Inter-Area Oscillation Damping by Optimal Design of PSS Using an Improved Differential Evolution Algorithm

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Abstract– **In this paper, the parameters of a power system stabiliser (PSS) with help of a combination of a Differential Evolution algorithm (DE) and Local Search Algorithm (called the DELSA (Memetic DE algorithm)) are introduced, which are designed independently, converge to the correct and optimal solution in a small number of iterations and are attuned to damping low frequency oscillations. Suppose that the DE algorithm searches in a wide-ranging area, whereas the local search focuses on the attraction area, which probably has the optimal solution. We studied the three-area power system that was simulated in the time domain by MATLAB. The outcomes of simulations showed that without the PSS at the time of error occurrence, the damping and synchroniser torque were reduced. Thus, the system becomes unstable, and low frequency oscillations such as inter-area oscillations are generated, which are damped if we employ optimal and coordinate PSS.**

Keywords– **Differential Evolution Algorithm (DE), Inter-area Oscillations, Local Search (LS), Memetic DE Algorithm (DELSA), PSS and Small Signal Stability**

I. INTRODUCTION

Small disturbances are caused by low frequency oscillations (LFO) in large scale multi-area power systems. In general, these power systems are connected with weak tie lines. Usually, local modes are controlled and damped by a power system stabiliser (PSS). Until now, all controller design methods, such as nonlinear, adaptive, multi-variable, optimal, robust [1], [2], fuzzy systems, neural networks and combinations of these methods [3], have been in use for PSS parameter design. In recent times, heuristic techniques based on search and evolution, such as genetic algorithms (GA) [4], particle swarm optimisation (PSO) [5], ant colony, memetic [6], Tabu search [7], and artificial immune algorithm (AIA), have been utilised. Results with these techniques are better than those with previous techniques. Among these, the genetic algorithm and AIA are most noteworthy. In this paper, analysis of dynamic stability for a three-area power system was performed with non-linearity. The instability growth of the rotor angle due to the lack of synchronisation torque and increasing rotor oscillation due to the lack of damping torque lead to instability and inter-area oscillation (influence weak damping). In order to limit these oscillations, PSS with optimal and coordinated parameters, which are designed by the DE algorithm and LSA, were used. Both of these algorithms are versions of a meta-heuristic algorithm [8], [9]. DE and LSA are called Memetic DE. Simulation outcomes show that with coordinated modification of PSS parameters by using the projected method, oscillations are damped, and the system has a reliable stability.

In this paper, the parameters of a power system stabiliser (PSS) with help of a combination of a Differential Evolution algorithm (DE) and Local Search Algorithm (called the DELSA (Memetic DE algorithm)) are introduced, which are designed independently, converge to the correct and optimal solution in a small number of iterations and are attuned to damping low frequency oscillations. Suppose that the DE algorithm searches in a wide-ranging area, whereas the local search focuses on the attraction area, which probably has the optimal solution. We studied the three-area power system that was simulated in the time domain by MATLAB. The outcomes of simulations showed that without the PSS at the time of error occurrence, the damping and synchroniser torque were reduced. Thus, the system becomes unstable, and low frequency oscillations such as inter-area oscillations are generated, which are damped if we employ optimal and coordinate PSS.

II. POWER SYSTEM MODELLING

The main duty of PSS is to improve the damping of generator rotor oscillations by controlling the excitation circuit with the use of additional stabilising signals [10], [11]. In this paper, the general structure of the power system stabiliser consists of a lead-lag blocks: a washout block and a gain block. Fig. 1 shows these blocks with the excitation system diagram.

In Fig. 1, K_{ps} is the gain that acts on frequency error and increases it. The washout block is a differentiator and only allows the variations to pass. This block removes the permanent part of the signal. The amount of T_{wp} is selected to be as large as needed. It should not have any interference with the lead-lag block. The exact value is not important.

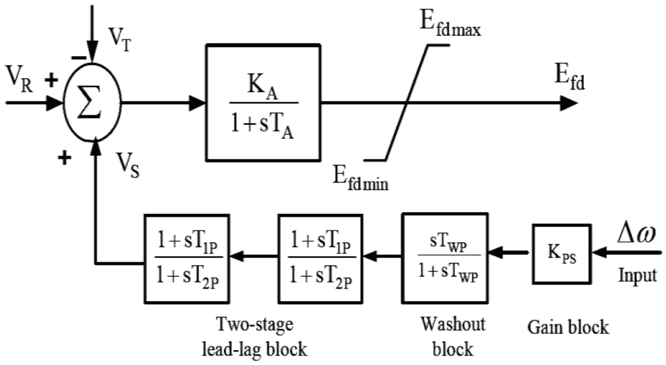

Fig.1. PSS, model IEEE-PSS1A, Input: variation of speeds with block diagram of excitation of system

After designed of Ts, the last stage is determined the K_{ps}. Theoretically, if the start point equation ($\Delta\omega$) is in-phase with the end point, with larger K_{ps} the damping torque will be greater. In practice, because of the limitations and nonlinearity of the system, K_{ps} cannot be selected to be as large as needed. The optimal value of this factor can be obtained by simulation and trial and error [12], [13]. The proposed power system is a three-area power system with three machines [14] that it was simulated in Simulink (See Fig. 2).

