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Design Optimal Feedback Control Using Evolutionary Particle Swarm Optimization in Multi-Machine Power System

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***Abstract*—This This paper proposes an application of Evolutionary Particle Swarm Optimization (EPSO) to design weighting matrices Q and R elements in Linear Quadratic Regulator (LQR) optimization process. Solving optimal feedback control has already established by LQR method. However, there still has some problem to find the weighting matrices Q and R. These weighting matrices are the most important components in LQR optimization method. Weighting matrices are calculated using trial and error, Particle Swarm Optimazation (PSO), and EPSO techniques and simulation results are compared. Static and Dynamic loads are considered and comparison is illustrated.**

***Keywords*—EPSO; PSO; LQR; static and dynamic load**

I. Introduction

Dynamic stability of synchronous machines has been discussed by many researchers for along time. Many papers have been published in this research area [1-2,13-14]. This concept is widely used to enhance the performance of power system stability [3-7]. There are many methods to improve the stability performance of an interconnected power system. One of those methods is an optimal control feedback using Linear Quadratic Regulator (LQR) that has established in which Controllable linear Time Invariant (LTI) system through a set of optimal feedback gain through minimizes a quadratic index and makes a closed loop system. This method has already applied in many applications [8-14]. One problem of LQR method is how to determine the R and Q matrices (called weighting matrix) for large power system. The other ones are reliably and robustness, when a design optimal control uses different load characteristic. This paper discusses and solves the above mention problem.

The elements of weighting matrices Q and R are determined by using a conventional method is a trial and error to yield optimal feedback gain K. This techniques can be found in [5,7]. Bryson proposed a simple iteration to calculate the weighting matrices in [6-7]. Both of those methods still require a long time for calculating process and difficult for large power system.

Robandi et al determined these weighting matrices using binary Genetic Algorithm (GA) method [13] and Fuzzy GA method [14]. Those techniques claim faster converge than previous techniques and can be applied for large power system. Those methods have a weakness calculating these weighting matrices, since binary value is used and it is quite difficult to find the exact values.

Particle Swarm Optimization (PSO) is one of the evolutionary computation (EC) techniques [21]. PSO has been proved powerful tool and outperform the other heuristic methods. Simplicity, robustness, effectiveness in performing difficult optimization tasks and ability to treat both continuous and discrete variables are the main features of PSO. This method has been applied in Power System Stabilizer (PSS) is reported [27].

Evolutionary PSO (EPSO) was first developed by Miranda, *et al.* [21] which combines conventional PSO with the evolutionary strategy. EPSO puts together the concepts of Evolution Strategies (ES) and of PSO. The particles are move according to the conventional PSO movement rule, but the strategic parameters are selected according to ES procedure. Therefore, it is expected that the exploratory power of PSO and self-adaptation power of ES is obtained. Successful application in power system problems is reported in [22, 23] while the results are compared with conventional PSO and simulated annealing.

The proposed method designs the elements of matrices Q and R using PSO and EPSO. The exact values of matrices Q and R elements can be determined, so that the matrices design is easy to produce the optimal feedback control gain K for large power system.

The proposed method also considers two kinds of loads are static and dynamic load. The static load illustrates a load characteristic as momentary function of magnitude voltage and frequency. The momentary load illustrated as constant impedance, current constant or power constant. The dynamic load describes active power and reactive power as a function of voltage and frequency magnitude at past and present instant times that is usually using a differential equation [16]. Dynamic load has already applied in power system stability is reported in [15,17]. Both of loads are applied in proposed method

