Grey wolf optimization algorithm based dynamic security constrained optimal power flow

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Abstract—**This paper proposes a Grey Wolf Optimization (GWO) based algorithm to solve Dynamic Security Constrained Optimal Power Flow (DSCOPF) problem. This endeavors to make changes of rescheduling of active power generation in power system subject to both static and dynamic constraints. The GWO algorithm shows the capability of improving diversity in search space and also to reach a near global optimal point. To validate the GWO algorithm, simulations are performed on IEEE 30-bus system and New England 39-bus system under different fault clearing times. The results are compared with different evolutionary algorithms reported in the literature.**

Keywords—dynamic security; optimal power flow; stability limits; grey wolf optimization

I. INTRODUCTION

Electric power system operation and control is a complex and challenging issue in today's large interconnected systems. Due to rapid increase of electricity demand, the modern power systems are run close to their stability limits. A secured power system is able to withstand, reasonably safe limits of security constraints from unforeseen contingencies [1]. Static security assessment checks limit violations after contingency. However, it doesn't capture dynamics in the power system. On the other hand, Dynamic Security Assessment (DSA) analyzes, the ability of a power system to withstand and survive the ensuring transient state and move into a steady state condition for a following contingencies [2]. The dynamic security assessment is a complex and challenging task in large interconnected power system because of transient rotor angle oscillations in the presence of contingencies. Contingency enhancement incorporates Security Constrained Optimal Power Flow (SCOPF), deals with rescheduling optimum active power generations to ensure the system back to normal/secure state.

When the system subjected to contingency, it may not able to maintain transient stability with base case optimal active power generations. For enhancing dynamic security, the stability constraints like rotor angle stability are embedded with static security constrained optimal power flow problem, called Dynamic Security Constrained Optimal Power Flow (DSCOPF) problem. This endeavors to make changes of rescheduling of active power generation of different generators in power system subject to both static and dynamic constraints. It contains both non linear algebraic and differential equations. The main issues to be considered for solving DSCOPF nonlinear optimization problem are modeling of transient stability limits, solving differential equations effectively and choosing an effective optimization algorithm to solve DSCOPF problem. In the past, a number of conventional (mathematical based) algorithms like linear programming method [3], interior point method [4], were proposed to solve Transient Stability Constrained Optimal Power Flow (TSOPF). Conventional methods face difficulty in handling inequality constraints and not guarantee to reach an optimal solution. These methods are struck in the local optimum point and exhibits poor convergence characteristics. In order to overcome these difficulties, several non-conventional (heuristic) methods are implemented for solving the TSOPF problem like genetic algorithm [5], particle swarm optimization [6], differential evolution [7] etc.

N.Mo et al. [6] proposed Particle Swarm Optimization (PSO) algorithm to solve TSOPF problem and compute optimal values of generations with presence of dynamic limits like rotor angles of machines. Differential evolution (DE) algorithm approach has effectively solved TSOPF problem to get the minimum fuel cost compared to other reported methods [7]. An improved micro-particle swarm optimization algorithm is proposed to solve TSOPF problem and results are compared with standard PSO and micro-PSO algorithms [8]. *S.W. Xia et al.* [9] proposed an Improved Group Search Optimization (IGSO) to solve discontinues non convex TSOPF problem. In[10], the artificial bee colony algorithm is successfully applied to TSOPF problem. Chaotic Artificial Bee Colony (CABC) algorithm is developed to evaluate minimum fitness function with subject to both thermal and rotor angle stability limits. In this paper proposes GWO based method to solve DSCOPF problem. The GWO method is a new meta-heuristic population based optimization approach inspired by nature of grey wolves. It has strong searching ability to reach near optimal value [11]. This algorithm is tested on IEEE 30-bus system and New England 10-generators, 39-bus systems with different fault clearing times. Finally, results are compared with the methods reported in the literature viz., GA [6], PSO [6], Evolutionary Programming (EP) [12], ABC [10], CABC [10] etc.

