i at position x_i with a fixed frequency f_{min}, varying wavelength k and loudness L_0 to attach the prey. It adjust the frequency of its released pulse and adjust the rate of pulse release r in the range of [0,1], relying on the closeness of its aim.

Step 3 Frequency, loudness and pulse emitted rate of each bat are varied.

Step 4 The loudness L_m^{iter} changes from a large value L_0 to a minimum constant value L_{min}.

The position x_i and velocity v_i of each bat defined and updated during the optimization process. The new solutions x_i^t and velocities v_i^t at time step t are performed by the following equations:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \qquad (1)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*) f_i \qquad (2)$$

$$x_i^t = x_i^{t-1} + v_i^t \qquad (3)$$

Where β in the range of [0,1] is a random vector drawn from a uniform distribution function. x_* is the current global best location, results after comparing all the locations among all the n bats. For implementation, every bat is randomly assigned a frequency which changes uniformly from $[f_{min}, f_{max}]$. For the local search, once a solution is selected among the current best solutions, a new solution for each bat is generated locally using a random walk.

$$x_{new} = x_{old} + \varepsilon L^t \qquad (4)$$

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Where ε is a random number between [-1, 1], while L_t is the mean loudness of all bats at this time step. As the loudness usually decreases once a bat has got its prey while the rate of pulse emission increases, the loudness can be selected as any value of convenience. Assuming L_{min} = 0 indicate that a bat has just found the prey and temporarily stop emitting any sound, one has:

$$L_i^{t+1} = \alpha L_i^t, r_i^{t+1} = r_i^0[1-\exp(-\gamma t)] \tag{5}$$

Where α is constant in the range of [0, 1] and γ is positive constant. As time reach infinity, the loudness tends to be zero, and γ_i^t equal to γ_i^0. The general framework of the BIA is described in Table I.

Table I: The Framework of BIA

Algorithm 1: The framework of BIA
Produce Initial bat population x_i (i = 1, 2, ..., n)
while (t <Max number of iterations)
Generate new solutions by determining frequency, and updating velocities and locations/solutions [equations (1) to (3)]
if (rand > r_i)
Select a solution between the best solutions
Produce a local solution around the selected best solution
end if
Generate a new solution by flying randomly
if (rand < L_i & $f(x_i) < f(x_*)$)
Accept the new solutions
Increase r_i and reduce L_i
end if
Select the current best x_*
t=t+1
end while
Print result

III. Multi-Agent Model Predictive Control

1.1. Model Predictive Control Overview

Model Predictive Control (MPC) has been evolved as an effective control strategy to stabilize dynamical systems in the presence of nonlinearities, uncertainties, and delays, especially in process control [20-23]. A general MPC scheme consists of prediction and controller unit. The prediction unit forecast future behavior of system depend on its current output, disturbance and control signal on a finite prediction horizon. The control unit uses the predicted output in minimizing the objective function in presence of system constraints. There are a lot of formulations of the MPC that are different either in a formulation of the objective function [19,31]. In the MPC, the measured disturbance can be compensated by the method of feed forward control. Unlike feedback controller, feed forward control rejects most of the measured disturbance before affect on the system. The feed-forward control used in association with feedback control; the feed-forward control reject most of the measured disturbance effect, and the feedback control reject the rest as well as dealing with unmeasured disturbances. More details of this control method could be found in [31, 32].

1.2. MPC Modeling

The MPC are based on the model shown in Fig. 1.

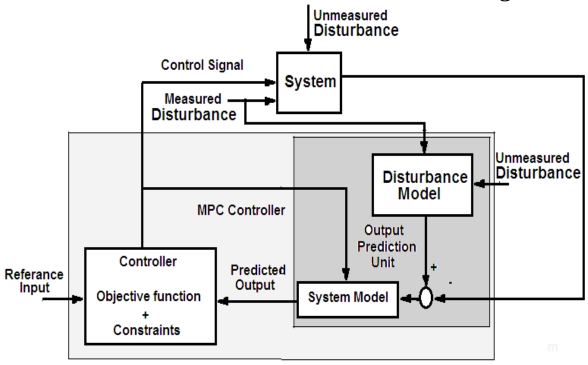

Fig. 1. Model used by the MPC block for prediction/state estimation.