II. THEORY

A. Power System Model

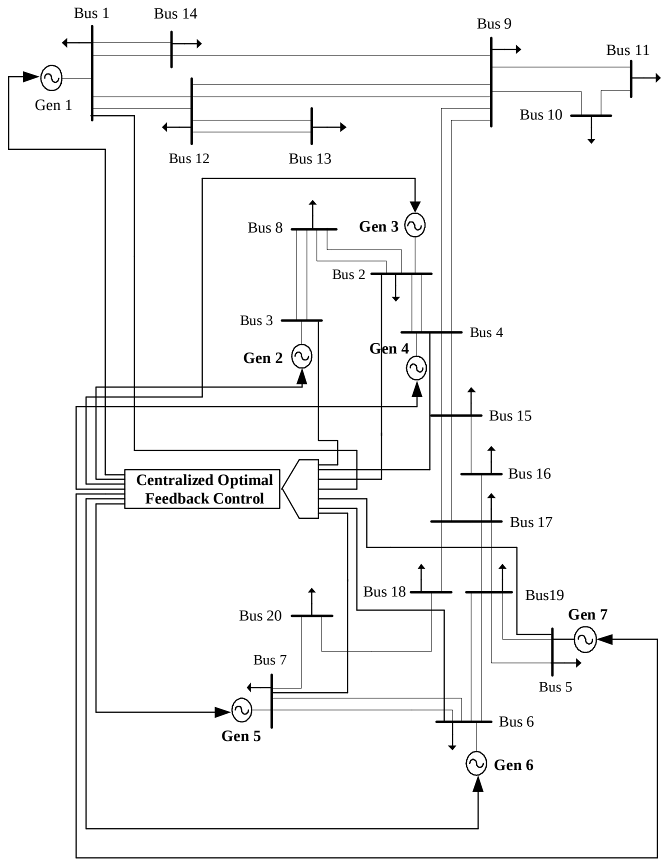

Figure 1. Multi-machine power system model in Indonesia

A power system model regarded as an interconnection system that consist of generation, transmission and load. This plant has modeled linear synchronous generator with current as state variable called two axis models. The modeling machine derived in reference [5,7].

The design of Centralized Optimal Feedback Control (COFC) showed in figure 1. This power system has demonstrated by using seven generators (n=7, e.g. four gas turbine generators, one combine cycle turbine generator, and two water turbine generators), twenty buses (e.g. one swing bus, six generator buses and thirteen load buses), and 500 kV transmission line with two signal controls (e.g. governor as frequency signal and excitation as voltage signal).

The linear model of Fig. 1 has six state variables i.e. ΔV_{di} (direct axes voltage), ΔV_{qi} (quadrature axes voltage), $\Delta\delta_I$ (power angle), $\Delta\omega_I$ (angular frequency of stator currents), ΔE_{fdi} (excitation machine voltage), ΔT_{mi} (prime mover torque) and two input signals i.e. ΔV_i (input signal control to excitation) and ΔGSC_i (input signal control to governor). The subscripts i (=1,…,n) corresponds to the number of machines.

B. LQR Optimal Feedback

The multi-machine power system model can be written in state space equation as follows [13]:

$$\dot{x}_i(t) = \mathbf{A}x_i(t) + \mathbf{B}u_i(t) \quad (1)$$

$$y_i(t) = \mathbf{C}x_i(t) + \mathbf{D}u_i(t) \quad (2)$$

Where, static and dynamic loads can be explained **A**(42,42) and **A**(44,44), **B**(42,14) and **B**(44,14), **C**(14,42) and **C**(14,44), and **D** (null) are system matrices.

To solve the LQR optimal feedback solution equation (1) and (2) have to be developed. Minimization index can be written as follows:

$$\mathbf{J_i} = \int_{\mathbf{t_0}}^{\mathbf{t_f}} \left[x^T(t)\mathbf{Q_i}x^T(t) + \mathbf{u}^T(t)\mathbf{R_i}\,u^T(t) \right]\mathbf{dt} \qquad i=1,\ldots,m \quad (3)$$

Where, m is total variable state of single machine. For static load m is defined as 6*n and for dynamic load is defined as 6*n+2.

The solution of equation (3) can be given as follows:

$$\dot{\mathbf{P}} = \mathbf{A}^T\mathbf{P_i} + \mathbf{P_i}\mathbf{A} - \mathbf{P_i}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{P_i} + \mathbf{Q_i} \quad (4)$$

If a time varying positive symmetric matrix $\mathbf{P}_i(t)$ converges at $t_f = \infty$, the solution of equation (4) can be obtained from an algebraic Riccati equation as follows:

$$0 = \mathbf{A}^T\mathbf{P_i} + \mathbf{P_i}\mathbf{A} - \mathbf{P_i}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{P_i} + \mathbf{Q_i} \quad (5)$$