If a disturbance is introduced into a multi machine power system (in stability analysis), the frequency, load angle and voltage of all units will changes. Usually the frequencies of these oscillations are from a 10th of a hertz to several hertz. These oscillations called low frequency oscillations (LFO). The LFO is divided into two modes: the first is the local mode and the other is the inter-area mode. In a synchronous generator, the main reason for oscillations is the opposition of mechanical and electrical torques. Mechanical torque is applied to the rotor by a turbine of a generator, and electrical torque is applied by the winding of a stator. The effect of the excitation field on the LFO is positive, and this effect can

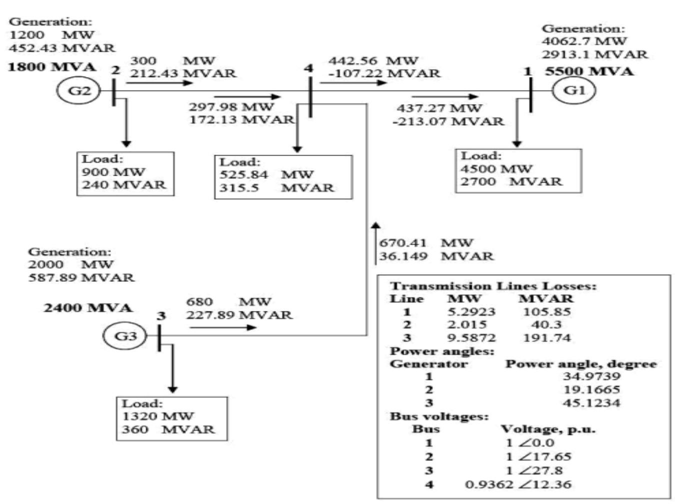

Fig. 2. Single-line diagram of three-area study system [14]

reduce the overshoot and settling time. In contrast, AVR has a negative effect on LFO. The AVR loop attenuates damping torque, and as result, the LFO time increases. To control the bus voltage, the AVR loop is necessary, so power system stabilisers are used to compensate the negative effect on the LFO. Thus, the PSS must be designed such that the torque applied to the rotor of the generator is in-phase with the angular velocity [15].

III. DIFFERENTIAL EVOLUTION ALGORITHM (DE)

The differential evolution algorithm was introduced by Storn and Price in 1996 [16]. The DE algorithm is an initial population of solution vectors that it updates sequentially. The DE algorithm uses sum/subtraction operators and other operators and is a stochastic, population-based optimisation algorithm. It was developed to optimise real (float) parameters of a real valued function. The DE algorithm is a simple and reliable method.

a) Initial population: the DE algorithm starts with making an initial population of individuals that has NP rows and D columns.
b) Mutation: In this step, the DE algorithm generates an offspring vector for each parent.
c) Boundary check or Mapping: If there is need, an offspring vector must be in [Lo, Hi]**.**
d) Crossover: In this step, the mutated vector and initial population vector generate test vectors.
e) Selection–Offspring are compared to the parents, and the DE algorithm generates the population of the next generation.

After the selection step, the calculation cycle in the DE algorithm continues to converge all of the vectors (until DE Algorithm receives a stop (end) condition). The general flowchart of the DE algorithm is shown in Fig. 5.

For mutation, the DE algorithm is divided into 5 strategies:

a) Best/rand strategy
b) Old/best/rand strategy
c) Best/rand/rand strategy
d) Rand/rand strategy
e) Rand/rand/rand strategy

In the first three methods, the next generation is generated from the best parents and the differentiation of random vectors, but in the two other methods, the next generation is generated from only random differential vectors.

