DESIGN OF PSO BASED AUTOMATIC GENERATION CONTROL WITH COST FUNCTIONS

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Abstract: *This article deals with the tuning of parameters for automatic generation control. A three-area interconnected reheat thermal system with proportional-integral controller is considered. Particle swarm optimization algorithm has been applied to optimize the controller parameters. The effectiveness of a variety of cost functions are considered based on the variation in area control errors and outputs of the controller in all the areas. Cost functions like integral square error, integral time-multiplied square error, integral absolute value of the error and integral time-multiplied absolute value of the error are considered. Performances of optimization algorithms are compared and it was found that proposed algorithm gives better results than traditional control algorithm for the problems of AGC. MATLAB/SIMULINK is used as a simulation tool.*

Keywords: *Automatic generation control, Particle swarm optimization, Cost functions*

1. INTRODUCTION

The generation of electrical power is produced depending upon the availability of generating plants. To meet the load demand in geographical areas the generators are interconnected by transmission network and form large complex power systems. The large power systems are normally divided into control areas based on the principle of coherency. The coherent areas are interconnected through tie-lines which are used for contractual energy exchange between areas and provide inter area support during exceptional operations. A mismatch in real power balance affects primarily the system frequency. The problem of controlling the generation in an area for maintaining the frequency at desired level by eliminating the mismatch between generation and load and also eliminating the inadvertent exchange of power with other areas via tie-lines is known as automatic generation control (AGC) [1, 2].

AGC in more than one area is operated alone by a frequency pulses in an interconnection. There will be huge amount of power oscillations between controlling areas except when regulating operations developed by all areas can be realized at the same time. In addition, the operation of such an interconnection would feel a greater severe problem if the areas trying to control frequency had measurement disturbance. Frequency measured of an area at a value more than others would minimize its generation, while others increased. Both of them are measuring to influence the frequency to the specified value [3, 4].

There have been a vast variety of research articles [5-11] relating to AGC controller designs which had made classical controllers structure as the basis for the development of more advanced and even intelligent technique (IT) based controllers for AGC applications in power systems.

ITs show its capability in the different scenarios of AGC problems of the power systems. Among these techniques, particle swarm optimization (PSO) technique seems to be good methods to solve optimization problems than the other intelligent (evolutionary) techniques. The application of PSO technique for AGC of interconnected power systems and thoroughly investigates its merits over other types of AGC schemes. The real power systems optimization problems are usually of multi-furious nature. The ultimate goal of this optimization algorithm is to find a global solution from a group of local solutions. These optimization algorithms are applicable to functions that are multi-modal, non-differentiable and discontinuous. PSO is a stochastic, population based Energy Management System problem solving algorithm; it is a kind of swarm intelligence that is based on social principles and provides insights into social behavior, as well as contributing to power systems.

Best efforts have been made to develop the tuning of parameters for a two-area interconnected hydro-thermal system with PI controller with the help of PSO algorithm as well as genetic algorithm scheme by R. N. Patel [12]. ISE and ITAE considered for optimization. The effectiveness of a cost function was considered based on the variation in tie-line power and change in frequency in both the areas, and then they [13] have addressed PSO algorithm to AGC strategy in interconnected power grid in the control performance standard (CPS) standard. PSO was analyzed on ACE and CPS to AGC Strategy.

A complex power system networks that are highly non-linear and non-stationary and enhanced particle swarm controller for solving constrained optimization problems for power system applications, in particular, the optimal allocation of multiple STATCOM units by [14, 15]. The study focused on the capability of the algorithm to find feasible solutions in a highly restricted hyperspace. The performance result of the enhanced particle swarm controller was proved its capability in compared of the classical PSO algorithm, genetic algorithm and bacterial foraging algorithm. Additionally, the enhanced PSO was capable of finding the global optimum without getting trapped in local minima.

In this chapter, the beauty and simplicity of PSO technique is demonstrated. The AGC controllers are designed based on PSO optimal control strategies. The AGC controller designs are investigated for load disturbance in a three-area reheat interconnected power systems model. Firstly, introduced a cost function ISE with standard Ziegler Nichols (ZN) algorithm based classical PI and optimal PSO technique based PI controller. Secondly, other cost functions i.e. IAE, ITSE and ITAE are evaluated and compared to each other through PSO.