The gain $\mathbf{K}_i$ can be written as follows:

$$\mathbf{K}_i = \mathbf{R}^{-1}\,\mathbf{B}^T\mathbf{P}_i \quad (6)$$

$$u(t) = -\mathbf{K}_i x(t) \quad (7)$$

The equation (1) can be written as a closed loop system, so that we can discuss the converging behavior using the following equations:

$$\dot{x}_i(t) = (\mathbf{A} - \mathbf{BK})x_i(t) \quad (8)$$

C. Dynamic Load Model

Developing dynamic load model has already done by J.V. Milanovic [13]. Expression this model can be written as follows:

$$\Delta P_d = (P_0 / V_0)\, n_{ps} \frac{((n_{pt}/n_{ps})T_p s + 1)}{(T_p s + 1)} \Delta V \quad (9)$$

Where,
P_d = load power demand
T_p = time recovery response of load
P_0 = value of power demand
V_0 = nominal voltage of load
n_{ps} = steady state of exponential voltage
n_{pt} = transient of exponential voltage

III. Proposed Solution Methods

This section introduces the solution methods which are used in this paper. Trial and error method has already in optimal feedback control problem [5]. To enhance the solution method, swarm techniques have been applied in this paper. The following section describes an overview of proposed method.

A. Trial and Error Method

The trial and error method designs the elements of matrices Q and R using experience and intuitive adjustment. This method is very simple and very familiar in LQR application. Matrices Q and R are square matrices that have dimension 42 x 42 and 14 x 14 for static load, and 44 x 44 and 14 x 14 for dynamic load. The elements of diagonal-off of matrices are zeros for simplicity as such as has been demonstrated in some references, e.g. reference [5]. The elements of diagonal of matrices are designed by trial and error iteration to obtain a satisfactory index of value J. The optimal solution has found by repeating several times, so that this method requires longer time, and is not feasible for application in large scaled power system.

B. Particle Swarm Optimization (PSO)

PSO is a kind of evolutionary algorithm, which is basically developed through simulation of swarms such as flock of birds or fish schooling [18]. Similar to evolutionary algorithm, PSO conducts searches using a population of random generated particles, corresponding to individuals (agents).However in PSO, particles evolve in the search space motivated by three factors: *inertia, memory and cooperation*. *Inertia* implies a particle keeps moving in the direction it had previously moved. *Memory* factor influences the particle to remember the best position of the search space it has ever visited. *Cooperation* factor induces the particles to move closer to the best point in space found by all particles. Each particle is a candidate solution to the optimization problem which, has its own position and velocity represented as x and v.

Searching procedure by PSO can be described as follows: a flock of agents optimizes an objective function. Each agent knows its best value (*pbest*), while the best value in the group (*gbest*) is also known. New position and velocity of each agent is calculated using current position and best values *pbest* and *gbest* as below:

$$v_i^{k+1} = wv_i^k + c_1 r_1 \times (pbest - x_i^k) + c_2 r_2 (gbest - x_i^k) \quad (10)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (11)$$

Where, w is called inertia weight; r_1 and r_2 are random numbers between 0 and 1; c_1 and c_2 are two positive constants, called cognitive and social parameter respectively.

The first term in (10) represents inertia, the second term represents memory and the third one stands for cooperation factor. The inertia weight was first introduced by Shi and Eberhart [23]. The inertia weight is used to control the impact of the previous velocities on the current velocity, influencing the trade-off between the global and local experience. Although Zheng *et al.* [24] claimed that PSO with increasing inertia weight performs better, linear decreasing of the inertia weight is recommended by Shi and Eberhart [23,25]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} iter \quad (12)$$

Where w_{max} and w_{min} are maximum and minimum of inertia weight value respectively, $iter_{max}$ is maximum iteration number and *iter* is the current iteration. The authors claimed that the following parameters are appropriate and the values *do not depend* on the problems:

$w_{max}=0.9$, $w_{min}=0.4$, $c_1=c_2=2$

The values are also reported to be appropriate for power system problems [19].