1.2.1. System Model

The system model is a linear Time Invariant (LTI). The MPC controller performs all the estimation and optimization computations using a discrete-time, delay-free, state-space system, with dimensionless input and output variables. Therefore, when a system model is specified in the MPC controller, the following model-conversion steps are automatically carried out, if needed

1. Conversion to state-space.
2. Discretization or resampling.
3. Delay removal.
4. Conversion to dimensionless input and output variables.

the plant input and output variables are converted to dimensionless form as follows:

$$x_p(k+1) = A_p x_p(k) + BS_i u_p(k) \tag{6}$$

$$y_p(k) = S_o^{-1} C x_p(k) + S_o^{-1} D S_i u_p(k) \tag{7}$$

Where

A_p, B, C, and D	Constant state space matrices.
S_i	Diagonal matrix of input scale factors in engineering units.
S_o	Diagonal matrix of output scale factors in engineering units.
x_p	State vector in engineering units. No scaling is performed on state variables.
u_p	Dimensionless plant input variables.
u_p	Dimensionless plant output variables.

The resulting plant model has the following equivalent form:

$$x_p(k+1) = A_p x_p(k) + B_{pu}u(k) + B_{pv}v(k) + B_{pd}d(k) \tag{8}$$

$$y_p(k) = C_p x_p(k) + D_{pu}u(k) + D_{pv}v(k) + D_{pd}d(k) \tag{9}$$

Where $C_p = S_o^{-1}C$, B_{pu}, B_{pv} and B_{pd} are the corresponding columns of BS_i. Also, D_{pu}, B_{pv} and B_{pd} are the corresponding columns of $S_o^{-1}DS_i$. Finally, $u(k)$, $v(k)$ and $d(k)$ are the dimensionless manipulated variables, measured disturbances, and unmeasured input disturbances, respectively. MPC controller enforces the restriction of $D_{pu} = 0$, which means that MPC controller does not allow direct feed through from any manipulated variable to any system output.

1.2.2. Disturbance Model

If the system model includes unmeasured disturbances, the disturbance model indicates how $d(k)$ changes with time. The disturbance model is provided as an LTI object. The MPC controller converts the disturbance model to a discrete-time, delay-free, LTI state-space system using the same steps used to convert the system. The result is:

$$x_d(k+1) = A_d x_d(k) + B_d w_d(k) \tag{10}$$

$$d(k) = C_d x_d(k) + D_d w_d(k) \tag{11}$$

Where

A_d, B_d, C_d, and D_d Constant state space matrices
$x_d(k)$ Disturbance model states
$d_k(k)$ Dimensionless unmeasured disturbances
$w_d(k)$ Dimensionless white noise inputs, assumed to have zero mean and unity variance

1.2.3. Measurement Noise Model

One of the controller design objectives is to distinguish disturbances, which require a signal from measurement noise. The measurement noise model has this purpose. The measurement noise model indicates how the noise changes with time. Using the same steps as for the plant model, the MPC controller converts the measurement noise model to a discrete-time, delay-free, LTI state-space system. The result is:

$$x_n(k+1) = A_n x_n(k) + B_n w_n(k) \tag{12}$$

$$y_n(k) = C_n x_n(k) + D_n w_n(k) \tag{13}$$

Where

A_n, B_n, C_n, and D_n Constant state space matrices
$x_n(k)$ Noise model states.
$y_n(k)$ Dimensionless noise signals to be added to the dimensionless measured plant outputs.
$w_n(k)$ Dimensionless white noise inputs, assumed to have zero mean, unity variance.

1.2.4. Single-Input, Single-Output MPC

Figure 2 shows a case in which MPC is trying to hold a single variable $\bar{y}$ at a target value r by adjusting the manipulated variable u. The system requires changes in u as well as to two types of disturbance signals: measured v and unmeasured d.

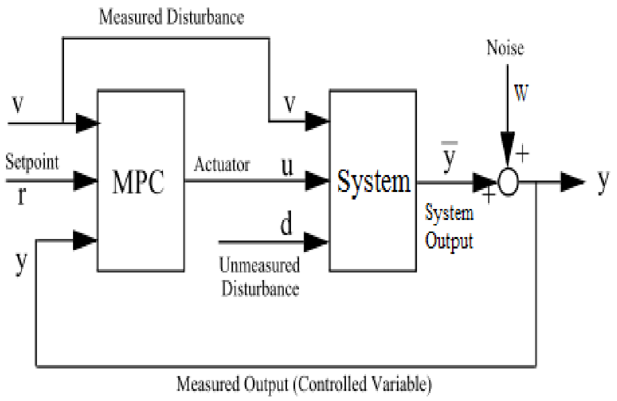

Fig. 2. Block diagram of a single-input, single-output MPC application.

The MPC block implicates models of the way in which v and u affect $\bar{y}$. It uses this information to adjust u that keep $\bar{y}$ at its setpoint. This adjustment considers the effect of any known constraints on the calculations (e.g., an actuator at its upper or lower bound). If the models are accurate and the system responds quickly to u, this “feedforward” compensation counteracts the effect of v perfectly. In reality, however, model shortage, plant limitations, and unmeasured disturbances cause the measurement y to deviate from its expected value. Thus, MPC uses the output measurement and a disturbance model to predict future values of $\bar{y}$. It then uses its model to calculate suitable adjustments (a form of “feedback” compensation). This calculation also considers the known constraints. MPC uses a noise model in combination with its disturbance model to remove the estimated noise component of the measurement.