2. POWER SYSTEMS MODEL UNDER INVESTIGATION

For the present study, a three-area interconnected power systems consisting of power plants with reheat thermal turbines is considered and is interconnected via alternating current (AC) transmission line only. The transfer function model is also presented in Fig. 1 similar to be [7].

In the power systems model, considering PI controller which is using standard ISE cost or fitness or objective function for developing controlling parameters. This cost function is also evaluated with other cost functions using PSO technique. According to this, different types of adequate cost functions are tested for this study. These cost functions deals according to its parameters inherent performing nature. Proper parameter setting is of great importance for a system to be stable. Having secured a stable system, cost must be to adjust the system parameters until an optimum response is achieved. Performance indices or cost function have proved to be most meaningful measures of dynamic performance. Such a cost function is usually formed of the structure:

$$C=\int_0^\infty F(e_1, e_2, e_3, \ldots.., e_n)\, dt \tag{1}$$

where; C is the cost of the function and e_1, e_2, e_3, ……, e_n are the different errors that control system is designed to eliminate [7]. Popular performance indices are ISE, IAE, ITSE and ITAE. Selection of an appropriate J will lead to better optimal values of the gain parameters, which in turn gives better dynamic response.

Classical PI control scheme is used ISE as a cost function.

3. PERFORMANCE INDEX MODELING

Systems performance quantification is achieved through a performance index. The performance selected depends upon the process under consideration and is chosen such that emphasis is placed on specific aspects of the systems performance. Alternatively a performance index is a quantitative measure of systems, and is chosen so that a set of parameters in the systems can be adjusted to meet the required specification optimally. Minimum or maximum value of this index then corresponds to the optimum set of parameter value [16].

When J is a cost function it has to optimize (minimize). Different performance indices used in practice are:

$$ISE=\int_0^\infty e^2(t)dt \quad (2)$$

$$IAE=\int_0^\infty |e(t)|dt \quad (3)$$

$$ITSE=\int_0^\infty te(t)^2dt \quad (4)$$

$$ITAE=\int_0^\infty t|e(t)|dt \quad (5)$$

In all of the above 'e(t)' is the error at time 't'. Area control errors i.e. ACE_1, ACE_2 and ACE_3 are the errors which are the $input_1$, $input_2$ and $input_3$ respectively in the power systems model.

$ACE_1 = B_1\ \Delta F_1+\Delta P_{tie12}$, for area-1, $ACE_2 = B_2\ \Delta F_2+\Delta P_{tie23}$, for area-2 and for area-3, $ACE_3 = B_3\ \Delta F_3+\Delta P_{tie31}$

The ACE_i (i=1, 2 and 3) is the summation of frequency biasing, deviation in the frequency and change in tie-line power flows. The ACE_is of respective areas is taken as the input to the PI controller which can be expressed as:

$$U_{PI} = K_P ACE_i + K_I \int_0^t ACE_i dt \quad (6)$$

The control parameters to be tuned through the optimization algorithm are feedback gains of PI and frequency biasing of outputs of the controller in the power systems.

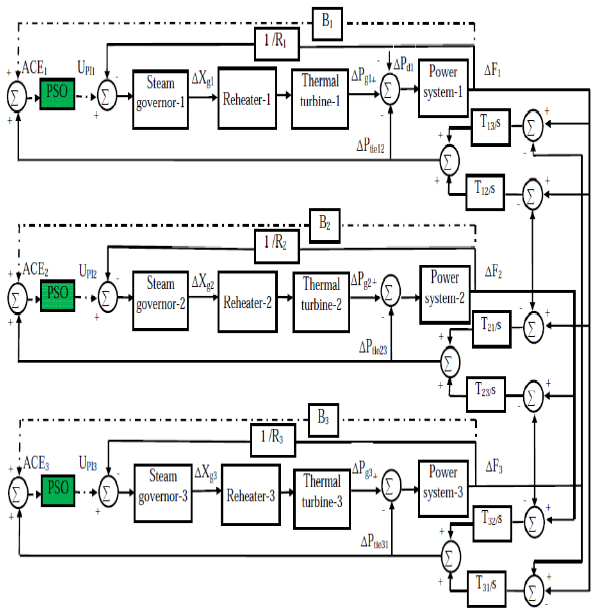

Fig. 1 Model of interconnected power systems consisting of reheat turbines with PSO (PI) controller

In this study, the optimum values of the controller parameters, which minimize the objective function, are accurately computed using PSO algorithm.

