CONGESTION MANAGEMENT USING GRAVITATIONAL SEARCH ALGORITHM (GSA): A REVIEW

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Abstract- The deregulated or restructured power systems scenario has resulted in optimum utilization of transmission capabilities. Due to which overloading transmission networks or network congestion held. Congestion has serious effects on power systems, including severe system damage. Congestion occurs when transmission networks fail to transfer power based on the load demand. However, congestion in transmission network may occur when producers and consumers of electricity tend to exchange power that operates transmission networks beyond one or more operation limit. These congestion problems are managed using congestion management methods, which play an important role in current deregulated power system For congestion management several methods have been proposed. This paper reviews some technical and non-technical congestion management methods. Use of PSO Method controller is one of the most impressive method for congestion management. In this paper the various optimization methods for optimal power flow is also reviewed. The various method used for to determine optimal location of PSO Method have been proposed. The work of various publications is used to review the proposed technique in relieving congestion.

Keywords- De-regulated or restructured power system market, Congestion and congestion management methods, Optimal power flow and optimization methods, PSO Method.

1. INTRODUCTION

De-regulated or Restructured Power System Market: There are two structures of power system: Vertically Integrated Structure and De-regulated or Restructure [1]. In vertically integrated structure, generation, transmission and distribution is owned and controlled by only one entity – Government only. Vertical structure suffers from the problem of inefficient system operation and the problem of market monopoly. For efficient Performance of the system, to improve the continuity of supply and quality of supply of electricity, to enhance competition and economic benefits government of India passed one resolution where in policies are restructured or deregulated power system in 2003.

In restructured or deregulated power system electricity price will go down due to the competitive prices. The producer will try to sell the power at its marginal cost, in a perfectly competitive environment. In this restructured system, the customer will have choice for its retailer. Under deregulated environment, the electric utility will always try to innovate something for the betterment of service and in turn save costs and maximize the profit. In this structure systems capacity will be used efficiently and reliability will improve. But, restructured power system scenario has resulted in optimum utilization of transmission capabilities due to which overloading transmission networks or network congestion held.

2. CONGESTION AND CONGESTION MANAGEMENT METHODS:

2.1 Transmission line congestion:

Congestion occurs due to the absence of matching generation and transmission services. Congestion is also caused by unexpected generation outages, unexpected increases in load demand, and equipment failure [2].However, congestion in transmission network may occur when producers and consumers of electricity tend to exchange power that operates transmission networks beyond one or more operation limit. The possible limits that may be hit in case of congestion are: line thermal limits, bus voltage limits, transient stability, etc.

Causes of congestion [3]:

- Sudden increment in load- Unpredicted generator outage
- Unexpected tripping of transmission line- Equipment failure

Disadvantages due to congestion

- May cause cascade outages with uncontrolled loss of load.
- Increment in energy price in some regions of electricity market
- Reduction in system reliability

Because of the above challenges, congestion management has become one of the prime considerations in power industries.

2.2 Congestion Management Methods:

Due to transmission congestion, cheaper power from some generator is not available at all loads so that exercising market power local (or nearby) generator may charge higher prices from consumer which lead in market inefficient. These problems are managed using congestion management methods, which play an important role in current deregulated power systems. Congestion management is controlling transmission system in a way that limits are not violated. This means that system security and reliability are within acceptable range.

Congestion management is described using technical methods and non-technical methods as in Fig. 1 [4].

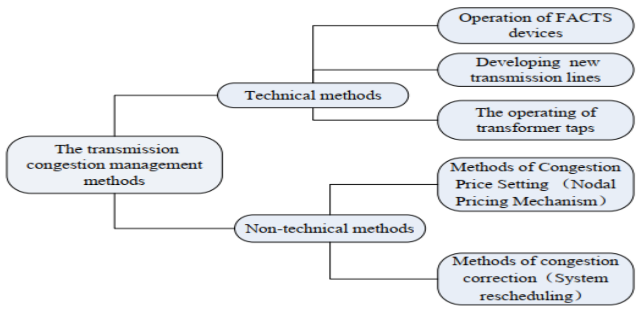

Fig. 1. Transmission congestion management methods.

Different models for power market have been developed all over the world to manage congested systems. In this paper some non-technical methods for congestion management like the generator rescheduling, load shedding, market splitting, nodal pricing or price setting, and distributed generator etc. are reviewed.

