Abstract—In competitive electricity market, congestion is a serious economic and reliability concern. Congestion is a common problem that an independent system operator faces in open access electricity market. This project presents a reliable and efficient meta-heuristic based approach to solve congestion problem. The proposed approach of the present work employs Firefly algorithm (FFA) for alleviation of transmission network congestion in a pool based electricity market via active power rescheduling of generators. FFA is a new meta-heuristic approach based on flashing patterns and behaviour of fireflies. Various important security constraints such as load bus voltage and line loading have been taken into account while dealing with congestion problem. The proposed methodology may help in removing the congestion of line with minimum rescheduling cost. The numerical results of modified IEEE 30-bus test power systems are illustrated.

Keywords—Firefly algorithm, Particle swarm optimization, congestion

I. INTRODUCTION

Deregulation is a new paradigm in the electric power industry. The goal of deregulation is to enhance competition and bring consumer’s new choices and economic benefits. Power system security, congestion management, power quality and power regulations are major concepts that draw the attention of power researchers in deregulated surroundings. In deregulated electricity market, most of the time power system operates near its rated capacity as each player in the market is trying to gain as much as possible by full utilization of existing resources. Congestion in the transmission lines is one of the technical problems that appear particularly in the deregulated environment.

In the deregulated power system, the challenge of Congestion Management (CM) for the transmission system operator is to create a set of rules that ensure sufficient control over producers and consumers (generators and loads) to maintain an acceptable level of power system security and reliability in both the short term (real time operation) and the long term (transmission and generation construction) while maximizing the market efficiency. The system is said to be congested when the producers and consumers of electric energy desire to produce in amounts that would cause the transmission system to operate beyond one or more transfer limits. Congestion has direct impact on security and reliability of the system. Discrete changes in system configuration may result, due to some contingency or outage rendering the system, into an unsecured state and make other lines to undergo congestion too, resulting in dynamic congestion. Congestion Management (CM), that is controlling the transmission system so that the transfer limits are observed, is perhaps the fundamental transmission management problem [1].

When a generator is a price taker, it can be shown that maximizing its profit requires bidding its incremental cost. When a generator bids other than its incremental costs in an effort to exploit imperfections in the market to increase profits, its behaviour is called strategic bidding. If the generator can successfully
increase its profits by strategic bidding or by any other means than the lowering costs, it is said to have market power and one of the main cause of market power is congestion. Various approaches have been presented in the literature for solving the CM problem. The general methods adopted to relieve the congestion involve the rescheduling of generator power outputs, providing the reactive power support, and curtail the load demands/transactions [2].

II. CONGESTION PROBLEM STATEMENT

The objective function of the proposed method is to find an optimal profile of active power generation so as to minimize the total congestion cost, while satisfying network constraints. Based on the bids submitted by the generators for congestion management, the optimal rescheduling values of generators are computed by solving the following optimization problem. The objective function of the proposed problem is define as:

\[
\text{Minimize} \sum_{g} IC_g(\Delta P_g) \Delta P_g
\]

Subjected to the following constraints;

Operation Limit Constraints:

\[
\Delta P_{g_{\text{min}}} \leq \Delta P_g \leq \Delta P_{g_{\text{max}}}, \quad g = 1,2, ..., \text{Ng}
\]

Where,

\[
\Delta P_{g_{\text{min}}} = P_{g_{\text{max}}} - P_{g_{\text{min}}}, \quad P_{g_{\text{max}}} = P_{g_{\text{max}}} - P_{g}
\]

Line Flow Constraints:

\[
\sum_{g=1}^{\text{Ng}} \left(GS_{ij}^g \Delta P_g\right) + F_{l0}^i \leq F_{l_{\text{max}}}, \quad l = 1,2, ..., n_l
\]