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II. PROBLEM FORMULATION

The solution of DSCOPF gives optimal active power generations to minimize the objective function. The objective of DSCOPF problem is to minimize the total production cost (F_{cost}) and it is expressed as follows [10].

$$\text{Production cost } (F_{cost}) = \sum_{i=1}^{N_g} a_i P_{gi}^2 + b_i P_{gi} + c_i \qquad i = 1,2......N_g \quad (1)$$

Where P_{gi} is the active power generation at i[th] generator, N_b represents number of generators, a_i, b_i and c_i are generator production cost coefficients at i[th] generator.

A. Equality Constraints

The basic power flow equations at given i[th] bus can be mathematically expressed as follows. These non linear algebraic equations are solved by using Newton- Raphson power flow method.

$$(P_{gen,i} - P_{load,i}) - V_i \sum_{j=1}^{N_b} V_j \left|Y_{ij}\right| \cos(\delta_{ij} - \theta_{ij}) = 0 \qquad (2)$$

$$(Q_{gen,i} - Q_{load,i}) - V_i \sum_{j=1}^{N_b} V_j \left|Y_{ij}\right| \cos(\delta_{ij} - \theta_{ij}) = 0 \qquad (3)$$

Where N_b is the total number of buses; $P_{gen,i}$ and $P_{load,i}$ are specified active power generation and load of i[th] generator respectively; $Q_{gen,i}$ and $Q_{load,i}$ are specified reactive power value and load of i[th] generator respectively; V_i, V_j and Y_{ij} represents bus voltage magnitudes and bus admittance matrix respectively; δ_{ij} and θ_{ij} are voltage and admittance angle differences between i-j buses. The classical generator model consists of a constant voltage source behind a transient reactance. The swing equation for i[th] generator without accounting the damping effect can be expressed as follows [12].

$$\frac{H_i}{\pi f_0} \frac{d^2 \delta_i}{dt^2} = P_{mi} - P_{ei} \qquad i = 1,2......N_g \qquad (4)$$

Where δ_i represents rotor angle of i[th] generator; H_i and f_0 are inertia constant of i[th] generator and frequency respectively; P_{mi} and P_{ei} are mechanical input power and electrical output power of i[th] generator. The electrical output power (P_{ei}) during fault is given by Eq. (5).

$$P_{ei}^f = \sum_{i=1}^{N_g} \left|E_i^{'}\right| \left|E_j^{'}\right| \left|Y_{ij}\right| \cos(\delta_{ij} - \theta_{ij}) \qquad i = 1,2......N_g \quad (5)$$

Here Y_{ij} are the elements of faulted reduced bus admittance matrix; $E_i^{'}$ and $E_j^{'}$ are voltages behind the transient reactance of i[th] and j[th] buses. The state space variable model above swing equation for each generator is expressed as follows.

$$\begin{aligned} \dot{\delta}_i &= \Delta\omega_i = \omega_{r,i} - \omega_s \\ \Delta\dot{\omega}_i &= \frac{\pi f_o}{H_i}(P_{mi} - P_{ei}^f) \end{aligned} \qquad (6)$$

Where δ_i and $\Delta\omega_i$ are two state variables; $\Delta\omega_i$ is the error speed between rotor speed ($\omega_{r,i}$) of i[th] generator and synchronous speed of the machine. These equations are solved by using modified Euler method.

B. Inequality constraints

The static and dynamic inequality constraints for generator and network limits are expressed in terms of lower and upper limits as follows.

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \qquad i = 1,2......N_g \qquad (7)$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \qquad i = 1,2......N_g \qquad (8)$$

$$V_i^{\min} \le V_i \le V_i^{\max} \qquad i = 1,2......N_b \qquad (9)$$

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad i = 1,2......N_{TF} \qquad (10)$$

$$S_i \le S_i^{\max} \qquad i = 1,2......N_{line} \qquad (11)$$

$$\left|\delta_{i+1} - \delta_1\right|_{\max} \le \delta_{\max} \qquad i = 1,2......(N_g - 1) \qquad (12)$$