Generator rescheduling involves the selections the appropriate generators tube rescheduled to meet load demands. The literatures [5] have presented generator rescheduling method to manage congestion in power systems. it focused on minimizing generation and reducing load operational costs. Generator rescheduling approach is a common method in congestion management, but it is slow and ineffective. Generator rescheduling also performed based on the real and reactive power rescheduling with the virtual power flow through the overloaded line. The virtual power flows are implemented based on the principle of superposition, which contributed to a simple and faster rescheduling method. The literature [6] proposed the optimal rescheduling of active power generators based on generator sensitivity. The re-dispatch generators are taken based on large value of generator sensitivity, which required a proper iteration of mathematical analysis to avoid errors, and maintaining the efficiency of generator rescheduling method.

Nodal pricing or price setting methods were introduced for the optimum use of transmission grids and generation resources with the provision of appropriate economic signals. The marginal cost of providing the next increment of power at a bus is known as a nodal pricing. Each participant involved in this congestion management was charged based on the nodal price available in the system. The literatures [7] have presented nodal pricing or price setting method for congestion management and has proved that the technique is a market based pricing schemes, in which the costs of the system change based on the selected nodal price.

Technical methods or conventional optimization methods are recently used to manage congested power systems. The methods are advanced methods that used FACTS devices as an alternative to efficiently minimize the power flows in the system especially during the heavy demands [8]. The use of FACTS devices helps improve power capability, lower system losses, and increase system stability by controlling power flows. Optimization methods are needed whenever FACTS devices are used in congestion management so that optimal performance is achieved [9].

3. OPTIMAL POWER FLOW AND OPTIMIZATION METHODS:

3.1Optimal Power Flow:

Optimal power flow is a major tool in the power system. As the name, optimal power flows attempt to optimize the power system according to a specific function. This function is called the objective function and is generally minimized by the OPF program. The advantage of optimal power flow is to minimize operating costs of the system. This is a major advantage for any power system utility.

OPF [10] is a nonlinear programming problem, and is used to determine optimal outputs of generators, bus voltage and transformer tap, setting in power system, with an objective to minimize total production cost. While the system is operating within its security limit.

3.2Optimization:

Optimization is the process of adjusting the inputs tour characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or result.

The input consists of variables; the process or function is known as the cost function, objective function, or fitness function; and the output is the cost or fitness. If the process is an experiment, then the variables are physical inputs to the experiment

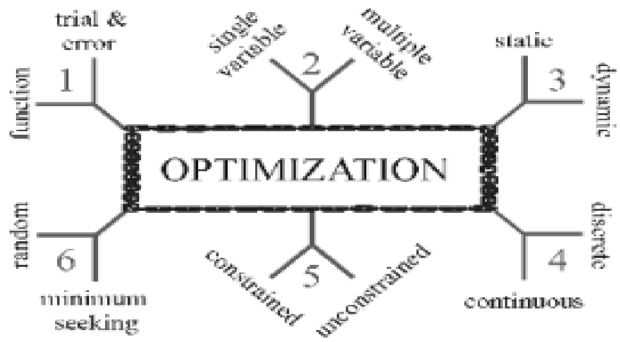

Fig. 2. Six categories of optimization algorithms [11].

Trial-and-error optimization: it is the process of adjusting variables that affect the output without knowing much about the process that produces the output. A simple example is adjusting the rabbit ears on a TV to get the best picture and audio reception. An antenna engineer can only guess at why certain contortions of the rabbit ears result in a better picture than other contortions.

Single variable and multivariable optimization: If there is only one variable, the optimization is known as one-dimensional or single variable optimization. If problem having more than one variable requires multidimensional optimization. Optimization becomes increasingly difficult as the number of dimensions ‘increases.

Static and dynamic optimization: In dynamic optimization the output is a function of time and in static optimization the output is independent of time.

Discrete and continuous optimization: In discrete optimization variables have only a finite number of possible values and in continuous optimization variables have an infinite number of possible values. If we are deciding in what order to attack a series of tasks on a list, discrete optimization is employed. However, if we are trying to find the minimum value of f(x) on a number line, it is more appropriate to view the problem as continuous.

Constrained and unconstrained optimization: In constrained optimization the variables have limits or constraints incorporates variable equalities and inequalities into the cost function. Unconstrained optimization allows the variables to take any value.

Random and minimum seeking optimization: Some algorithms try to minimize the cost by starting from an initial set of variable values. These minimum seekers easily get stuck in local minima but tend to be fast. Moving from one variable set to another is based on some determinant sequence of steps. On the other hand, random methods use some probabilistic calculations to find variable sets. They tend to be slower but have greater success at finding the global minimum.