A so-called constriction factor K, is presented in [26]. It has been claimed that this factor increases the algorithm's ability to convergence to a good solution and can generate higher quality solution than the conventional PSO approach. In this case, the expression used to update the particle's velocity becomes:

$$v_i^{k+1} = K*(v_i^k + c_1 r_1 \times (pbest - x_i^k) + c_2 r_2 (gbest - x_i^k)) \quad (13)$$

Where,

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \varphi = c_1 + c_2, \varphi > 4 \quad (14)$$

C. Evolutionary PSO (EPSO)

EPSO was developed by Miranda *et al*. [20] that combines conventional PSO with the evolutionary strategy. EPSO starts the same as PSO, with a population of particles, generated randomly in the search space. Then, within the number of iterations, the following steps are implemented:

1) *Replication*: Each particle is replicated r times (usually r is considered 2*)*

2) *Mutation*: The weights of the replicated particles are mutated according to:

$$w_{ik}^* = w_{ik} + \tau N(0,1) \quad (15)$$

Where τ is a learning parameter (either fixed or treated also as strategic parameters and therefore also subject to mutation), and N(0,1) is a random variable with Gaussian distribution, 0 mean and variance 1.

3) *Reproduction*: Each particle generates as offspring a new particle according to the movement rule by (16) and (17), similar to the equations (10) and (11) of conventional PSO. The replicated particles make use of the mutated weights. The offspring is held separately for the original particles and the mutated ones.

$$v_i^{k+1} = w_{i0}^* v_i^k + w_{i1}^* \times (pbest - x_i^k) + w_{i2}^* (gbest^* - x_i^k) \quad (16)$$

$$gbest^* = gebst + \tau^{'} N(0,1) \quad (17)$$

τ` is a learning parameter (either fixed or treated also as strategic parameters and therefore also subject to mutation).

4) *Evaluation:* Each particle is evaluated according to their current position.

5) *Selection*: The best particles are selected by stochastic tournament or other selection procedure, to form a new generation.

EPSO puts together the concepts of Evolution Strategies (ES) and of PSO. The particles move according to the conventional PSO movement rule, but the strategic parameters are selected according to ES procedure. Therefore, it is expected that the exploratory power of PSO and self-adaptation power of ES is obtained.

The diagonal elements Q and R matrices are saved in gbest for both of swarm techniques.

IV. Simulation Results

Calculated processes determine the optimal feedback control K that form flowchart using PSO and EPSO methods showed in Figure 2. This PSO method has used randomly 80 populations the same as an EPSO method. Whereas, this EPSO has used replication process, mutation process with randomly normal, reproduction process with communication factor 1, evaluation process, and selection process with randomly normal. The end of proposed methods processes yield the elements of Q and R matrices. The exact values of matrices Q and R are obtained by using PSO and EPSO. For example, one of diagonal elements of matrix Q and one of diagonal elements of matrix R using PSO method are 5.03483557528304 x 1.0e+004 and 0.000519116082757, and one of diagonal elements of matrix Q and one of diagonal elements of matrix R using EPSO method are 5.63809607985969 x 1.0e+004 and 1.0e-003 x 0.18388795687739. Those values of matrices used to determine optimal feedback control K by using expression (5) and 6. The closed loop system calculated with values of optimal feedback control K by using expression (8).

This simulation considers for power system about the voltage and frequency behaviors when various step signals are applied as small load disturbance in peak load condition. Even if, the static and dynamic loads are applied to illustrate the real time load characteristic.

The both of swarm techniques and trial and error method are compared in this simulation. The result of comparisons showed in figure 3 – 6 and table 1 – 3.

The both of the proposed method yield the directly exact values of Q and R matrices that reduced the error calculating processes. Therefore, these methods can be used as the best methods to determine the directly exact values of elements matrices of Q and R. Whereas, an advantage of an EPSO method has the processing of replacement, mutation, reproduction, evaluation and selection inside calculating processes. Those processes are required to converge as fast as possible.