MPC operates at discrete intervals of time units name sampling period T_s. If MPC starts at time t = 0. They are integer multiples of the sampling period: 0, T_s, 2 T_s, 3 T_s, ..., k T_s, where the integer index k represents the current sampling instant. Fig. 3 shows the state of a single-input, single-output MPC system which has been operating for some time; k is the current sampling instant. The current measured output y_k and previous measurements y_{k-1}, y_{k-2}, ..., are known and are the filled circles in Fig. 3 (a). Figure 3 (b) shows MPC’s previous and current moves of u. MPC calculate the current move u_k in two phases:

1. Estimation. In order to make an intelligent move, MPC needs to know the current state of the system. This includes the true value of the controlled variable $\bar{y}_k$ and any internal system variables that influence the future trend, $\bar{y}_{k+1}$, ..., $\bar{y}_{k+p}$.
2. Optimization. Values of setpoints, measured disturbances, and constraints are specified over a finite horizon of future sampling instants k+1, k+2, ..., k+P, where P is a finite integer ≥ 1 and name

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prediction horizon as shown in Fig. 3 (a). MPC then computes the M moves u_k, u_{k+1}, ... u_{k+M-1}, where $1 \leq M \leq P$ and name control horizon.

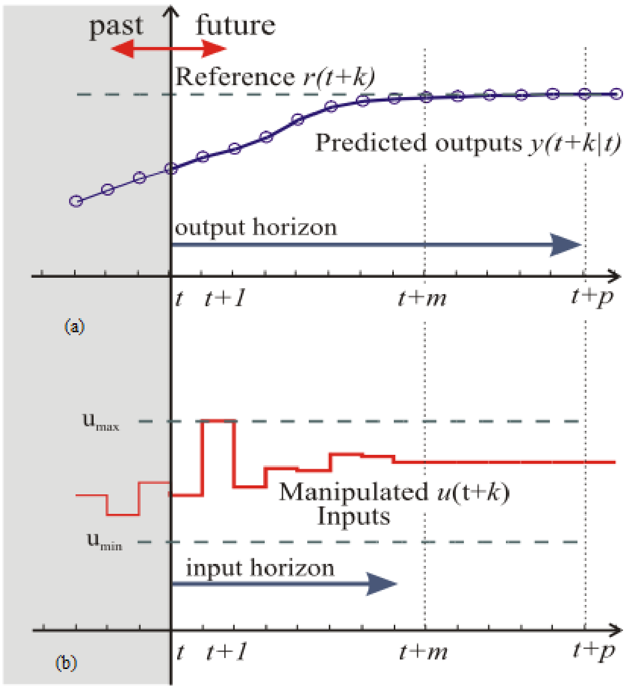

Fig. 3. The MPC problem at the sampling instant t.

MPC determines its moves by solving the following optimization problem (formulated for the k^th sampling instant):

$$\underset{u_k,\ldots,u_{k+p-1}}{Min} \sum_{i=1}^{P} [Q(r_{k+i} - \hat{y}_{k+i})^2 + R(\Delta u_{k+i-1})^2] \tag{14}$$

Such that

$$u_{\min} \leq u_{k+i} \leq u_{\max} \tag{15}$$

$$y_{\min} \leq \hat{y}_{k+i} \leq y_{\max} \tag{16}$$

$$|\Delta u_{k+i}| \leq \Delta u_{\max} \tag{17}$$

Where $\Delta u_j = u_j - u_{j-1}$ is the adjustment at sampling instant j, and Q and R are non-negative weights.

1.3. Model Predictive Load Frequency Control

An MPC controller has been used to generate the control signal based on area control error ACE_i, change in load demand ΔP_{Di} and the reference value of ACE_i as its inputs. Where reference value of ACE_i equal zero. A model predictive load frequency control scheme is shown in Fig. 4.

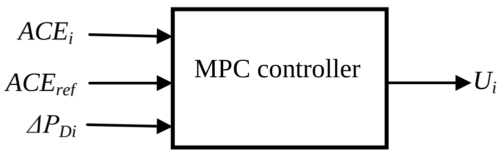

Fig. 4. A model predictive load frequency control scheme.

In this paper the MPC, toolbox in Matlab Simulink has been used to design an MPC controller. The controller design requires a Linear Time Invariant (LTI) model of the system that is to be controlled. The rate at which MPC operates is $1/NT_S$, where T_S is the sampling period, N is the number of controls that are applied to the system. In most cases, N is chosen equal one. The value of T_S is important because it is the length of each prediction step. The method for selecting T_S for this problem is based on tracking performance. Selecting the prediction horizon P and control horizon M were also affected by the controller. Weights (Q and R) on system's input and output are chosen at their best quantities. The BIA is proposed in this paper to get the best value of T_S, P, M and weights on system's input and output.