3.3Optimization Methods:

Optimization methods are needed whenever FACTS devices are used in congestion management for achieving optimal performance. Recently many methods are used for optimal load flow study like some conventional programming methods and artificial intelligence methods. Among that method some methods are review in this paper.

Genetic algorithm [12]: The GA as an optimization method was created by John Holland, who elaborated and realized an idea how to transform the characteristics of natural evolution into a computer program. Through a series of GA operations, a new population is obtained and its individuals are created by the individuals from the previous population according to the natural evolution principles: the selection, crossover, and mutation.

Differential evolution algorithm [13]:Differential evolution (DE) algorithm was developed by Storm and Price. This is a population-based algorithm which uses operators similar as GA: mutation, crossover, and selection. DE differs from GA in a mutation scheme that makes DE self-adaptive and in the selection process. In DE, all the solutions have the same chance of being selected as parents. DE employs a greedy selection process: the better one of new solution and its parent wins the competition providing significant advantage of converging performance over GAs.

Evolutionary programing technique [14]:Evolutionary programing (EP) is a met heuristic population-based technique developed by Fogell. Starting from a randomly generated initial population, during each iteration the EP produce a new population through the use of amputation operator, competition, and selection. The mutation operator makes a new individual (potential solution) by perturbing each component of an existing individual by a random amount.

Particle swarm optimization [15]:The PSO algorithm was developed by Kennedy and Eberhart and is based on simulation of bird flocking in two-dimensional space. It uses a number of particles(candidate solutions) which fly around in the search space to find best solution. Meanwhile, the particles all look at the best particle (best solution) in their paths. In other words, particles consider their own best solutions (pbest) as well as the best solution found so far (gbest). Each particle tries to modify its position using the following information: the current position, the current velocity, the distance between the current position and pbest, and the distance between the current position and gbest.

Ant colony optimization [16]:Dorigo developed the ant colony optimization (ACO) algorithm inspired by ants' behavior in determining the optimal path from the nest to the food source. Initially, ants wander randomly for food in the surrounding regions of nest. An ant's movement is observed by the neighboring ants with the pheromone intensity it lays down while searching for food. Once a food source is found, the pheromone intensity of the path increases due to the movement of ant from source to nest and other ants instead of searching at random, they follow the trail. With the progress in time, the pheromone intensity starts to evaporate and reduce its attraction. Theamount of time taken for an ant to travel to food source and back to the nest isdirectly proportional to the quantity of pheromone evaporation. In addition, evaporation of the pheromone has the advantage of allowing the algorithm to avoid In the convergence toward a local optimum solution. So with time an optimal shortestpath is achieved to maintain the high pheromone intensity. The ACO algorithm was successfully applied to a large number of combinatorial optimization problems.

Gravitational search algorithm [17]:The GSA is a met heuristic optimization algorithm developed by Rashedi. In GSA, the search agents are a collection of masses which interact with each other based on the Newtonian gravity and the laws of motion. The position of the mass corresponds to the solution of the problem, and its gravitational and inertial masses are determined using a fitness function. In other words, each mass presentsa solution. The algorithm is navigated by properly adjusting the gravitational and inertial masses.

Gray wolf optimizer [18]:The gray wolf optimizer (GWO) algorithm is based on mimics of the leadership hierarchy and hunting mechanism of gray wolves in nature and developed by Mirjalili. In the hierarchy of GWO, four types of members (search agents) can be considered: alpha (a), beta (b), delta (d), and omega (w). The dominance gradually decreases from a wolves to w wolves.

3.4Formulation of Optimal power flow problem [19]:

The OPF problem solution aims to optimize a chosen objective function though optimal adjustment of the power system control variables, while simultaneously satisfying various system operations, such as power-flow equations and inequality constraints.

Mathematically, the OPF problem can be formulated as follows: Optimize $F(x, y)$

Subject to $g(x,y)=0$

$$h(x,y) \leq 0$$

$$x \in X$$

where,Fis the objective function to be optimized (minimized or maximized).

x is the vector of control variables, consisting of generator active power outputs P_G(except at the slack bus, supposed P_{G1}), generator voltages V_G, transformer tap settings T, and shunt Var compensations Q_C.
y is the vector of dependent variables consisting of slack bus power P_{Gsl}, loadbus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_l.
Equality constraints: The equality constraints (eq. 1 &2) are the typical nonlinear power-flow equations.