In this paper, the VSHDE (or the DE algorithm with a variable SCALE factor) algorithm is used and within q iterations the factor F in this algorithm is modified as follows:

$$F_t + 1 = \{ c_d * F_t \quad \text{If} \quad P_{st} < 1$$
$$C_i * F_t \quad \text{If} \quad P_{st} > 1 \qquad (1)$$
$$F_t \quad \text{If} \quad P_{st} = 1\}$$

Where $C_d = 0.82$ and $C_i = 1/0.82$ are constant values and P_{st} represents the number of successful mutations (the number of offspring that have better values than their parents). This step will perform after the selection step, and the parameters are adjusted as

$Np = 5$, $F = 1.2$, $q = 10$

The algorithm begins with NP solution vectors chosen randomly. For each i in $(1,...,NP)$, a 'mutant vector' is calculated as:

$$V_i = X_{r1} + F.(X_{r2} - X_{r3}) \quad (2)$$

Where r_1, r_2 and r_3 are mutually distinct and drawn randomly. The indices are $(1,...,NP)$, and $0 < F <= 2$. Fig. 6 shows the generation of the mutated vector V_i in the DE algorithm.

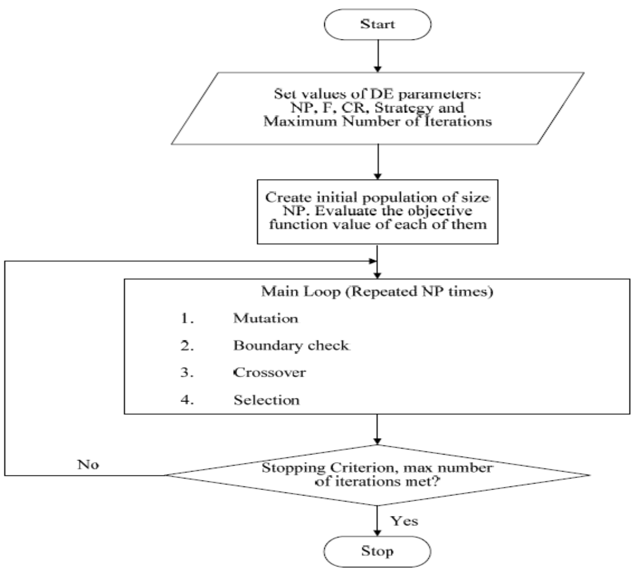

Fig. 3. Differential Evolution Algorithm flowchart [17]

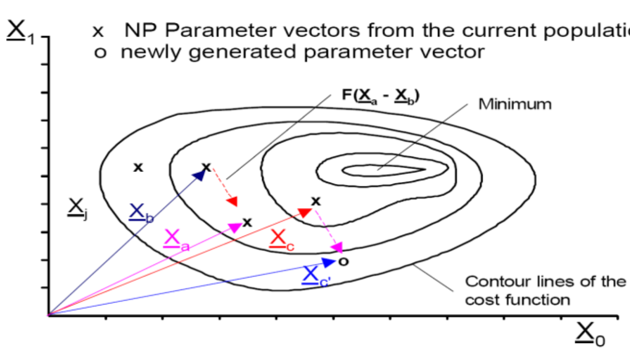

Fig. 4. Generation of mutated *Vi* in DE algorithm [18]

In order to form the trial vectors U_i, the crossover operator is applied to the mutated vector V_i and the initial population vector X_i:

$$X_i = (X_{i1}, X_{i2}, X_{i3}, X_{i4}, X_{i5}) \quad (3)$$

$$V_i = (V_{i1}, V_{i2}, V_{i3}, V_{i4}, V_{i5}) \quad (4)$$

$$U_i = (U_{i1}, U_{i2}, U_{i3}, U_{i4}, U_{i5}) \quad (5)$$

For each component of this vector, a random number in U [0, 1] selected and called $rand_j$.

$0 \le CR < 1$ is a crossover rate and $randj \le CX$, $U_{ij} = V_{ij}$ else $U_{ij} = X_{ij}$

To ensure at least some crossover exists, one component of U_i is selected randomly for V_i.

For example:

$$U_i = (V_{i1}, X_{i2}, X_{i3}, X_{i4}, V_{i5}) \quad (6)$$

First, array (V_{i1}) was selected randomly (as one definite crossover)

$rand_5 \le CR$, (V_{i5} is a definite crossover, too)

In the selection step, if the objective value (U_i) is lower than (X_i), then U_i replaces X_i in the next generation. Otherwise, we keep X_i.