1.4. Multi-Agent Technique

Recent advances in computer technology will certainly have a great impact on the methodologies used in power system expansion and operational planning as well as in real-time control. Parallel processing appears to be among the most favorable ones of these new developments [24,25]. Parallel processing consists of multiple microprocessors which are used to exploit synchronism in the computation job. The main advantage of parallel processing in power system applications is the speed up of computations in order to make viable the solution of problems intractable in conventional computers. The benefit obtained in moving an application to a parallel microprocessor usually is measured in terms of speedup and efficiency of the parallel processing implementation when compared to the sequential version. Therefore, usually communication is used to reduce the uncertainty since this allows agents to inform one another about their aims. Typically, at each control step, the agents perform a number of iterations, within which each agent performs a local computation and communication step. The agents can in this way take into account the plans of other agents and anticipate any undesirable disturbance. Through coordination, agents may obtain agreement on taking actions that yield a good overall performance [33]. In multi-area electrical power system, the controller of each individual area can be represented as control agent as shown in Fig. 5. Each control agent needs to the value of the area control error to give appropriate control value. Therefore, a central agent is used to represent the tie line between areas. The central agent takes the change in frequency of each area and gives the tie line power and area control error of each individual area and these details are shown in Fig. 6. Each control agent takes its area control error from the central agent and chooses the control signal. Figure 5 shows such a model of nonlinear controlled hydrothermal plants in a two-area interconnected power system with the necessary interchange data between the central agent and the different control agents.

Where

B_i :Frequency bias parameter

ACE_i :Area control error

U_i :Controller output

R_i :Speed regulation in pu Hz

T_{gi} :Governor time constants in sec

T_{ti} :Turbine time constant in sec

T_{ri} :Time constant of reheater in sec

k_{ri} :Gain of reheater

B_i :Frequency bias parameter

T_i :Hydro governor time constant in sec

T_w :Water starting time in sec

ΔP_{Di} :Load demand change

ΔP_{tie} :Change in tie line power in p.u Mw

T_{pi} :Power system time constant in sec

K_{pi} :Power system gain

T_{12} :Synchronizing coefficient

Δf_i :System frequency deviation in Hz

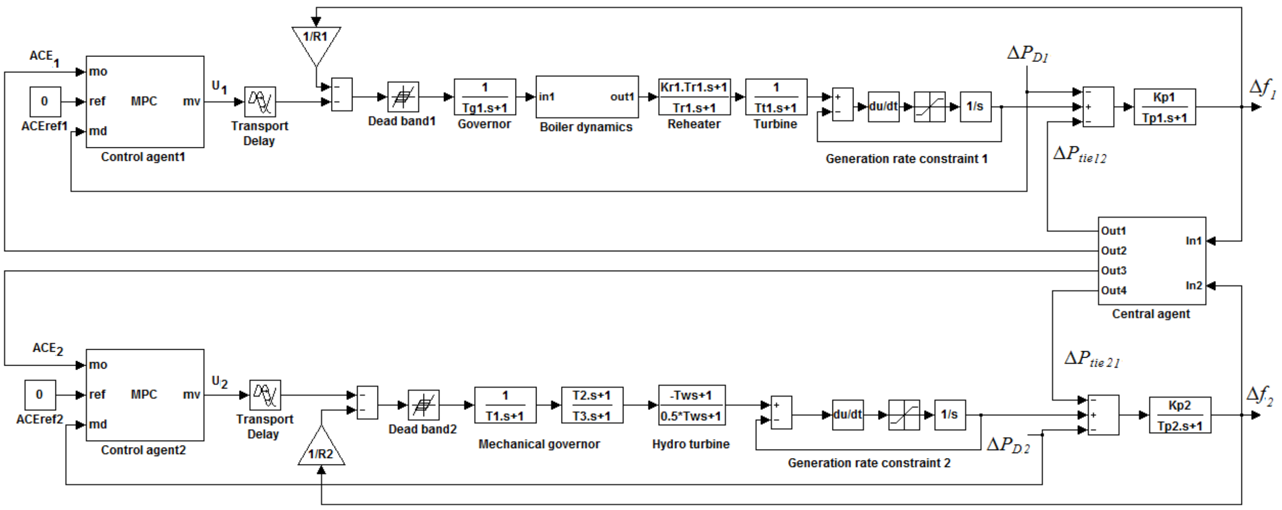

Fig.5. Two-area interconnected power system with multi-agent model predictive control.