Where ICg(ΔPg) is the incremental or decremental bid submitted by GENCO. ΔPg is the real power adjustment at GENCO. Ng represents the number of GENCOs in the sensitive zone. \(F_{l0}^i\) is the power flow caused by all contracts previously settled on line-l. \(F_{l_{\text{max}}}^i\) is the line flow limit of line-l connecting buses. The generators in the system under consideration have different sensitivities to the power flow on the congested line. A change in real power flow in a transmission line-l (connected between bus i and bus j) due to a change in power generation by generator g can be termed as generator sensitivity (GS) to the congested line. Mathematically, GS for line connected between buses i and j can be expressed as:

\[
GS_{ij}^g = \frac{\Delta P_{ij}}{\Delta P_{g}} = \frac{\partial P_{ij}}{\partial P_{g}} = \frac{\partial P_{ij}}{\partial \theta_t} \frac{\partial \theta_t}{\partial P_{g}} + \frac{\partial P_{ij}}{\partial \theta_j} \frac{\partial \theta_j}{\partial P_{g}}
\]

The power flow equation on the congested lines can be calculated by

\[
P_{ij} = -V_i^2V_{ij} + V_iV_jG_{ij}\cos(\theta_i - \theta_j) + V_iV_jB_{ij}\sin(\theta_i - \theta_j)
\]

The differentiations of the equations with respect to \(\theta_t\) and \(\theta_j\) are;

\[
\frac{\partial P_{ij}}{\partial \theta_t} = -V_iV_jG_{ij}\sin(\theta_i - \theta_j) + V_iV_jB_{ij}\cos(\theta_i - \theta_j)
\]

\[
\frac{\partial P_{ij}}{\partial \theta_j} = V_iV_jG_{ij}\sin(\theta_i - \theta_j) - V_iV_jB_{ij}\cos(\theta_i - \theta_j)
\]

The active power delivered at bus-s referring to any bus in system can be calculated as:

\[
P_s = |V_s|^2 \sum_{t=1,t\neq s}^{n} ((G_{st}\cos(\theta_s - \theta_t) + B_{st}\sin(\theta_s - \theta_t))|V_t|)
\]

\[
P_s = |V_s|^2G_{ss} + |V_s|^2 \sum_{t=1,t\neq s}^{n} ((G_{st}\cos(\theta_s - \theta_t) + B_{st}\cos(\theta_s - \theta_t))|V_t|)
\]

Differentiating with respect to \(\theta_t\),
\[ P_z = |V_s||V_t| \{(G_{st} \sin(\theta_s - \theta_t) + B_{st} \cos(\theta_s - \theta_t)) \} \]

\[ P_z = |V_s| \sum_{t=1, t \neq s}^{n} \{(-G_{st} \sin(\theta_s - \theta_t) + B_{st} \cos(\theta_s - \theta_t))|V_t| \} \]

The relation between the change in active power at any bus and voltage phase angles can be written as,

\[ [\Delta P]_{nx1} = [H]_{nxn}[\Delta \theta]_{nx} \]

\[ [H]_{nxn} = \left[ \begin{array}{cccc}
\frac{\partial P_1}{\partial \theta_1} & \frac{\partial P_1}{\partial \theta_2} & \cdots & \frac{\partial P_1}{\partial \theta_n} \\
\frac{\partial P_2}{\partial \theta_1} & \frac{\partial P_2}{\partial \theta_2} & \cdots & \frac{\partial P_2}{\partial \theta_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial P_n}{\partial \theta_1} & \frac{\partial P_n}{\partial \theta_2} & \cdots & \frac{\partial P_n}{\partial \theta_n}
\end{array} \right]_{nxn} \]

Given, \[ [M] = [H]^{-1} \]

\[ [M]_{nxn} = \left[ \begin{array}{cccc}
0 & 0 & \cdots & 0 \\
0 & \frac{\partial \theta_2}{\partial \theta_1} & \cdots & \frac{\partial \theta_n}{\partial \theta_1} \\
\vdots & \vdots & \ddots & \vdots \\
0 & \frac{\partial \theta_n}{\partial \theta_1} & \cdots & \frac{\partial \theta_n}{\partial \theta_n}
\end{array} \right]_{nxn} \]

Thus, \[ [\Delta \theta] = [M][\Delta P] \]

Since bus 1 is the reference bus, the first row and first column of \[ [M] \] can be eliminated. Therefore, the modified \[ [M] \], is written as

\[ [\Delta \theta]_{nx1} = \left[ \begin{array}{c}
0 \\
0
\end{array} \right]_{nxn} [M_{-1}]_{nxn} [\Delta P]_{nx1} \]