IV. COMBINATIONS IN DELSA (MEMETIC DE ALGORITHM)

Memetic algorithms (MAs) are one of the general heuristic search methods, while evolutionary algorithms are special solver algorithms. Evolutionary algorithms can be used as local search heuristic techniques, approximation and estimation algorithms, or some times as exact methods. "Combination" can improve the convergence speed of the best solutions, but "evolution" is too slow, and sometimes it cannot reach the solution. It has been proven the MAs are very effective and successful in various problems, such as combinational optimisation (Merz, 2000) [6], optimisation of non-stationary functions [19], and multi-objective optimisation [2]. In 1989, Dr. Moscato [20] created the Memetic algorithm for a variety of techniques based on evolutionary search combined with one or several local searches. The advantages of one algorithm can be further improved by combination with evolutionary algorithms and local search or other solution improvement methods. However, a trade off must be made between the advantages and the complexity. Therefore, how the combination is performed must be considered carefully. Any dark-coloured and bold point in Fig. 7 is a good opportunity for combination. For example, the initial population can be generated by solving a heuristic complex problem or using EA to obtain better searching capability mutation operators, showing that special limitations can be improved. However, local search can be applied to each inter-level solution or all of them.

Evidence shows that a problem with more special and exact information can be better solved if using the DE algorithm. The famous combination form is applying one or several local search models based on stochastic parameters, which are applied to each member in any generation (according to Fig. 7).

In order to improve the effectiveness of the algorithm, elitism can also be used, where the best offspring of a generation are transferred to the next generation (without any modification). To compare the DE algorithm performance with DELSA, the fitness evaluation should be the same for

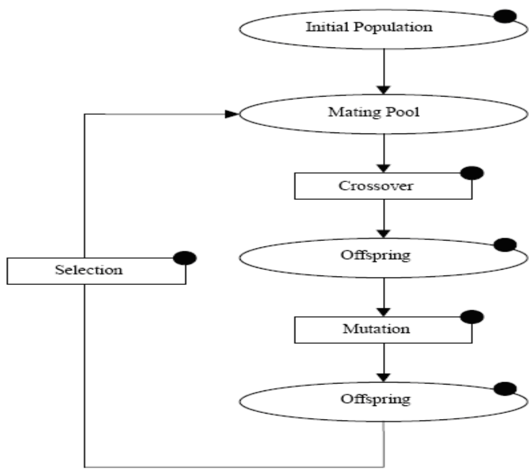

Fig. 5. Combination of EAs and LS flowchart and resulting in Memetic

the two algorithms. Local search can also be applied to all or some offspring that have better fitness. (In this paper, Local Search is applied to all of offspring.) In this method the "combination" step is performed after the "selection" step and comparison between offspring vector and parent (from the point of view of fitness).

V. LOCAL SEARCH ALGORITHM (LS) AND OBTAINING DELSA (MEMETIC DE ALGORITHM)

With modification of the evolution algorithm, the Memetic algorithm will change accordingly. For example, by replacing the DE algorithm with the PSO algorithm we have the Memetic PSO algorithm, and by replacing the DE algorithm with GA and offspring with chromosomes we have Memetic GA. In this article, we study the DE algorithm combined with local search. We suppose that the DE algorithm performs a search in a wide-area, but local search focuses on attraction areas that may almost certainly include optimum points. As a result, complex and difficult problems can be broken down into smaller problems, which can be solved simply.

The DE algorithm is an evolutionary algorithm and can be used before or after each step for the duration of the solution. In order to best adjust the solution or improve the solution, a local search can be performed after the evolutionary algorithm. Here, a performance called DELSA is introduced. To improve the robustness of the solution, an evolutionary algorithm can be performed after some period of local search. Local search can combine the objective domain with evolutionary algorithms.

If evolutionary algorithms have sufficient information, they can perform successfully in the real-time domain. The special information can be transformed into mutation performance or crossover performance. This information can also be employed as the starting point of search in local search methods. In a number of cases, there are correct or combinational methods to solve sub-problems. Nevertheless, it should be noted that an optimiser is not suitable for all classes of problems, which is the reason behind the success of evolutionary algorithms in combinational structures.

The steps of the LS algorithm combined with the DE algorithm (DELSA) progress along these lines:

a) All steps of EAs, for example, the DE Algorithm up to the first step of the combination with LS.
b) Start the combination by organising offspring vectors (according to their fitness).
c) Set the best fitted offspring vectors as the population of new parents (the next generation).
d) Add a division of the stochastic initial population to the new parents population in order to achieve local search.
e) Continue the steps of EA, perform local search and calculate the fitness for parent vectors, for example, the steps of the DE algorithm to produce DELSA.
f) Computation of mainly fitted offspring vectors for the next regeneration.

VI. DESIGN OF PSS BY DELSA FOR INTER-AREA OSCILLATIONS DAMPING

In this paper the objective of design is to achieve optimum parameters of the PSS with the aim of recognising power system stability against inter-area oscillations as well as developing the damping speed of the system. The DE and LS algorithms are utilised for this purpose. The number of variables of this problem is $D = 18$, including PSSs controller parameters in each area of the power system.