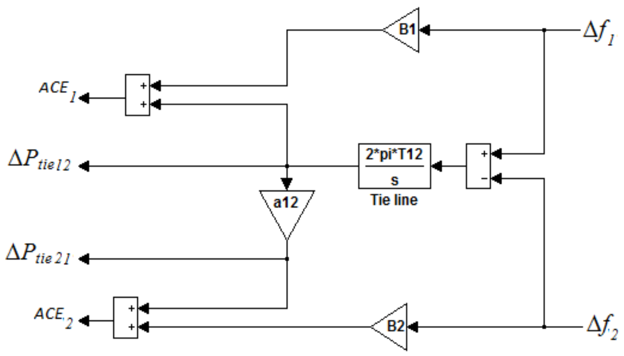

Fig. 6. Central agent of multi-agent model predictive

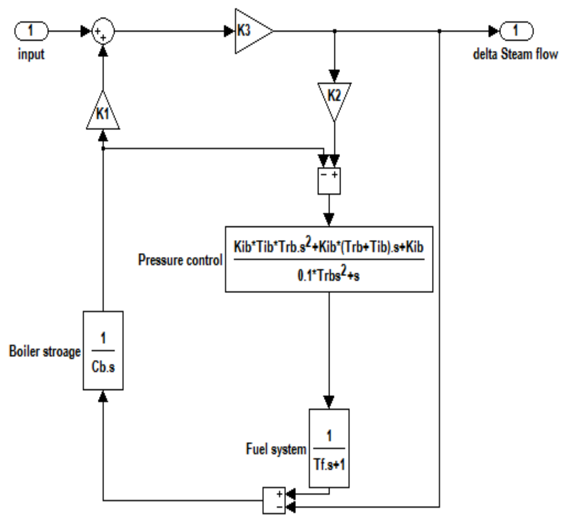

Fig. 7. Boiler dynamics.

The speed governor dead band has a significant effect on the dynamic performance of the system. For this analysis, in this paper backlash nonlinearity of about 0.05% for thermal system and the dead band non-linearity of about 0.02% for hydro system are considered. The system is provided with single reheat turbine with suitable GRC, for thermal area 0.0017MW per sec and hydro area 4.5% per sec for raising generation and 6% for lowering generation. The boiler is used to producing steam under pressure. In this study, the effect of the boiler in a steam area in the power system is also considered and detailed scheme is shown in Fig. 7 given in [34].

The performance index which selected in this paper can be defined by (18).

$$J = (1-e^{-\beta})M_p + e^{-\beta} \times t_s \qquad (18)$$

This objective function can satisfy the designer requirements using the weighting factor value (β). The factor is set larger than 0.7 to reduce the overshoot. On the other hand is set smaller than 0.7 to reduce the settling time.

This study focuses on the optimal tuning of controllers for LFC using BIA. The aim of the optimization is to search for the optimum multi-agent MPC parameters that improve the damping characteristics of the system under all operating conditions and various loads and finally designing a low order controller for easy implementation.

IV. SIMULATION RESULTS

In this section, different comparative cases are examined to show the effectiveness of the proposed BIA method for optimizing controller parameters of multi-agent MPC. Table II gives the optimum values of controller parameters for different methods. The PI controller parameters of the conventional controller due to [35].

Table II: Controller parameters and objective function (J).

	Conventional PI	GA-PI	Multi-agent MPC
Controller Parameters	K_{pr1}= K_{pr2} =0.3, K_{I1}= K_{I2}=0.12	K_{pr1}=0.979, K_{I1}=0.0399, K_{pr2}=1.071, K_{I2}=0.0440	T_{s1}=4.3123, P_1=10.000, M_1=5.8288, Q_1=0.6752, R_1=4.2568, T_{s2}=8.5418, P_2=6.8928, M_2=4.3846, Q_2=2.6881, R_2=7.0801
J	180.9325	28.753	24.6337

Case 1: a 1% step increase in demand of the first area (ΔP_{D1}), the second area (ΔP_{D2}) simultaneously and time delay equal 2 seconds are applied (nominal test case). The change in frequency of the first area Δf_1, the change in frequency of the second area Δf_2, and change in tie-line power of the closed loop system are shown in Figs. 8-10. Remarkably, the response with conventional PI controller has high settling time and undesirable oscillations. Also compared with PI-based GA the proposed method is indeed more efficient in improving the damping characteristic of the power system.