The inequality constraints are represented as active power limits of all generators, voltage magnitudes of all buses, transformer tapping positions (T), thermal limits (S) of each line and relative rotor angles of all generators with respect to the slack/reference generator. In order to enforce all inequality penalty functions, the total fitness value of optimization problem is given in (13). Here, $I_j(x,u)$ represents the penalty functions of all inequality constraints and λ is the penalty coefficient.

$$Min\, \tilde{f}(x,u) = F_{cost} + \lambda * \max[0, I_j(x,u)^2] \quad j = 1,2.....N_{inequal} \, (13)$$

III. GENERAL FRAMEWORK OF GWO ALGORITHM

Nature-inspired evolutionary algorithms like Genetic Algorithm (GA), swarm intelligent algorithms like Particle Swarm Optimization (PSO), Cuckoo Search algorithm (CS), BAT algorithm and physics inspired methods like Simulated Annealing (SA), Center Force Optimization (CFO) are proven in solving complex global optimization problems. Grey Wolf Optimization (GWO) is a recently developed meta-heuristic optimization method inspired by grey wolves suggested by Mirjalili [11]. This algorithm is proven to solve non-convex engineering optimization problems and attained aggressive results compared to DE, PSO, GSA and EP optimization methods. The entire search space of the GWO algorithm is guided by three wolves, namely alpha (α), beta (β) and gamma (γ). The dominant grey wolves are named as alpha; these are a male or female. Whereas the second dominant wolves are beta and lowest ranking grey wolves are named as gamma. If a wolf is not a including these groups, it is called a delta wolves. The delta wolves' positions are updated according to first three grey wolves' positions. The main stages of grey wolf hunting are tracking the prey, encircling and attacking.

When designing GWO algorithm, we consider best fitness value as the alpha (α) and consequently second and third best ones are beta (β) and gamma (γ). These three wolves are guided to other wolves during hunting. After finding the prey, grey wolves encircle and harassing the pray until it stops moving. The mathematical model for encircling behavior of grey wolves as followed.

$$\vec{D} = \left|\vec{C} * \vec{X}_{prey}(t) - \vec{X}_{GW}(t)\right| \tag{14}$$

$$\vec{X}_{GW}(t+1) = \vec{X}_{prey}(t) - \vec{A} * \vec{D} \tag{15}$$

Where t indicates current position, $\vec{X}_{prey}$ is the position vector of the prey, $\vec{X}_{GW}$ represents a position vector of grey wolf, $\vec{A}$ and $\vec{C}$ are coefficient vectors and calculated as follows.

$$\vec{A} = 2\vec{a} * \vec{r}_1 - \vec{a} \tag{16}$$

$$\vec{C} = 2 * \vec{r}_2 \tag{17}$$

Here $\vec{a}$ is decreased from 2 to 0 over the course of iterations and $\vec{r}_1$, $\vec{r}_2$ are random values between 0 and 1. In real time optimization problem, we don't have an idea about the location of the optimum value (prey). So in order to mathematically simulate the hunting behavior of the grey wolf, store first three best fitness values as alpha, beta and gamma. These are having prospective knowledge about the optimum location of the prey.