To determine the justified number of vectors specifying the optimum results for local search, the severed first results have been selected compared with the best efficiency. In this method NP is considered as local searching for all results. The three-area power system is simulated by MATLAB and Simulink (dynamic in time-domain). Designable parameters of PSS are T_1, T_2, T_3, T_4, T_w and K_s, which is the product of $T_w * K_{ps}$. The system considered here has some initial oscillations. Within one second after the zero time, the system contains a three-phase short-circuit fault with a resistance of 0.001 ohms for 12 cycles (12/60 seconds) at the middle of the tie line in the largest machine and middle bus (bus 4) for the worst state. The system is simulated for 30 seconds without PSS. The variation of the speeds of the machines, the transmission power (in the weak tie line) and the variation of a bus voltage are shown in Figs 8, 9 and 10, respectively. The figures show that the power system reaches instability (in a short time) after the occurrence of the fault at *t=1* sec.

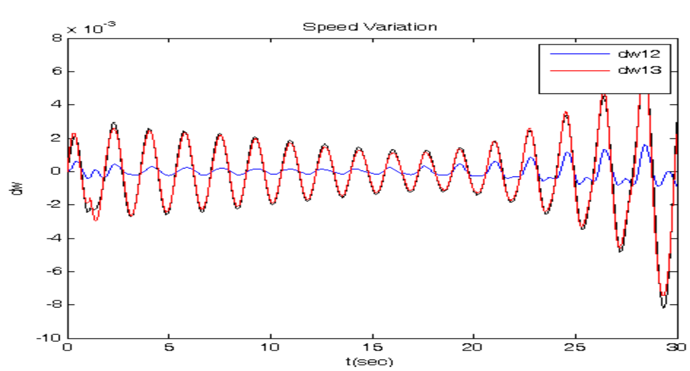

Fig. 6. Variation of machines speed

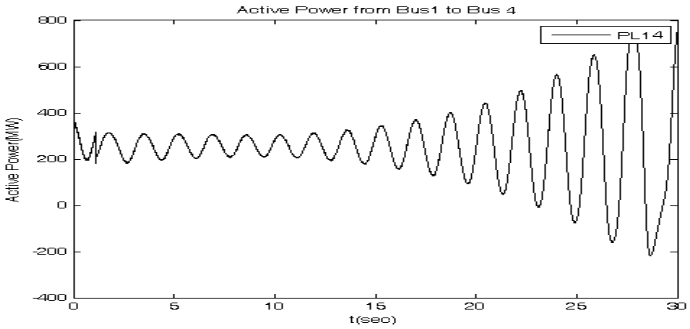

Fig. 7. Variation of tie line power between bus 1 and 4

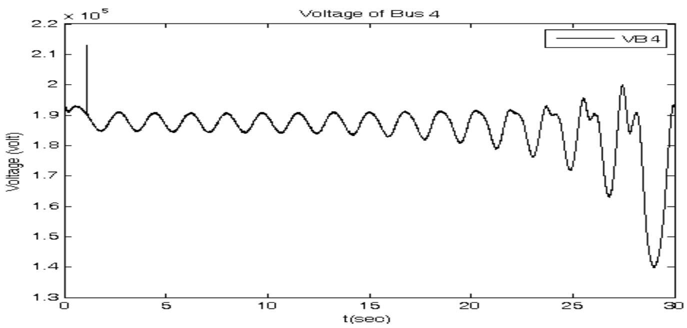

Fig. 8. Voltage variation in Bus3

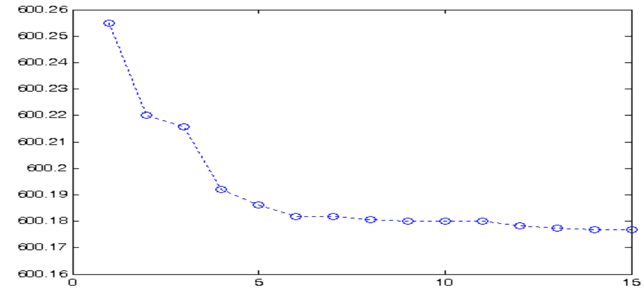

Fig. 9. Convergence characteristics of the averaged optimum value of objective function in DE with variable Scale factor for 15 iterations