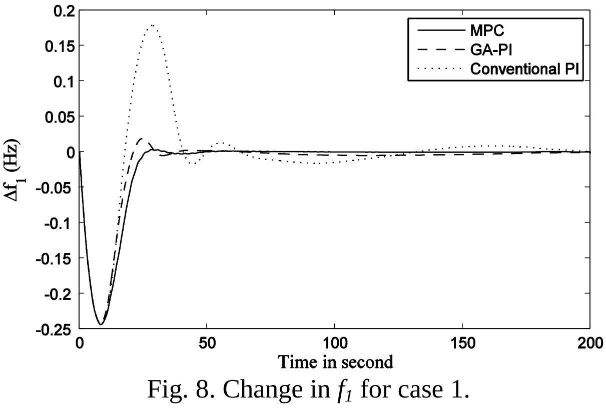

Fig. 8. Change in f_1 for case 1.

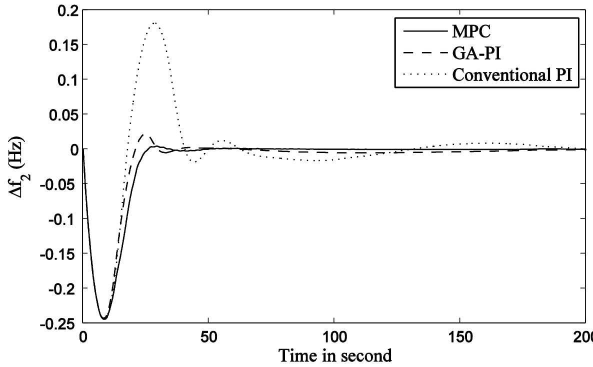

Fig. 9. Change in f_2 for case 1.

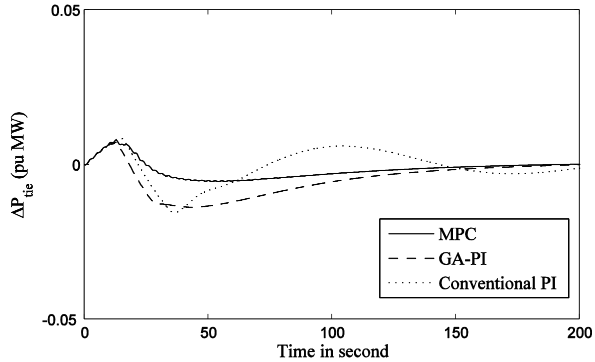

Fig.10. Change in P_{tie} for case 1.

Case 2: a 1.5% step increase is applied as a change of demand in the first area (ΔP_{D1}), the second area (ΔP_{D2}) simultaneously and time delay equal 2 seconds. The change in frequency of the first area Δf_1, the change in frequency of the second area Δf_2 and change in tie-line power of the closed loop system are shown in Figs. 11-13. From these Figures, the response with the conventional controller is unstable. Moreover, the proposed method outperforms and outlasts PI-based on GA in damping oscillations effectively and reducing settling time. Hence compared to the conventional controller, and PI-based on GA, multi-agent MPC based on BIA greatly enhances the system stability and improves the damping characteristics of the power system. Because of the large values of conventional PI controller response, a sub figure of this part is shown beside the main response.

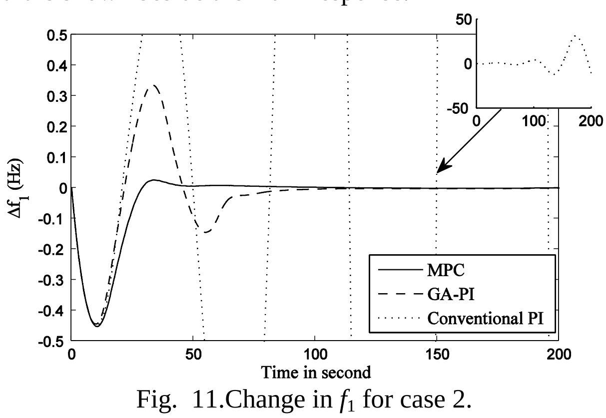

Fig. 11.Change in f_1 for case 2.

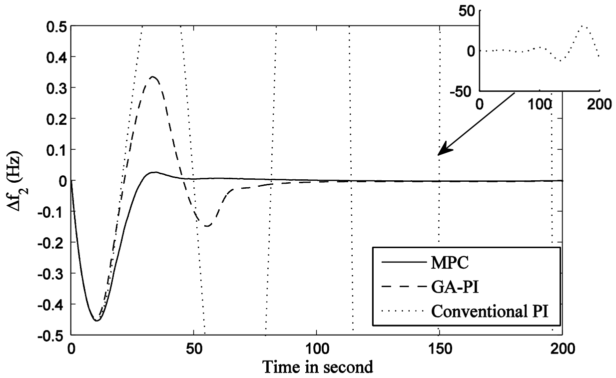

Fig. 12.Change in f_2 for case 2.