III. PARTICLE SWARM OPTIMISATION METHOD

All PSO is a simple and efficient population-based optimization method proposed by Kennedy and Eberhart[12]. PSO consists of a swarm of particles and each particle flies through the multi-dimensional search space with a velocity, which is constantly updated by the particle’s previous best performance and by the previous best performance of the particle’s neighbours. The position and velocity of each particle are updated at each time step (possibly with the maximum velocity being bounded to maintain stability) until the swarm as a whole converges to an optimum. Particles update their velocity and position through tracing two kinds of ‘best’ value. One is its personal best (pbest), which is the location of its highest fitness value. In global version, another is the global best (gbest), which is the location of overall best value, obtained by any particles in the population. Particles update their positions and velocities according to equation:

\[ V_{id}^{K+1} = \omega V_{id}^{K} + c_1 rand_1 (p_{id}^{K} - x_{id}^{K}) + c_2 rand_2 (p_{gd}^{K} - x_{id}^{K}) \]

\[ X_{id}^{K+1} = X_{id}^{K} + V_{id}^{K+1} \]

Here, \[ V_{id}^{K+1} \] is the velocity of dth dimension of the ith particle in the Kth iteration, \[ X_{id}^{K} \] is the corresponding position and \[ p_{id}^{K} \] and \[ p_{gd}^{K} \] is personal best and global best respectively. Finally, the position of the ith particle for dth dimension is updated by equation written above. Here \( w \) is the inertia weight parameter which controls the global and local exploration capabilities of the particle. A large inertia weight helps in good global search while a smaller value facilitates local exploration.

PSO is an optimization algorithm that falls under the soft computing umbrella that covers genetic and evolutionary algorithmic techniques. In PSO, the selection operation is not performed and it can generate a high-quality
solution within shorter calculation time and stable convergence characteristic than other stochastic methods. Generally, in population-based optimization methods, it is desirable to encourage the individuals to wander through the entire search space, without clustering around local optima, during the early stages of the optimization. On the other hand, during the latter stages, it is important to enhance convergence toward the global optima, to find the optimal solution efficiently.

A. Advantages of the basic particle swarm optimization algorithm [1]:
1. PSO is based on the intelligence. It can be applied into both scientific research and engineering use.
2. PSO have no overlapping and mutation calculation. The search can be carried out by the speed of the particle. During the development of several generations, only the most optimist particle can transmit information onto the other particles, and the speed of the researching is very fast.
3. The calculation in PSO is very simple. Compared with the other developing calculations, it occupies the bigger
4. Optimization ability and it can be completed easily.
5. PSO adopts the real number code, and it is decided directly by the solution. The number of the dimension is equal to the constant of the solution.

B. Disadvantages of the basic particle swarm optimization algorithm [1]:
1. The method easily suffers from the partial optimism, which creates less exact results for regulation of its speed and the direction.
2. The method cannot work out the problems of scattering and optimization
3. The method cannot work out the problems of non-coordinate system, such as the solution to the energy field and the moving rules of the particles in the energy field

IV. FIREFLY METHOD
The Firefly Algorithm was developed by the author (Yang 2008, Yang2009), and it was based on the idealized behaviour of the flashing characteristics of fireflies. For simplicity, we can idealize these flashing characteristics as the following three rules;

- All fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex;
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If no one is brighter than a particular firefly, it moves randomly;
- The brightness or light intensity of a firefly is affected or determined by the landscape of the objective function to be optimised.

For a maximization problem, the brightness can simply be proportional to the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms. In the FA, there are two important issues: the variation of light intensity and formulation of the attractiveness. For simplicity, we can always assume that the attractiveness of a firefly is determined by its brightness or light intensity which in turn is associated with the encoded objective function.

In the simplest case for maximum optimization problems, the brightness, I of a firefly at a particular location x can be chosen as;
I(x) ∝ f(x)

However, the attractiveness β is relative, it should be seen in the eyes of the beholder or judged by the other fireflies. Thus, it should vary with the distance rij between firefly i and firefly j. As light intensity decreases with the distance from its source, and light is also absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption.