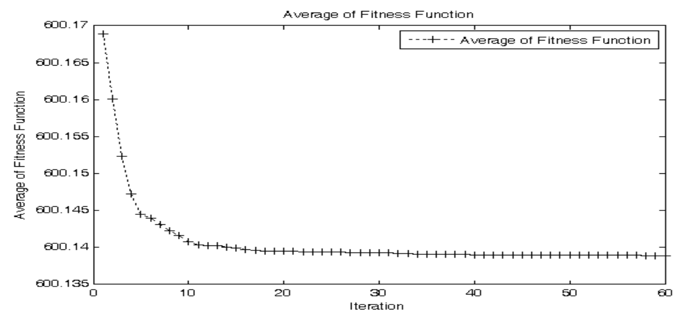

Fig. 10. Convergence characteristics of the averaged optimum value of objective function in DE with variable Scale factor for 60 iterations

VII. RESULTS OF SIMULATION WITH DE ALGORITHM

The least number of iterations to achieve the preferred solution is 10 $(NP*ITER=8*10=80)$, but for the exact result 15 iterations are required $(NP*ITER=8*15=120)$ and 60 iterations for more exact and correct results $(NP*ITER=10*60=600)$. Nonetheless, with all of the variation and iterations, there is a small variation in PSS parameters. Even this small variation leads to damping time reduction from an amount smaller than 5 sec to less than 3 sec and finally under 2 sec.

Objective functions that are utilised in this problem are the squared summation integral of speed variations, the difference of variation in mechanical and electrical power, and the infinity norm of speed variations of large scale machines in three areas, and the best convergence and infinity norm of speed variations are preferred. Minimization and maximization values of PSSs parameters are necessary to generate the initial population (See Table 1). Figs 9 and 10 show the convergence characteristics of the averaged optimum value of the objective function in the DE algorithm with a variable SCALE factor for two sets of repeats.

Table 1: PSSs parameters range for producing initial population

PSS	Tw	T1	T2	T3	T4	Ks
Hi	15	5	5	10	10	10
Lo	0	0	0	0	0	0

The averaged convergence characteristics of the best objective function for these states are 600.214, 600.177 and 600.139. The largest difference of these values is 0.075. Fig. 11 shows that the difference between the damping of speed variations of different machines, in contrast with the area 1 machine (the largest generator, 5500 MVA) arrive at the zero in less than 2 seconds. Fig 12 shows the variation of the active power transmission from bus 3 to 4. The difference between the electrical and mechanical power variations for the generator in area 1 is shown in Fig. 13. The stability of the voltage of bus 4 in Fig. 14 is accomplished in a smaller amountless than 2 sec (after the fault at the first second) and the curve of the transmission power between bus 3 and 4 converges to 500 MW. The PSS optimum parameters after 60 iterations of the DE algorithm are easily reached in Table 2.

The difference between the electrical and mechanical power of generator in area 1 converges to zero, and the voltage of bus 4 converges with high speed.

Table 2: PSSs optimum parameters after 60 iterations of DE

PSS	Tw	T1	T2	T3	T4	Ks
PSS1	13.6042	4.9646	4.7789	9.9279	9.9879	9.9965
PSS2	14.9192	4.9527	4.9640	9.9880	9.9927	9.9955
PSS3	14.4676	4.9603	4.9828	9.8748	9.7193	9.9966