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} Vj(G_{ij} \cos \Theta_{ij} + B_{ij} \sin \Theta_{ij}) \qquad (1)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} Vj(G_{ij} \sin \Theta_{ij} + B_{ij} \cos \Theta_{ij}) \qquad (2)$$

where i=1, . . . ,NB; NB is the number of busses, $P_{Gi}$is the active power generation,$Q_{Gi}$is the reactive power generation, $P_{Di}$is the active load demand, $Q_{Di}$is the reactive load demand, $\Theta_{ij}$is the voltage angle between busses iand j, and $G_{ij}$and $B_{ij}$are the real and imaginary terms of bus admittance matrix corresponding to the ithrow and jth column, respectively.
Inequality constraints:Inequality constraints (eq. 3,4 & 5) are the functional operating constraints, such as load bus voltage magnitude limits, generator reactive power output limits, and branch flow limits.

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, \quad i = 1, \ldots, NL. \qquad (3)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, \quad i = 1, \ldots, NG. \qquad (4)$$

$$S_{li} \le S_{li}^{max}, \quad i = 1, \ldots, NTL. \qquad (5)$$

Objective function: The objective function can take different forms. Classical objective function for the OPF is the total fuel cost in the system. However, many other objectives are possible, such as minimization of system losses, voltage-profile improvement, voltage stability enhancement, etc. In addition, simultaneous optimization of different objective functions is often stated as objective of the OPF.

(a) Minimization of fuel cost:

The basic objective function F considered in OPF problems is that the total fuel cost of the system Fcost, where the generator cost characteristics f are defined asquadratic cost function of generator power output PG. The OPF solution aims to minimize the total generation cost in the system:

$$\min_x F(x,y) = \min_x F\,cost\,(x,y) = \min_x \sum_{i=1}^{NG} fi(P_{Gi}) = \min_x \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P^2_{Gi})$$

where x is the vector of control variables, NG is the number of generators; ai, bi,and ci are the cost coefficients of the ith generator, and $P_{Gi}$is the corresponding active power output.

(b) Minimization of active power loss :

In this case, the objective is to minimizing the total active power loss (Ploss) in thesystem. The objective function has the following form:

$$\min_x F(x,y) = \min_x P\,loss\,(x,y) = \min_x \sum_{L=1}^{NTL} P_{loss,L}$$

where $P_{loss,L}$is the active power loss at line L, and NTL is the number of transmission lines.

(c) Voltage-profile improvement:

One of the most important and significant safety and service quality indices is busvoltage. In this case, the objective is minimization of the load bus VDs:

$$\min_x F(x,y) = \min_x VD\,(x,y) = \min_x \sum_{i=1}^{NL} |V_I - V_i^{ref}|$$

where NL is the number of load buses, Vi is the voltage magnitude at bus i, and $Vi^{ref}$is the reference value of the voltage magnitude of the ith bus, which is usually set to1 p.u.

4. GRAVITATIONAL SEARCH ALGORITHM (GSA)

Methods for Transmission Line Congestion Management
Gravitational search algorithm (GSA) belongs to the nature-inspired metaheuristic optimization methods. A metaheuristic optimization method consists of a generalized set of rules that can be applied to solve a variety of optimization problems. Many metaheuristic optimization methods have been developed on the model of some well-known processes in nature. For example, well-known genetic algorithm is based on mimicking of the process of evolution in biology; simulated annealing emulates the physical process of annealing, etc.

Metaheuristic optimization methods are the population-based stochastic search techniques. The population is defined by a set of individuals (agents) which represent potential solutions of the optimization problem. The number of agents (N) is named as the size of the population. In general, an agent can be represented as vector whose elements are the values of the control variables of the optimization problem. The number of control variables (n) is the search space dimension of the optimization problem. The essence of metaheuristic methods is iterative correction of the solution, i.e., generating a new population by applying algorithmic operators with stochastic search mechanism on agents from the current population.

The way in which the algorithmic operators are defined constitutes the essence of a particular metaheuristic optimization method. The efficiency and performance of met heuristic optimization methods are dependent on the proper setting of the corresponding algorithmic parameters. The main performances of metaheuristics are fast search of large solution spaces, ability to find global solutions and avoiding local optimum. Their main advantage compared to the classical (deterministic) optimization methods is that they are not limited with requirements for differentiability, non-convexity and continuity of the objective function or types of control variables. Moreover, these methods can be used for practical optimization problems taking into account various types of objective function and constraints. In recent years, various populations based metaheuristic optimization methods have been suggested for solving the different engineering problem. The basic elements of metaheuristic optimization methods can be defined as follows:

Agent, x(t): It is a candidate solution represented by an n-dimensional vector, where n is the number of control variables. At time (iteration) t, Population, POP (t): It is a set of N agents at time (iteration) t.