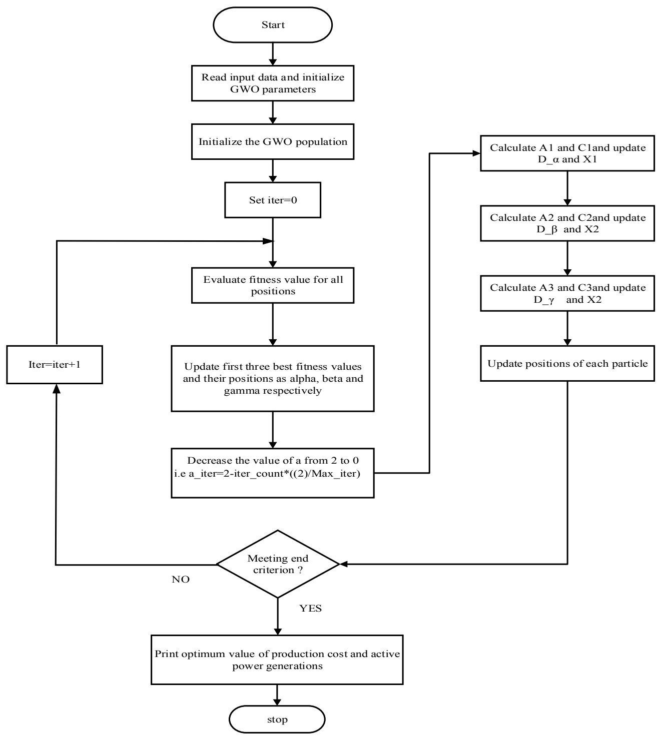

Fig.1. Flowchart of GWO algorithm

The remaining positions in search space are updated according to the position of the best search agent position. The position vectors with respective alpha, beta and gamma can be formulated mathematically as follows. The general steps involved in GWO algorithm is shown in Fig.1.

$$\vec{X}_1 = \vec{X}_{\_\alpha}(t) - \vec{A}_1 * \vec{D}\_\alpha \tag{18}$$

$$\vec{X}_2 = \vec{X}_{\_\beta}(t) - \vec{A}_2 * \vec{D}\_\beta \tag{19}$$

$$\vec{X}_3 = \vec{X}_{\_\gamma}(t) - \vec{A}_2 * \vec{D}\_\gamma \tag{20}$$

Where $\vec{D}\_\alpha, \vec{D}\_\beta$ and $\vec{D}\_\gamma$ are defined as,

$$\begin{aligned} \vec{D}\_\alpha &= \left|C * \vec{X}_{\_\alpha}(t) - \vec{X}_{GW}(t)\right| \\ \vec{D}\_\beta &= \left|C * \vec{X}_{\_\beta}(t) - \vec{X}_{GW}(t)\right| \\ \vec{D}\_\gamma &= \left|C * \vec{X}_{\_\gamma}(t) - \vec{X}_{GW}(t)\right| \end{aligned} \tag{21}$$

The best position of grey wolf is calculated taking average sum of positions as given in (22).

$$X_{GW}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{22}$$

IV. SIMULATION RESULTS AND DISCUSSIONS

The proposed work intends to reschedule of active power generations to satisfy both static and dynamic constraints. All simulations were carried out on Intel, 2.40 GHz, core i5-4210U processor; 4GB RAM and MATLAB 8.4 version. The algorithm is tested on IEEE 30 bus system (6-generators) and New England 10-generators, 39 bus systems. The results are compared with other algorithms published in the literature. The simulation results of two test systems are elucidated in the following subsections. In order to do fair comparison between GWO method and other algorithms published in the literature in terms of minimum objective function reached, same three phase short circuit contingency with different fault clearing times have been considered for the both the test systems. The population size has taken as 50 and total number of iterations is considered as 100.

A. IEEE 30-bus system

This system comprises of 6 generators, 24 load- buses and 41 transmission- lines. The test data and network topology along with generator units and their constraints are taken from [10]. Bus 1 has been assigned as the slack/reference bus. The total load demand is 189.2 MW. Two different fault clearing times viz., i) t=0.18 s and ii) t= 0.35 s are considered to analyze the system security for IEEE 30-bus system. The value of maximum allowable rotor angle deviation (δ_{max}) is determined by hit and trail.

A single contingency consisting of three phase short circuit fault is applied at bus 2 and cleared by tripping the line between buses 2-5 at t= 0.18 s [10]. To observe the rotor oscillations, the maximum integration period considered is 3.0s and maximum rotor angle deviation from reference bus (δ_{max}) is set to 120^{O}. For GWO algorithm, 20 independent runs were performed. The minimum, maximum and average production costs are obtained for DSCOPF problem using GWO algorithm is shown in Table-1 and compared with different optimization methods reported in the literature. The optimal total production cost obtained by the GWO algorithm is 576.59$/hr. The respective convergence characteristic of GWO method is shown in Fig.2.