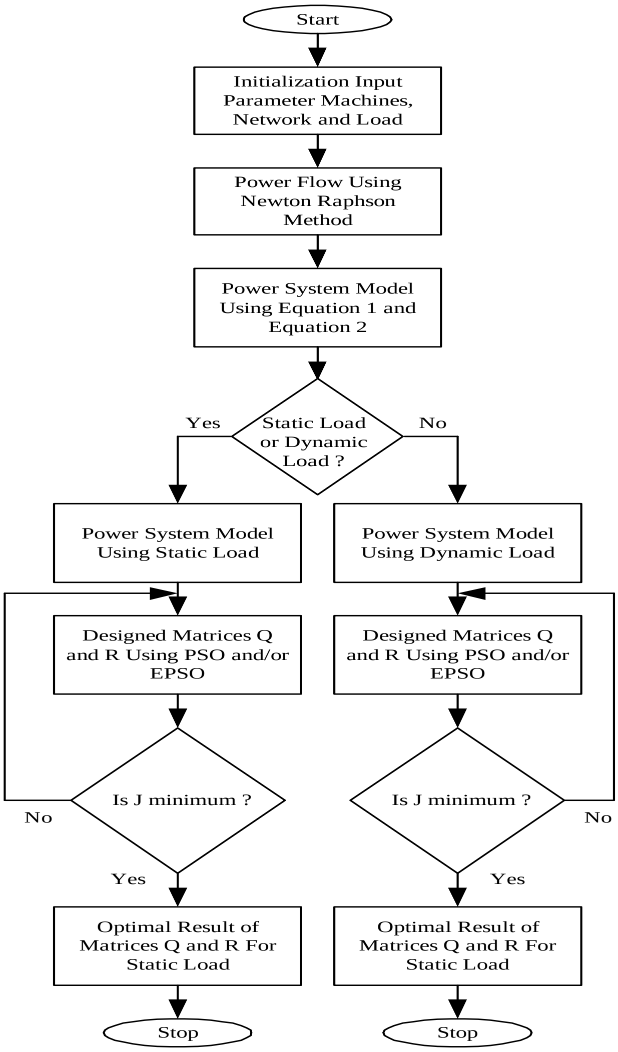

Figure 2. Flowchart of PSO or EPSO – LQR Optimal Feedback

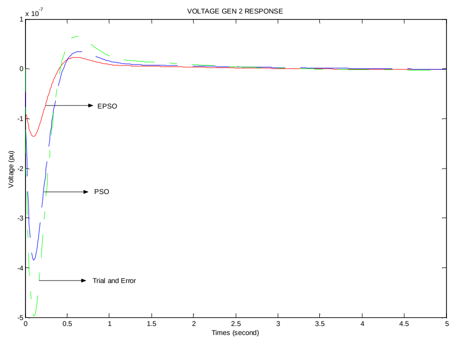

Figure 3 Voltage of generator 2 response with static load

Figure 3 illustrates voltage response for generator 2 with static load by using trial and error, PSO, and EPSO methods. The best performance of design optimal control feedback is obtained by EPSO method. The calculation maximum overshoot of each generator is shown in table 1. The smallest overshoot is obtained by an EPSO method e.g. maximum overshoot of voltage response of generator 2 are 0.65249744259 x 1.0e-007 of trial and error, 0.346138012814 x 1.0e-007 of PSO, and 0.230497805358 x 1.0e-007 of EPSO.

Table 1 Maximum Overshoot of Voltage Response Using Static Load

Gen	Trial and Error 1.0e-007 *	PSO 1.0e-007 *	EPSO 1.0e-007 *
1	0.70844077364	0.540501815930	0.118370343315
2	0.65249744259	0.346138012814	0.230497805358
3	60.24613781916	25.123913376981	16.276894980325
4	27.18310960764	20.290358553411	5.782205099902
5	6.12778608026	3.746639128191	1.988166952616
6	12.60077476666	5.355129642643	3.043142628093
7	00.27302872110	0.115715077594	0.078117221227