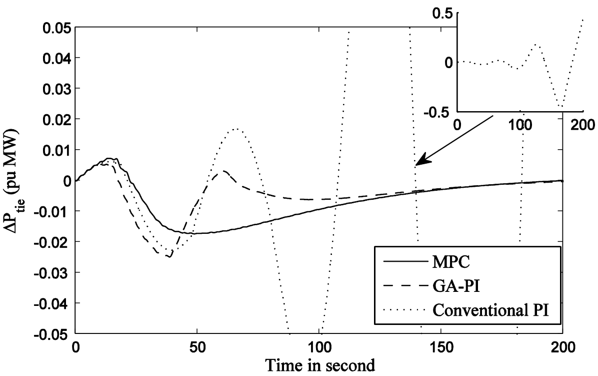

Fig.13. Change in P_{tie} for case 2.

Case 3: a 1% step increase in demand of the first area (ΔP_{D1}), the second area (ΔP_{D2}) simultaneously and time delay equal 15 seconds are applied. The change in frequency of the first area Δf_1, the change in frequency of the second area Δf_2, and change in tie-line power of the closed loop system are shown in Figs. 14-16. It is clear from these Figures that the response with PI-based on GA and conventional controller are unstable. The potential and superiority of the proposed method over the conventional and PI-based on GA is demonstrated.

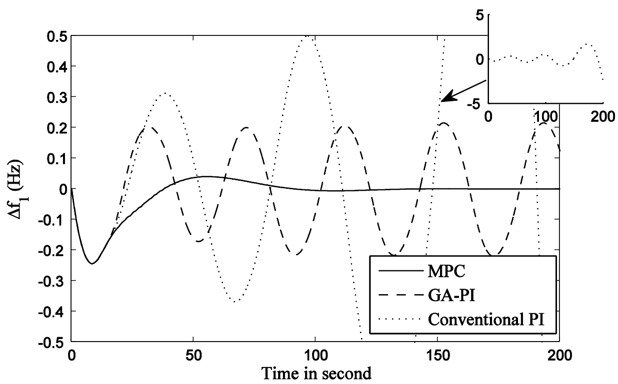

Fig. 14.Change in f_1 for case 3.

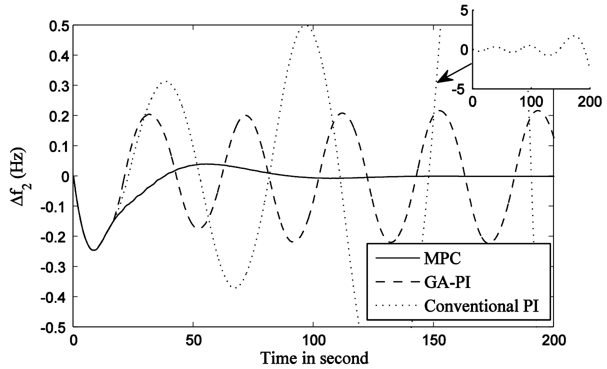

Fig. 15.Change in f_2 for case 3.

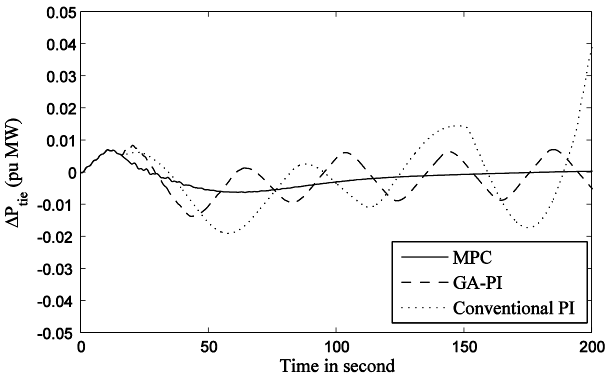

Fig. 16.Change in P_{tie} for case 3.

Case 4: a parameter variation test is also applied to validate the robustness of the proposed controller. Figs. 17-19 shows the change in frequency of the first area Δf_1, the change in frequency of the second area Δf_2, and change in tie-line power of the closed loop system with variation in T_{12}. It is clear that the system stable with the proposed controller.

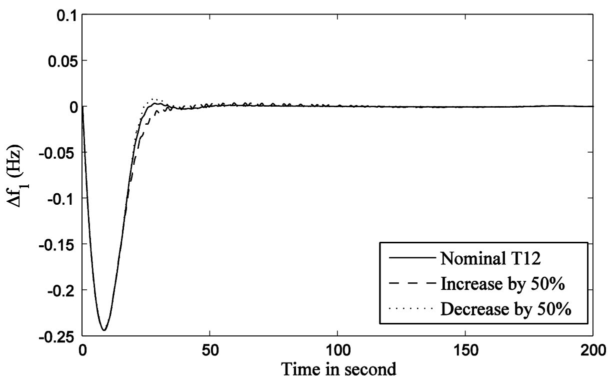

Fig. 17.Change in f_1 for case 3.