TABLE 1

IEEE 30-BUS SYSTEM: PRODUCTION COST OF GENERATORS FOR T=0.18S

Cost ($/hr)	**GWO** [11]	**ABC** [10]	**CABC**[10]	**PSO**[6]	**GA**[6]
Minimum cost	576.591	577.78	577.63	585.17	585.62
Maximum cost	576.595	583.90	580.83	585.69	585.71
Average cost	576.593	580.84	579.23	585.34	585.66

The results reveal that, GWO method reaches the near optimal solution (minimum fitness value) compared to other optimization methods like ABC, CABC, PSO and GA. The generator relative rotor angles obtained by the GWO method with respect to slack bus generator are shown in Fig. 3. The maximum rotor angle deviation with respect to the slack bus generator is nearly 42^{o}. This shows that all generators with reference to slack bus generator do not exceed the maximum allowable rotor angle (i.e 120^{o}) in the presence of available active power generations.

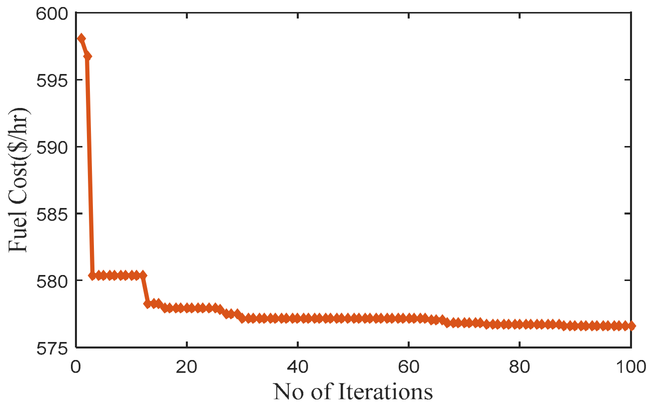

Fig.2. 30-bus system: convergence characteristics for t=0.18s

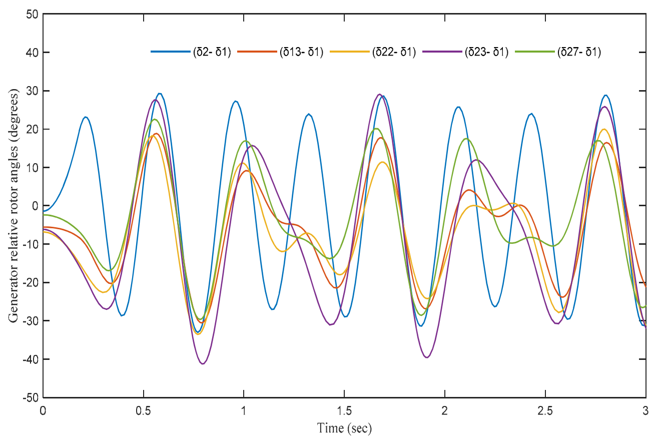

Fig.3. 30-bus system: Generator relative rotor angles for t=0.18s

A three phase short circuit fault is applied at bus 2 and cleared by tripping the line between buses 2-5 at t = 0.35 s [10]. To observe the rotor oscillations, the maximum integration period considered is 3.0 s and δ_{max} is set to 120^{o}. The minimum, maximum and average production costs are obtained for DSCOPF problem using GWO algorithm is shown in Table-2 and compared with different optimization methods reported in the literature. The optimal total production cost obtained by the GWO algorithm is 576.59$/hr.

TABLE 2

IEEE 30-BUS SYSTEM: PRODUCTION COST OF GENERATORS FOR T=0.35S

Cost ($/hr)	**GWO**[11]	**ABC**[10]	**CABC**[10]	**EPNN**[12]	**EP**[12]
Minimum cost	576.592	577.71	577.47	585.12	585.15
Maximum cost	576.599	583.26	580.74	586.73	586.86
Average cost	576.595	580.21	579.10	585.84	585.83