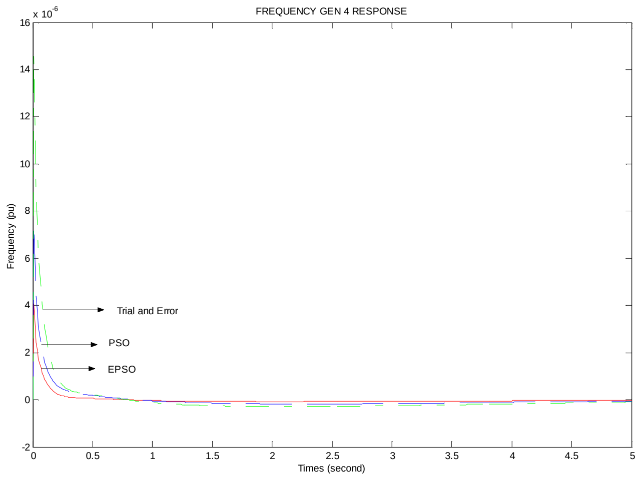

Figure 4. Voltage of generator 4 response with static load

Figure 4 illustrates frequency response of generator 4 with static load by using trial and error, PSO, and EPSO methods. The best performance of design optimal control feedback is yield by EPSO method. The calculation maximum overshoot of each generator is given in table 2. The smallest overshoot is produced by an EPSO method e.g. maximum overshoot of frequency response of generator 4 are 146.1750850207 x 1.0e-007 of trial and error, 74.080429563469 x 1.0e-007 of PSO, and 40.849689934540 x 1.0e-007 of EPSO.

Table 2 Maximum Overshoot of Frequency Response Using Static Load

Gen	Trial and Error 1.0e-007 *	PSO 1.0e-007 *	EPSO 1.0e-007 *
1	33.49065240436	16.013546649986	10.048633736500
2	27.07255546684	13.562858058764	7.655616091115
3	62.85066035132	31.529983530803	17.748546074702
4	146.17508502072	74.080429563469	40.849689934540
5	1.66405863693	0.945335049464	0.463930199154
6	3.30303299007	1.647299972790	0.902014055427
7	4.50754904214	2.333080947134	1.251617219570

Figure 5 illustrates voltage response for generator 5 with dynamic load by using trial and error, PSO, and EPSO methods. The best performance of design optimal control feedback is obtained by EPSO method. The calculation maximum overshoot of each generator is shown in table 3. The smallest overshoot is achieved by an EPSO method e.g. maximum overshoot of voltage response of generator 5 are 4.13688713428 x 1.0e-007 of trial and error, 1.293562395281 x 1.0e-007 of PSO, and 0.142059413130 x 1.0e-007 of EPSO.

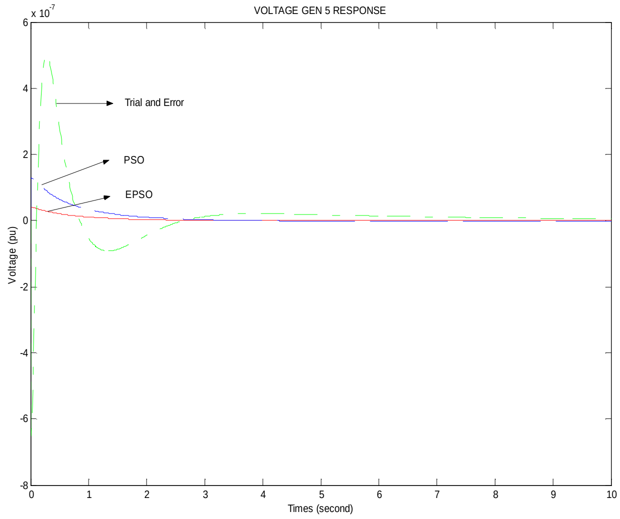

Figure 5. Voltage of generator 5 response with dynamic load

Table 3 Maximum Overshoot of Voltage Response Using Dynamic Load

Gen	Trial and Error 1.0e-007 *	PSO 1.0e-007 *	EPSO 1.0e-007 *
1	0.39108802560	0.101334532492	0.010859781907
2	0.49273744972	0.152137596469	0.034606262193
3	52.15707181193	14.458483710335	3.503643884029
4	22.38416049919	6.610743457029	2.185481073320
5	4.13688713428	1.293562395281	0.401490847393
6	1.79681082890	0.285713963595	0.142059413130
7	0.19241330381	0.068698305998	0.019544838086