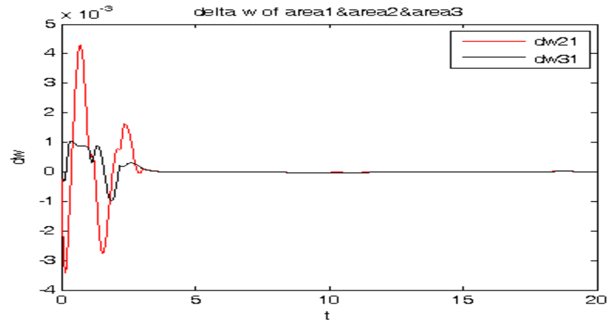

Fig. 11. Variation of machines speed

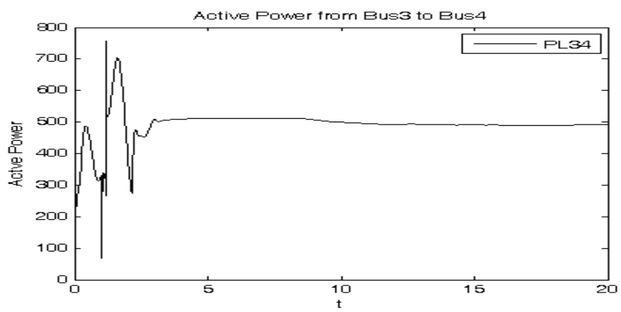

Fig. 12. Variation of tie line power between bus 3 and 4

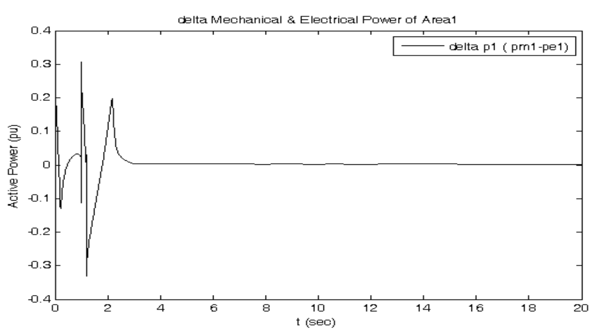

Fig. 13. The difference between electrical and mechanical power variations for the generator in area 1

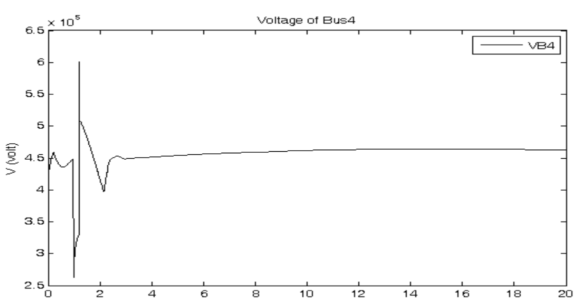

Fig. 14. Voltage variation in Bus4

Hence, according to the curves, the inter-area oscillations are damped, and therefore inter-area modes are shifted to the left-half imaginary axis plane. It can be seen that dynamic stability is attained.

VIII. RESULTS OF SIMULATION WITH DELSA ALGORITHM

The minimization of the number of iterations that is required for the accurate solution is 5, $((NP + NLOCAL) * ITER = (6+6)*5 = 60)$, and with the aim of the extremely accurate solution 15 iterations are needed $((NP + NLOCAL) * ITER = (6+6)*15 = 180)$.

In PSS parameters just a small variation is seen, and this small value causes a reduction in the damping time from 2.5 sec to less than 2 sec and a drop in the overshoot in speed variation, transmitted power and voltage. In this problem, to evaluate these results with the previous ones, the infinity norm of machine speed variations was selected as the objective function. The minimization value and maximization values of the PSSs parameters for generating the initial population are shown in Table 1. Fig. 15 and Fig. 16 show the characteristics of convergence of the averaged value of the objective function for DELSA in two positions of iterations.

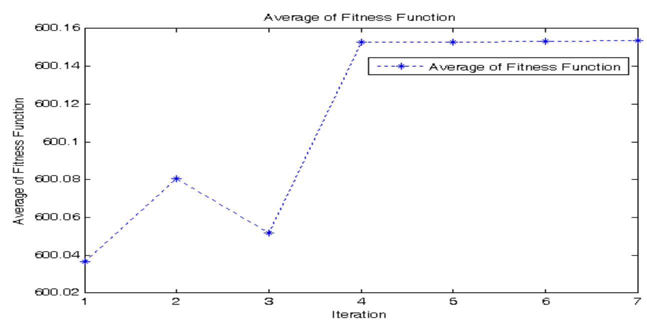

Fig. 15. Convergence characteristics of the averaged optimum value of objective function in DELSA with variable Scale factor for 7 iterations

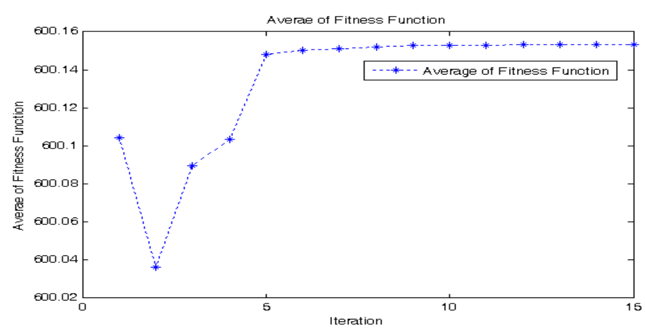

Fig.16. Convergence characteristics of the averaged optimum value of objective function in DELSA with variable Scale factor for 15 iterations

It is importance to note that because of the existence of local search in DELSA, two convergence characteristics are similar to minimization curves, though they are minimization curves headed for a definite number. Fig. 17 shows that the differentiation between machine variation speeds arrives at zero in less than 2 sec. The results of simulation are presented in Figs 17-20. It can be seen that stability is gated in less than 2 sec, and the transmitted power curve from bus 3 to 4 converges to 500 MW. Table 3 shows the optimal parameters of PSS after 15 iterations of DELSA.