The GWO algorithm outperform in terms of getting near optimal production cost. The relative rotor angles of all generators obtained GWO method with respect to slack bus generator are shown in Fig. 5. The maximum rotor angle deviation from slack generator is obtained nearly 110^{o}. This shows that the relative rotor angle deviation of the generators reaches to its maximum allowable rotor angle deviation (i.e 120^{o}) because of increasing fault clearing time from 0.18s to 0.35s. The generators are reallocated the active power generations according to the satisfying both static and dynamic constraints. The graph shows that all generators with reference to slack bus generator do not exceed the maximum allowable rotor angle (i.e 120^{o}). It can be seen that, the system is secured during contingencies in the presence of optimal rescheduled active power generations. The optimal active power generations obtained for satisfying the both static and dynamic constraints using GWO algorithm for both fault clear timings are tabulated in Table-3. The convergence characteristic is shown in Fig.4.

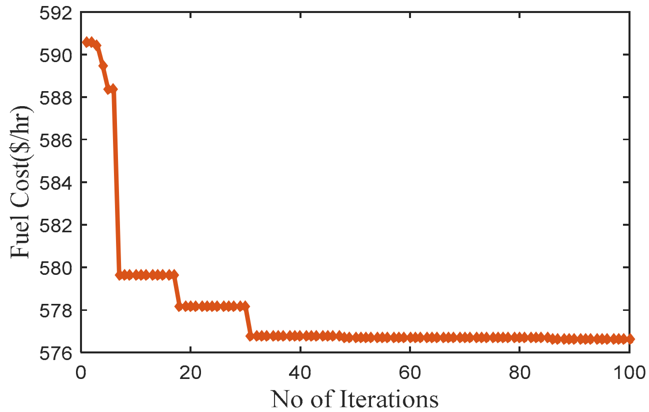

Fig.4. 30-bus system: convergence characteristics for t=0.35s

TABLE 3

OPTIMAL RESCHEDULING OF ACTIVE POWER GENERATIONS (IN MW)

Fault clearing times	**Generator numbers**					
	1	***2***	***13***	***22***	***23***	***27***
T=0.18s	43.90	58.13	17.65	23.16	16.81	32.48
T=0.35s	43.74	58.16	17.73	23.31	16.78	32.41

B. New England 39-bus system

The system comprises 10 generators and 41 transmission lines. In this, bus no 31 has assigned as the slack/reference bus. The line data, bus data and network topology along with generator units and their constraints are taken from [10]. The total load demand of test system is 6098.0 MW.