4. OVERVIEW OF PSO TECHNIQUE

PSO is a population based optimization technique based on intelligent scheme developed by J. Kennedy and R. Eberhart in 1995 [17]. PSO has emerged as one of the most assuring optimizing scheme for effectively dealing near to global optimization tests. The inspiration of the mechanism is established by the social and cooperative nature represented by flying birds. The algorithm simulates a simplified social milieu in capable solutions of a swarm which means particles that a single particle bases its search on its own experience and information given by its neighbours in the specified region.

Particles are flown in the solution region with their randomized assigned velocity. Among these particles, each particle keeps track of its coordinates in the solution region which are associated with the best fitness it has achieved so far. This value is known as '*pbest*'. Another '*best*' value that is tracked by the particle is the best value, obtained so far by any particle in the group of the particles. This best value is also known as a global best '*gbest*'. This pattern forwards to successful solutions. These solutions contribute to increase the fame of PSO algorithm [18-21].

This random velocity is usually limited to a certain maximum limit. PSO technique using equation (7) is known as the *gbest* structure. PSO is a population based EA that has many primitive benefits over other optimization techniques.
Few of them outlined below:

1. Number of present parameters is less for the adjustment.
2. Derivative-free technique unlike many traditional algorithms.
3. Other optimization techniques can be easily corporate by this technique.
4. Implementation is simple with the help of basic mathematical and logical operations.

A most attractive quality of the PSO approach is its simplicity as it involves only two main reference equations. The each particle coordinates represent a possible solution assisted with two real vectors, the position x_i and velocity v_i vectors in this technique. $x_i = [x_{i1}, x_{i2}, x_{i3}, \ldots\ldots x_{iN}]$ and $v_i = [v_{i1}, v_{i2}, v_{i3}, \ldots\ldots, v_{iN}]$ are the two vectors assisted with each particle 'i' in N-dimensional search space. Number of particles or possible solutions of a swarm can go forward through the feasible solution place to explore optimal solutions. Each particle modifies its position based on its own best exploration, and overall experience of best particles [19]. This particle also considers its previous velocity vector according to the following reference equations:

i. Velocity Modifications

Each particle velocity can be modified by the following equation:

$$v_i^{m+1} = v_i^m + c_1 * r_1 * (pbest_i - x_i^m) + c_2 * r_2 * (gbest - x_i^m) \qquad (7)$$

ii. Position Modifications

Positions of the particles are modified at each interval of the flying time. The position of the particle may be change or not, it's depending upon the solution value.

$$x_i^{m+1} = x_i^m + v_i^{m+1} \qquad (8)$$

where, v_i is velocity of particle 'i' at iteration m, v_i^m = modified velocity of particle 'i' at iteration m, c_1 and c_2 are accelerating constant, and select value of c_1 , c_2 is 2. Random numbers r_1 and r_2 are in between 0 to 1, x_i^m is current position of particle 'i' at iteration m, x_i^{m+1} = Modified position of particle 'i ' at iteration (m +1), *pbesti* is *pbest* of particle 'i', and $gbest_i$ is *gbest* of the group of the particles.

Depictions in the equations (7) and (8), [17] describe the velocity and modify position, respectively. Equation (7) predicts a new velocity for each particle based on the particle's previous velocity, the particle's location at which the best fitness has been achieved so far, and the population global location at which the best fitness has been achieved so far. In addition, c_1 and c_2 are positive constants known as the social parameters, respectively. These constants provide the correct balance between individuality and sociality of the particles. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *gbest* locations. The random numbers provide a stochastic characteristic for the particles velocities in order to simulate the real behavior of the birds in a flock. Fig. 2 shows the concept of modification of searching points highlighted by indications in the equation (7).

An inertia weight parameter w was introduced in order to improve the performance of the original PSO model [18]. This parameter deals the role of balancing the global search and local search capability of PSO. It can be a positive constant or even a positive linear or non-linear function of time.

$$v_i^{m+1} = w*v_i^m + c_1*r_1*(pbest_i - x_i^m) + c_2*r_2*(gbest - x_i^m) \quad (9)$$