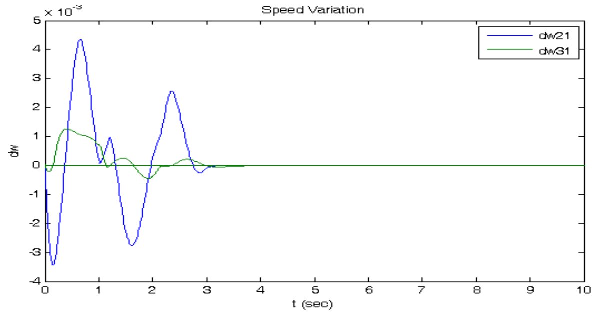

Fig. 17. Variation of machines speed

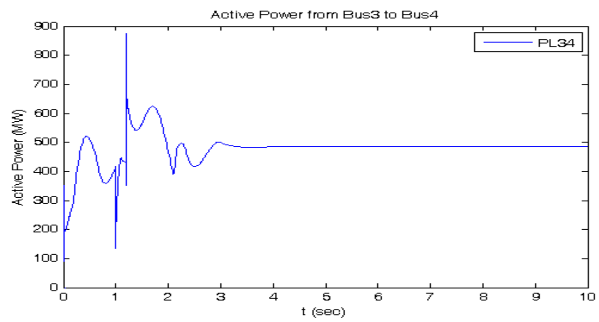

Fig. 18. Variation of tie line power between bus 3 and 4

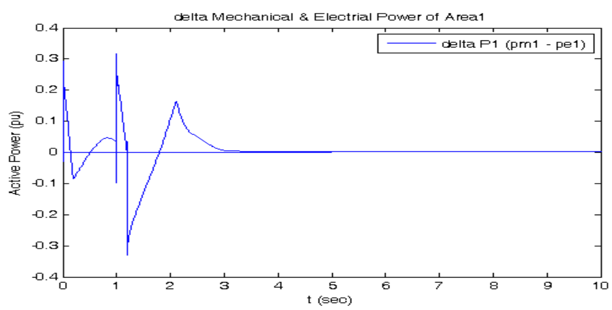

Fig. 19. The difference between electrical and mechanical power variations for the generator in area 1

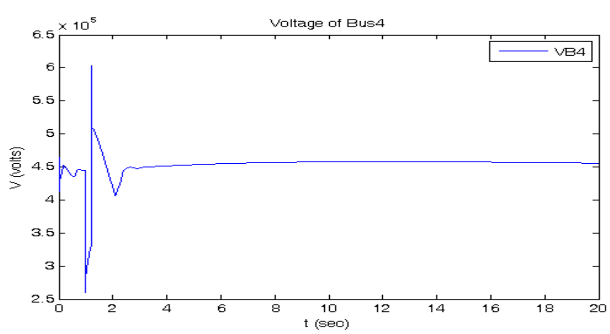

Fig. 20. Voltage variation in Bus4

Table 3. Optimal parameters of PSSs after 15 iterations of DELSA

PSSs	Tw	T1	T2	T3	T4	Ks
PSS1	15.5919	5.1498	5.2827	10.419	10.554	10.6438
PSS2	15.0396	5.2728	4.9953	10.1385	10.6504	10.6037
PSS3	15.5481	5.2324	5.3142	10.3731	10.3032	10.5488

In accordance with results, low frequency oscillations and then local and inter-area oscillations are damped, and after damping, local modes are shifted to the left-half of the imaginary axis, and dynamic stability is realised.

IX. CONCLUSIONS

Many investigations have been devoted to classic controller design. These methods include evolutionary algorithms, the annealing algorithm, and the stochastic evolutionary algorithm. DE is an evolutionary algorithm that can search the correct and optimal solution space without any disagreement. The DE algorithm often attains a correct and better solution than other methods. Among these methods, the DE algorithm with a variable SCALA factor has had suitable results and converged to the optimal value. In this paper, optimal adjustment of PSS parameters for the DE algorithm and also a combination of the DE algorithm with LS (DELSA, Memetic DE Algorithm) can damp the inter-area oscillations of power systems with a small number of iterations and as fast as or even faster than comparable algorithms with a larger stability margin. Comparing the results of this paper with [19] and [21-28], one can shows that the results are in agreement, and oscillations are dampened with little iteration and faster. The comparison of the DE algorithm and DELSA outcomes shows the advantages of DELSA over DE; specifically:

a) Better optimal results with a smaller amplitude in speed variation and inter-area transmitted power variation and a smaller number of iterations, and

b) Faster search optimal results.

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