V. SIMULATION AND RESULTS

The IEEE 30-bus system has been used to show the effectiveness of the proposed algorithm. The IEEE 30-bus System consists of six generator buses and 24 load buses. In the paper, FFA for CM is implemented using MATLAB software. To verify the effectiveness of the proposed FFA in solving CM problem, simulations are carried out on modified IEEE 30-bus test systems. The bus data and line data are entered in the software. Generation rescheduling cost is calculated for the simulated cases and is compared with results of other research. Details of simulated cases carried out on the two test systems are given in Table I.

Congestion is created in lines for the simulation purpose by overloading the lines. In this paper, line overloads are created either by reducing the capacity of lines as to the compared standard limits or by considering generator or line outage. The proposed FFA has been executed for 100 independent trial runs, out of which the best solution set is presented here.

The values of α and γ are taken in the range of 0 to 1, while the value of β₀ is kept constant at 10. It has been found that population of 40 fireflies is sufficient in solving the CM problem of the present work. The maximum number of iteration is set to 150 for all the test cases. The major observations of the present work are documented as results.

The modified IEEE 30-bus test system is taken for consideration. It has forty-one transmission lines, twenty-four load buses and six generator buses. The total active and reactive power of load for this test system is 283.4MW and 126.2 MVAR, respectively. Generation and load values, are taken as the initial market clearing values for \( P_G \) and \( P_D \), respectively. Contingencies like unexpected line outage and increase in system load are considered for the simulation purpose. Two different cases of this example viz. case 1A and case 1B are considered for this example.

![Fig.1. FFM Algorithm](image)

TABLE I. CONTINGENCY ANALYSIS

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CONGESTION MANAGEMENT USING FIREFLY ALGORITHM IN DEREGULATED POWER SYSTEM FOR IEEE-30 BUS SYSTEM

<table>
<thead>
<tr>
<th>Test system</th>
<th>Test case</th>
<th>Contingency considered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modified IEEE 30-</td>
<td>1A</td>
<td>Outage of line 1–2</td>
</tr>
<tr>
<td>bus</td>
<td>1B</td>
<td>Outage of line 1–7 with increase in load at all buses by 50%</td>
</tr>
</tbody>
</table>

1. Case 1A
In this case, congestion is created by considering outage of line number-1 connected between bus-1 and bus-2. Due to outage of line 1, congestion occurs in lines number-2 and -4, connected between buses 1–7 and 7–8, respectively. Optimal power flow results reveal that powerflows in those lines become 147.463 MW and 136.292 MW, respectively, against the line flow limit of 130 MW for both lines. Details of the congested lines are presented in Table II. Hence, the congestion has to be alleviated by the optimal rescheduling of active power generation of generators. The results, obtained by employing the proposed FFA for the solution of CM problem for case 1A, are tabulated in Table III.

<table>
<thead>
<tr>
<th>Test case</th>
<th>Congested lines</th>
<th>Actual flow (MW)</th>
<th>Line limit (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1A</td>
<td>1-7</td>
<td>147.463</td>
<td>130</td>
</tr>
<tr>
<td></td>
<td>7-8</td>
<td>136.292</td>
<td>130</td>
</tr>
</tbody>
</table>

For comparison purpose, the results obtained from PSO techniques reported in are also included in the same table. From Table III it may be concluded that the results obtained by proposed FFA is the best, providing minimum rescheduling cost compared to other methods reported in the literature, without overloading the other lines. The total system loss before CM was 16.023 MW while the same is decreased to 13.10 MW after CM. A comparative pictorial representation of active power rescheduling and congestion cost offered by different methods like PSO. The convergence profile of fitness function for this test case, as yielded by the proposed FFA, is shown in figure below.

![Fig. 2. Comparative active power rescheduling of generators for modified IEEE 30-bus test system](image)

2. Case 1B
For this case, congestion is created by considering outage of line number-2 connected between bus-1 and bus-7 accompanied by increase of load at all the buses by 50%. This considered contingency causes overloading of lines connected between buses 1–2, 2–8 and 2–9 with power flow of 310.917 MW, 97.353 MW and 103.524 MW, respectively, which are beyond the limits of their maximum power flow limits (130 MW for line 1–2 and 65 MW each for both the lines 2–8 and 2–9).