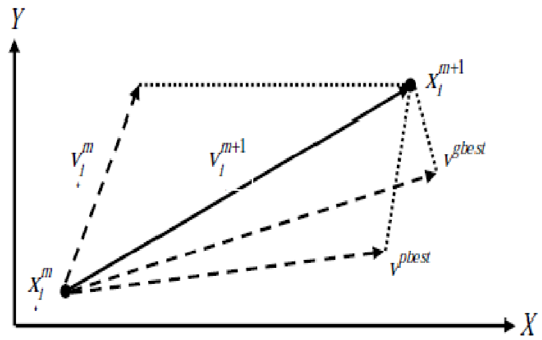

Fig. 2 Concept of modification of searching point

A better method of near to global optimum within a reasonable number of iterations can be achieved by incorporating this parameter into the velocity update in equation (7), as follows: Typical values for the inertia parameter are in the range [0.5, 1]. On the other side several different approaches using a construction factor s, which increase the algorithm's capability to converge to a better solution and the equation used to modify the particle's velocity becomes:

$$v_i^{m+1} = s*(v_i^m + c_1*r_1*(pbest_i - x_i^m) + c_2*r_2*(gbest_i - x_i^m)) \quad (10)$$

Where,

$$s = \frac{2}{|2-\varphi-\sqrt{\varphi^2-4\varphi}|}, \; c_1 + c_2 = \varphi > 1 \quad (11)$$

The PSO algorithm with constriction factor can be considered as a special case of the algorithm with inertia weight since the parameters are interacted through the equation (11). From investigational studies, the best approach to use with PSO as a rule of thumb is to utilize the constriction factor approach or utilize the inertia weight approach while selecting w, c_1 and c_2 according to equation (9). All parameters introduced in equations (9-11) may vary depending of the characteristics of the problem at hand. Adjustments of these parameters are different for every type of power systems problem and need to be carefully adjusted in order to achieve better performance of the algorithm. In this chapter, apply the inertia weight approach to use with PSO on multi-area case study of AGC.

5. DESIGN OF PSO BASED CONTROLLER

The proposed algorithm will proceed as follows:

Twenty particles are used, and Two hundred iterations are chosen for converging to solution in the PSO algorithm.

Step 1 – Inputs (data of the systems) consisting of ACE_i in the AGC of power systems model.

Step 2 - Initialize the particle with random positions, and velocities. The group of the particles are determined according to the ACE_i under real dimensions.

Step 3 - Calculate and compare the fitness value for each particle (control parameters U_{PI}) in the group of particles.

Step 4 – Particle correspondence the lowest fitness will be *pbest*. If the new fitness value for U_{PI} is less than that obtained with $pbest_i$, then replace the coordinates of $pbest_i$ with the present coordinates of U_{PI}.

Step 5- Check the velocity v of each particle according to

$$v_i^{m+1} > v^{max}, \text{ then } v_i^{m+1} = v^{max}$$
$$v_i^{m+1} > v^{min}, \text{ then } v_i^{m+1} = v^{min}$$

Step 6 - Compare the fitness values of $pbest_i$ of all particles to determine the best particle. Store the coordinates of the best particle as gbest.
Step 7 - Modify the velocity of each particle according to equation (10).
Step 8 - Modify the position of each particle according to equation (8).
Step 9 - If the number of iterations reaches the maximum, then go to Step 10. Otherwise, go to Step 3.
Step 10 - The particle that creates the newest *gbest* is the optimal solution of the AGC problem (optimal values of K_P and K_I for the controller, and B for the systems).
Step 11 - Stop (a sufficiently good fitness value or a maximum number of iterations).

After the fitness function has been calculated or the number of the iteration determines, the evolution procedure is stopped.

6. RESULTS DISCUSSION

The observations are performed on MATLAB 7.10.0 software which has technical specifications like Core2 Duo of 2.4 GHz and 2 GB RAM etc. The computer simulations are investigated in the case of multi-area interconnected power systems consisting of reheat turbines with perturbations in area-1 (ΔP_{d1} = 0.01 pu MW). The dynamic response plots of the settling time of system dynamics according cost function ISE is shown in Fig. 3 respectively.

The investigations of response plots given in Figs. 4-6 reveal that implemented PSO (PI) AGC controller reduces the overshoots to a great extent and completely removes the oscillations from the dynamic responses as compared to that obtained with classical PI AGC controller in the power systems. The observations show that the proposed control configuration with optimal cost function achieves good dynamic performance of the proposed PI controller. Especially, the investigated cost functions parameters expose better solutions than the standard cost functions. In addition to this, the proposed PI controller using ISE function with the rates of changes in the frequency and tie-line deviations shows the better results than classical PI controller for the AGC. It can be clearly seen that the PSO based gain scheduling of PI controller, improves the AGC scheme in order to minimize the ACE_i. It also improves the movement of governor valve position according to the level of the perturbations in the power systems.