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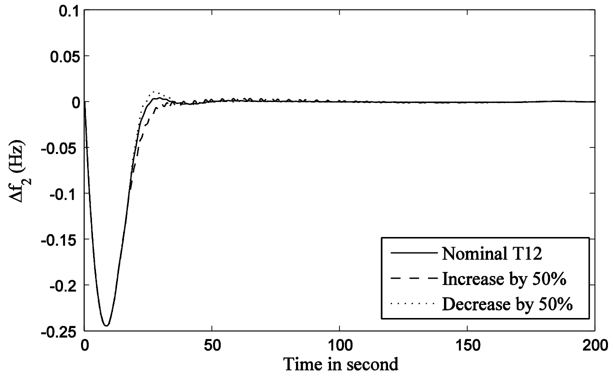

Fig. 18.Change in f_2 for case 4.

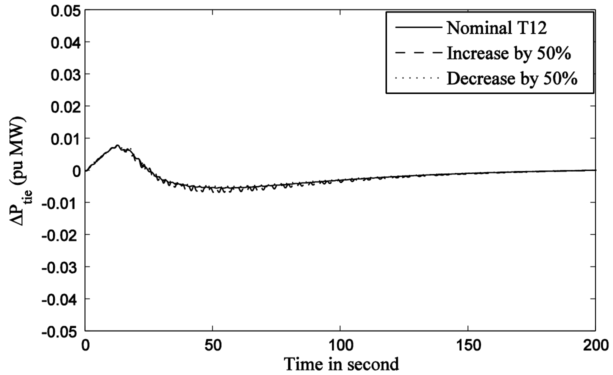

Fig. 19.Change in P_{tie} for case 4.

V. CONCLUSION

This paper presents the application of the BIA algorithm as a new artificial intelligence technique in order to optimize the AGC in a two-area interconnected power system. BIA algorithm is proposed to tune the parameters of multi-agent MPC controller. A two-area power system is considered to demonstrate the proposed method. The simulation results emphasize that the designed multi-agent MPC-based on BIA is robust in its operation and gives a superb damping performance for frequency and tie line power deviation compared to conventional PI controller, and PI-based on GA. Besides the simple architecture of the proposed controller, it has the potentiality of implementation in real-time environment.

APPENDIX

The typical values of parameters of system under study are given below: T_{t1} =0.3 s; T_{g1} =0.2 s; T_{r1} = 10 s; K_{r1} = 0.333; T_1 = 48.7 s; T_2 =0.513 s; T_3 =10 s; T_w =1 s; T_{P1} =20s; T_{P2} = 13 s; K_{P1} =120 Hz/p.u MW; K_{P2} = 80 Hz/p.u MW; T_{12} = 0.0707 MW rad^{-1}; a_{12} = -1; R_1 = R_2 =2.4 Hz/p.u MW; B_1 =B_2 =0.425 p.u MW/Hz.

Boiler (oil fired) data: K_1 =0.85; K_2 =0.095; K_3 =0.92;C_b=200; T_f=10;K_{ib} =0.03;T_{ib} =26;T_{rb} =69.

LTI model of the system can obtain by removing all nonlinearities. LTI_1 model of $area_1$ is obtained by remove MPC_2 of $area_2$ and open MPC_1 and click design. Export LTI_1 model of $area_1$ to the workspace and save it. LTI_2 model of $area_2$ is obtained by remove MPC_1 of $area_1$ and open MPC_2 and click design. Export LTI_2 model of $area_2$ to the workspace and save it.

Table III: Objective Function

```
function z=Fun(x)
global Ts1 P1 M1 R1 Q1 MPC1 Ts2 P2 M2 R2 Q2
MPC2 LTI1 LTI2
Ts1=x(1) ;P1=x(2);M1=x(3); R1=x(4);Q1=x(5);
Ts2=x(6);P2=x(7);M2=x(8); R2=x(9);Q2=x(10);
w1=struct('ManipulatedVariables',0,'ManipulatedVariable
sRate',R1,'OutputVariables',Q1,'ECR',0);
MPC1=MPC(LTI1,Ts1,P1,M1,w1);
w2=struct('ManipulatedVariables',0,'ManipulatedVariable
sRate',R2,'OutputVariables',Q2,'ECR',0);
MPC2=MPC(LTI2,Ts2,P2,M2,w2);
sim('two_area_hydro_thermal')
c1=stepinfo(dF1,T,0);
a1=c1.SettlingTime;
b1=c1.Peak;
c2=stepinfo(dF2,T,0);
a2=c2.SettlingTime;
b2=c2.Peak;
z=(1-exp(-0.7))*b1+exp(-0.7)*a1+(1-exp(-.7))*b2+exp(-
0.7)*a2
```

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