Space of possible solutions, X: It is an n-dimensional solution space which is defined by lower and upper limits of control variables.

Fitness is a direct metric of the performance of the individual population member (agent). The fitness of each agent of the population is calculated from the value of the function being optimized.

4.1 STRUCTURE OF GSA ALGORITHM:

General structure of metaheuristic optimization methods can be represented as follows:

Initialization

1. Defining the objective function $F(\mathbf{x}_i)$ and the space of possible solutions $\mathbf{X}$.
2. Generate initial population of N agents: $\mathbf{POP}(1) = [\mathbf{x}_1(1), \mathbf{x}_2(1), \ldots, \mathbf{x}_N(1)]^T \subseteq \mathbf{X}$.
   The initial positions of each agent are randomly selected between minimum and maximum values of the control variables.
   Set the iteration counter: $t = 1$

Iterative procedure

3. Calculate the fitness value $F(\mathbf{x}_i(t))$ for each agent $\mathbf{x}_i(t)$, $i = 1, \ldots, N$ in the current population $\mathbf{POP}(t)$.
4. Generate new population $\mathbf{POP}(t+1) = [\mathbf{x}_1(t+1), \mathbf{x}_2(t+1), \ldots, \mathbf{x}_N(t+1)]^T \subseteq \mathbf{X}$ by applying the algorithmic operators on search agents from the current population $\mathbf{POP}(t)$.
5. Repeat the iterative procedure until the stop criteria is reached.
6. The optimal solution $\mathbf{x}^*$ is determined.

End

4.2 STEPS FOR SOLUTION OF GSA ALGORITHM

Step 1: Load the power-system configuration, lines data, transformers data, shunt Var compensators data, loads data, and generation unit's data. Use the per unit system.

Step 2: Specify the control variables x and their lower and upper limits, specify the dependent variables y and their lower and upper limits and specify the objective function to be optimized F(x,y).

Step 3: Initialize GSA parameters, such as the population size (N), maximum iteration number (tmax), initial constant K0, initial gravitational constant G0, and constant alpha (a).

Step 4: Generate an initial random population of N agents. The initial positions of each agent are randomly selected between minimum and maximum values of the control variables. Initialize the velocity of agents by a zero matrix of dimension N x n, where N is the number of agents (population size) and n is the number of control variables.

Step 5: Run the power-flow program based on fast decoupled power-flow method for each agent xi(t) from the current population POP(t) and calculate the corresponding values of the objective function (fitness values).

Step 6: Calculate the gravitational constant G(t), the best and worst fitness value, and the mass of each agent Mi(t), i=1, . . . N.

Step 7: Calculate the total force in different directions and the acceleration of each agent.

Step 8: Update the velocity of each agent using,

Step 9: Update the position of each agent.

Step 10: Repeat steps 5–9 until the stop criteria are reached, that is, the maximum number of iterations tmax.

Step 11: Return best solution obtained in the last iteration; Stop.

4.3 FLOW CHART OF GRAVITATIONAL SEARCH ALGORITHM

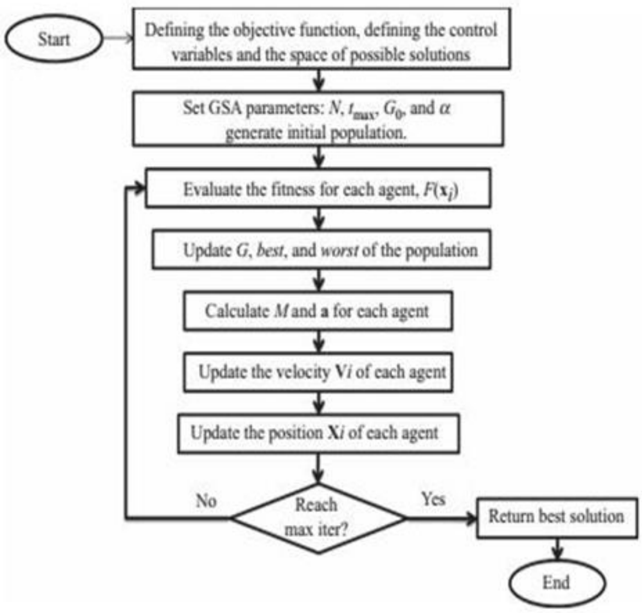

Fig. General flow chart of GSA

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