Dynamic response plots presented that the PSO based PI controller with different cost functions improve AGC scheme with in order to inputs (ACE_i) and outputs ($U_{PI,\ i}$) of the proposed controller. These deviations determining the settling times are also depicted in Figs. 7-8.

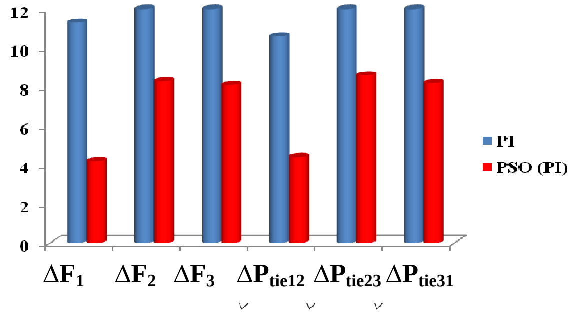

Fig. 3 The comparison of settling times according to ISE cost function

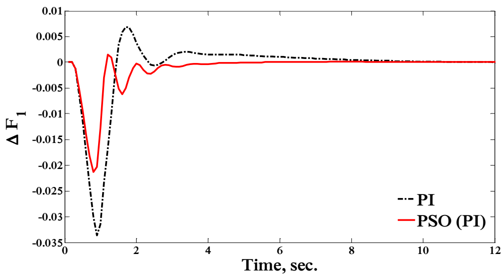

Fig. 4 Dynamic response of ΔF_1 for 1% load disturbance in area-1

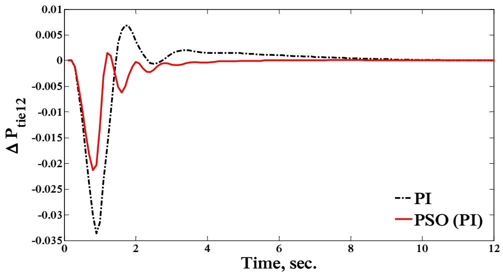

Fig. 5 Dynamic response of ΔP_{tie12} for 1% load disturbance in area-1

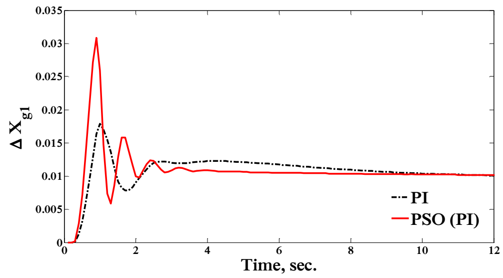

Fig. 6 Dynamic response of ΔX_{g1} for 1% load disturbance in area-1

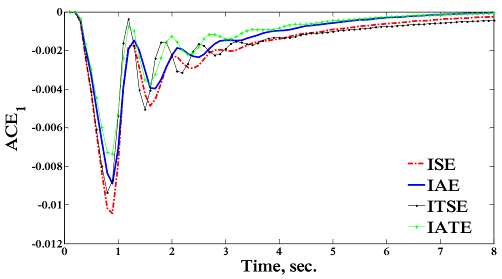

Fig. 7 Dynamic response of ΔACE_1 for 1% load disturbance in area-1

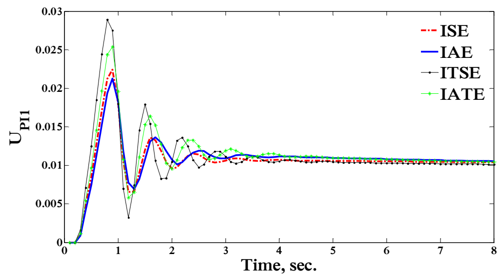

Fig. 8 Dynamic response of ΔU_{PI1} for 1% load disturbance in area-1

7. CONCLUSION

Optimization of the PI controller gains for a three-area interconnected power systems using PSO has been proposed. The PSO technique is utilized to evaluate the PI controller gains which improve the dynamic performance of the system to an operating condition with perturbations.

A comparison between the standard and optimal cost function revealed that the system performance can be improved. A variety of different costs functions are also presented by its effectiveness in the model. Such proposed optimal PI controller has the advantage of being systematic, derivative-free and weakly dependent on the power systems model.

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