<table>
<thead>
<tr>
<th>Test case</th>
<th>Congested lines</th>
<th>Actual flow (MW)</th>
<th>Line limit (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1B</td>
<td>1-2</td>
<td>310.917</td>
<td>130</td>
</tr>
<tr>
<td></td>
<td>2-8</td>
<td>97.35</td>
<td>65</td>
</tr>
<tr>
<td></td>
<td>2-9</td>
<td>103.524</td>
<td>65</td>
</tr>
</tbody>
</table>

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It is worth indicating out that the distance defined above is not restricted to the Euclidean distance. We can define other distance in the $n$-dimensional hyperspace, contingent on the type of problem of our interest. For example, for job scheduling problems, it can be defined as the time lag or time interval. For complicated networks such as the Internet and social networks, the distance can be defined as the amalgamation of the degree of local clustering and the average proximity of vertices. In fact, any measure that can effectively characterize the quantities of interest in the optimization problem can be used as the distance. The archetypal scale should be concomitant with the scale concerned in our optimization problem. If it is the typical scale for a given optimization problem, for a very large number of fireflies $n >> m$ where $m$ is the number of local optima, then the initial locations of these $n$ fireflies should distribute comparatively homogeneously over the entire search space. As the iterations proceed, the fireflies would converge into all the local optima (including the global ones). By comparing the best solutions among all these optima, the global optima can easily be achieved. Our recent research suggests that it is possible to prove that the firefly algorithm will approach global optima when $n \to \infty$ and $i > 1$. An additional improvement of FFA is that dissimilar fireflies can work almost autonomously; it is thus predominantly suitable for parallel implementation.

It is even better than genetic algorithms and PSO because fireflies aggregate more closely around each optimum. It can be expected that the interactions between different sub regions are minimal in parallel implementation.

In order to demonstrate how the firefly algorithm works, we have implemented it in MATLAB, where we have used a simple function.
CONGESTION MANAGEMENT USING FIREFLY ALGORITHM IN DEREGULATED POWER SYSTEM FOR IEEE-30 BUS SYSTEM

\[ f(x, y) = (|x| + |y|) \exp[-0.06250(x^2 + y^2)] \]

which has four equal peaks at (-2, -2), (2,2), (2,-2) and (2,2). This function can easily be extended to any higher dimensions. In order to show that both the global optima and local optima can be found simultaneously, we now use the following four-peak function. This function has four peaks. Two local peaks and two global peaks as shown in figure 5. We can see that all these four optima can be found using 25 fireflies in about 20 generations (see figure 7). So, the total number of function evaluations is about 500.

![Fig.7. Final locations of 25 fireflies after 20 iterations (right).](image)

CONCLUSION
This paper demonstrates a novel optimization technique for solution of the CM problem in open access electricity market. FFA is successfully implemented to minimize the rescheduling cost for alleviating congestion completely. Contingencies like line outage and sudden load variation are considered in this work. The proposed method is implemented on modified IEEE 30 -bus systems and the results are compared with random search method, simulated annealing and PSO. It is observed that the proposed FFA effectively relieves congestion, and rescheduling cost obtained is much lower than the costs reported by the other approaches. Moreover, total amount of rescheduling and losses are also found to be lower.

From all the considered simulated cases, it may be observed that FFA is a potential tool to solve a non-linear, multimodal problem. Compared to other optimization algorithms like PSO, SA and RSM, FFA has added advantage of random reduction, lesser time to produce optimum value and automatic subdivision among the fireflies. Apart from the self-improving process within the current space, the FFA also includes the improvement among its own space from the previous stages. Thus, it may be concluded that FFA is a powerful and strong approach to solve optimization problems, providing most economical, reliable and secure operating conditions. Use of sensitivity analysis for selection of participating generators along with rescheduling may be the direction of future research work. FFA may be recommended as an effective optimization tool for some other power engineering optimization applications.

References

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