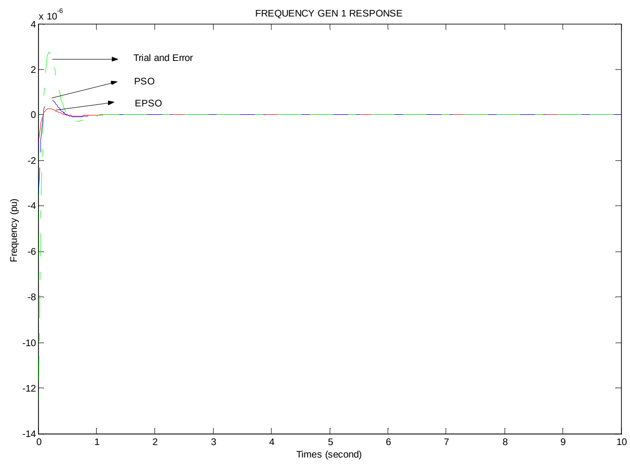

Figure 6. Frequency of generator 1 response with dynamic load

Table 4 Maximum Overshoot of Frequency Response Using Dynamic Load

Gen	Trial and Error 1.0e-007 *	PSO 1.0e-007 *	EPSO 1.0e-007 *
1	27.70627374169	7.683404037506	2.801027472277
2	22.20541735540	6.218409038046	2.070166412623

3	51.64105640853	14.486010616920	4.809794831918
4	100.3927731849	33.574406222470	11.139090734940
5	0.17971659259	0.049544950905	0.017108281481
6	5.06306320534	1.408360736998	0.478164574724
7	5.72327755810	1.637640058571	0.541081274951

Figure 6 illustrates frequency response of generator 1 with dynamic load by using trial and error, PSO, and EPSO methods. The best performance of design optimal control feedback is given by EPSO method. The calculated maximum overshoot of each generator showed in table 4. The smallest overshoot is yield by an EPSO method e.g. maximum overshoot of frequency response of generator 1 are 27.70627374169 x 1.0e-007 of trial and error, 7.683404037506 x 1.0e-007 of PSO, and 2.801027472277 x 1.0e-007 of EPSO.

Table 5 Dynamic Load Effect by Changing Places of Dynamic Load

Gen.	Bus 1		Bus 2		Bus 5		Bus 7	
	Vol.	Freq.	Vol.	Freq.	Vol.	Freq.	Vol.	Freq.
1	O	O	O	O	X	X	X	X
2	O	O	O	O	X	X	X	X
3	O	O	∆	∆	X	X	X	X
4	O	O	O	O	X	X	X	X
5	O	O	O	O	O	O	∆	∆
6	∆	O	O	O	O	O	∆	O
7	O	O	O	O	∆	∆	O	O

Where, X – did not give effect, ∆ - gave small effect, and O – gave big effect

Table 5 showed the effect of dynamic load by changing places of dynamic load. The power system had few influences, when, dynamic load placed in bus 5 and bus 7. However, it obtained significant influences, when, dynamic load placed in bus 1 and bus 2. The reason of this phenomenon is bus 1 and bus 2 near generator has small capacity and far from others generators (i.e. there are one or two generator with small capacity). Whereas, bus 5 and bus 7 is near generator has big capacity and near to others generators (i.e. there are three generators near bus 5 and 7 with big and medium capacity).

V. Conclusion and Discussion

The proposed methods (PSO and EPSO) yield exactly values of matrices Q and R. For example, one of diagonal elements of matrix Q and one of diagonal elements of matrix R using PSO method are 5.03483557528304 x 1.0e+004 and 0.000519116082757, and one of diagonal elements of matrix Q and one of diagonal elements of matrix R using EPSO method are 5.63809607985969 x 1.0e+004 and 1.0e-003 x 0.18388795687739.

The best performance of voltage and frequency behaviors were obtained by using proposed method (EPSO) that has the processing of replacement, mutation, reproduction, evaluation and selection inside calculating processes.

The dynamic load that placed far from generator with big capacity influenced the performance of voltage and frequency behaviors significantly.

The objective function can develop to obtain the minimum index J better than using in this paper.

The settling time, error steady state and percent time steady state did not calculate in this research.

An EPSO method can develop to consider with communication factor (P) that did not use only value equal 1 as in this paper, but used also other value e.g. 0.2.

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