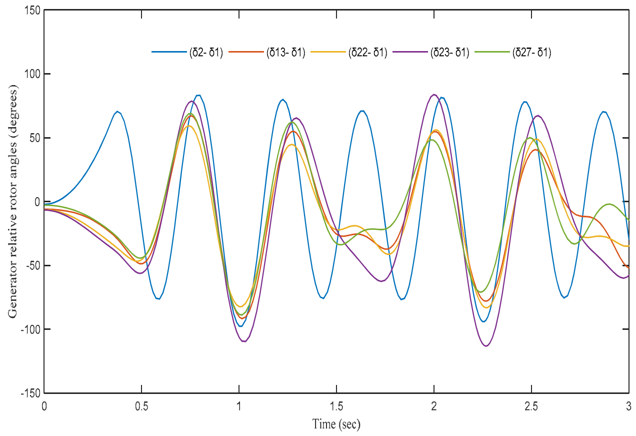

Fig.5. 30-bus system: Generator relative rotor angles for t=0.35s

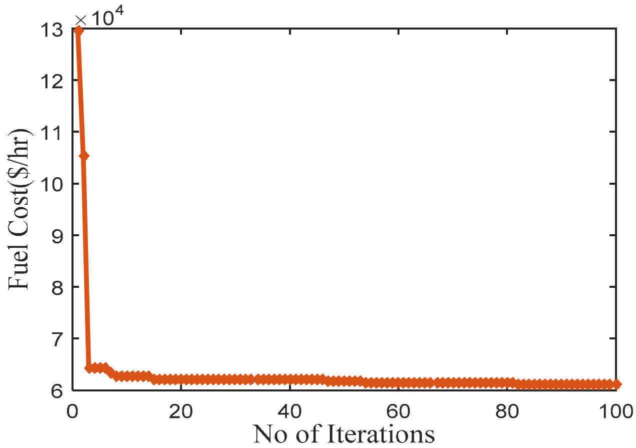

Fig.6. 39-bus system: convergence characteristics

A three phase short circuit fault is applied at bus 17 and cleared by tripping the line between buses 17-18 at t= 0.2s [10]. To observe the rotor oscillations, the maximum integration period is set to 3.0 s and δ_{max} is set to 170°. The minimum, maximum and average production costs for DSCOPF problem employing the GWO algorithm is shown in Table-4 and compared with the ABC and CABC methods. The respective convergence characteristic of GWO method is shown in Fig.6.

TABLE 4

39-BUS SYSTEM: PRODUCTION COST OF GENERATORS

Cost ($/hr)	**GWO** [11]	**ABC** [10]	**CABC**[10]
Minimum cost	61129.0	61485.48	61369.00
Maximum cost	61151.0	61703.42	61602.53
Average cost	61140.0	61594.45	61485.86

The minimum production cost obtained by the proposed algorithm is 61129.0$/hr. The results reveal that, the GWO algorithm outperforms in terms of reaching near optimal production cost. The relative rotor angles of all generators obtained by the GWO method with respect to the slack bus generator are shown in Fig. 7. The graph shows that all the generators with respective to slack bus generator do not exceed the maximum allowable rotor angle (i.e 170°). The maximum rotor angle deviation from slack generator is obtained nearly 118°. Hence, the system is dynamically secured during contingency in the presence optimal active power generations. The optimal active power generations obtained for satisfying the both static and dynamic constraints using GWO algorithm is tabulated in Table-5.

TABLE 5

OPTIMAL RESCHEDULING OF ACTIVE POWER GENERATIONS (IN MW)

Fault clearing time at t=0.2s	**Generator numbers**				
	30	31	32	33	34
	226.46	568.81	649.12	666.99	509.21
	35	36	37	38	39
	689.87	602.71	542.78	860.95	829.52

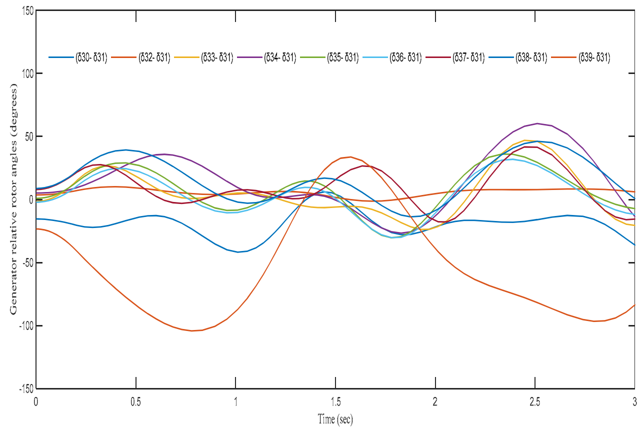

Fig.7. 39-bus system: Generator relative rotor angles for GWO algorithm

V. CONCLUSIONS

In this paper, a new population based GWO meta-heuristic optimization algorithm is applied for solving dynamic security constrained OPF problem. The simulation results are presented for 30-bus and 39-bus systems under different fault clearing times. For the IEEE 30-bus system, the minimum production cost is 576.59$/hr for t=0.18s and 0.35s after optimal rescheduling of active powers, whereas for the New England 39-bus system the minimum production cost is 61129.0$/hr. The maximum rotor angle deviation with respect to slack bus is 42° for t=0.18s, whereas 110° for t=0.35s for the IEEE 30-bus system. Whereas for the 39-bus system the maximum rotor angle deviation is 118° for fault clearing time 2s. Therefore it shows that the system is secured for both the cases. The results are compared with other optimization methods like GA, PSO, ABC, and CABC. Hence, in view of reaching near optimal production cost, the GWO method is superior and more efficient and it can be used for large power system to enhance system security.

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