Optimal Power Flow in Deregulated Power Systems by using Optimization techniques

Dr.M.Lakshmi Swarupa
Professor, EEE, CVRCE
swarupamalladi@gmail.com

Abstract: The independent system operator responsible for delivering inexpensive and comparable transmission services in an open market setting has the problem of dynamic, security-controlled transmission of the electric power grid. In this review, a clever strategy is given dependent on iterative solidness compelled ideal power stream and moth swarm strategies. Optimizing social welfare using particle swarm and moth swarm methodologies takes into consideration both static and dynamic functional operational restrictions as well as dynamic loading margin needs under normal and contingency settings. An additional method has been developed to compute the touchy stacking pattern related with a powerful burden edge since it is difficult to foresee load rise patterns in the present market scenario. The suggested solution will be shown and tested using an IEEE 14 bus test equipment that has both supply and demand displays.

Keywords: particle swarm optimization, dynamic load margin, and optimal power flow, moth swarm algorithm, Load flow.

1. Introduction

In power system the operation has remarkably considered with deregulation power flow process. The majority of developed countries are developing new transmission lines in response to rising demand. To consider transactions in a secure market, system operators who lead participants in the market with appropriate including practical means for evaluating, maintaining, and pricing system security. However, the demand for loads has increased because of the need to work the electrical framework, which has economic implications, leading to many concerns about the operation and safety of the electrical system.
Charges for grid electricity stability, security, and reliability are charged in distinct systems with various environment operators (ISOs). Complex simulations and models are used in conjunction with suitable system pricing, security requirements, and a number of other concerns. Various models have been proposed in the market, including safety [1, 2].

There is a correlation between system load and the likelihood of a connection issue. At the point when the working point moves toward the greatest stacking point on the PV bend [5], the locale of fascination for unequivocally stacked frameworks is extremely small. Therefore, the system cannot tolerate interruptions. For HB considering with several methods including recognition and prediction with proximity of bifurcation points in power systems. Bifurcation index is one popular way.

Proposals for HB and SNB point indexes [6–8] have been made in [6–8]. to increase the pressure on detecting bifurcation, a new approach with a variable step-length was implemented. Finding the Dynamic Load Margin Method (DLM) with increasing load phase size, which is determined by its speed based on the index in eigenvalue and [9]. Using this partition recognition technique, it is guaranteed that the partition will occur within five or six rounds. Additionally, identifying the network load direction is critical to system administration. Static voltage stability has been taken into consideration extensively in the assessment of the loadability margin [10-14].

By tracking system P-V curves relative to the SNB or LB, the continuous current flow method is the most accurate method for determining the loadability margins for a particular loading direction [10, 11]. [12] provides a mathematical technique for determining the load capacity margin of the Treasury and SNB for the worst-case voltage breakdown. In the context of SNB, this approach identifies the worst-loading direction. To determine the maximum loading situation, [13] It provided repetitive and direct technology for energy flow. In [14] the authors introduced continuous current flow modulation to track the behaviours of the static power system due to parameter change. To trace the solution curve, this approach employed a predictor-corrector continuation method. SNB is only considered in static models by all of the approaches listed.

The article proposes with an iterative sensitive load direction, which includes SSC-OPF algorithm. For evaluating the load direction sensitive to SSC-OPF, a novel approach is provided. It is used in conjunction with the PSO technique, which incorporates optimization. The proposed procedure fuses a market arrangement with a security edge work as to the N - 1 possibility models. To optimize the goal of social welfare, which involves keeping a safe distance from the maximum loading condition while adhering to voltage limitations in bus or system stability limits.

II. Standard OPF-based Market

As shown below, the market for OPF-based optimization, which is a constrained non-linear issue, it discusses optimization using an objective function that has equality and inequality bounds:

$$\text{Min. } f(x, p, k), \qquad \ldots\ldots\ldots\ldots\ldots(1)$$
$$\text{s.t.} \quad g(x, p) = 0,$$
$$h_{min} \leq h(x, p, k) \leq h_{max}$$
$$p_{min} \leq p \leq p_{max}$$

The goal function included as well as the f, g, and h functions.

$$f(x, p,k) = -(C^T{}_D P_d - Cs^T P_d - Cs^T P_s) \quad \ldots\ldots\ldots\ldots\ldots(2)$$

Negative producer surplus, plus consumer surplus, is denoted by Eq. (2) It is a net social benefit. Equal Opportunity Limits: With conventional equations, g.x; p/ D_0 indicates the flow of power;

$$G(x, p. k) = g(\delta, V, Q_{G,} Ps, Pd) = 0\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

The following is a common description of system loads in steady state: Constant PQ loads are expected to increase with a constant power factor with the intention of stressing the system:

$$P_L = P_{L0} + P_d \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$
$$P_d \leq k\, P_{Lo}$$

$$Q_L = P_L \tan \varphi \text{ ………………………….(5)}$$
$$P_G = P_{G0} + P_S \text{…………………………..(6)}$$

Inequality constraints: The system's physical and security boundaries are referred to as inequality constraints. Thermal limits of the transmission line are fixed in both physical and safety limits.

$$I_{ij} (\delta, V) \leq I_{ijmax} \text{ ………………………….(7)}$$

Generator reactive power limits:

$$Q_{Gmin} \leq Q_G (\delta, V) \leq Q_{Gmax} \text{………………………..(8)}$$

Voltage "Security" limits:

$$V_{min} \leq V \leq V_{max}$$

Power limits on transmission lines:

$$| P_{ij} (\delta, V)| \leq P_{ij\ max}$$

Which are used to represent the security limits of the system. The limits are represented as follows:

$$P_{smin} \leq P_s \leq P_{smax}$$
$$P_{dmin} \leq P_d \leq P_{dmax}$$

III. OPF with Small Perturbation Stability Constrained

a) System Modelling

To accurately analyze for the segmentation of a given system, including the use of virtual dynamic models. Small signal stability in power networks can only be estimated using load flow and dynamic equations. Changes in the dynamic state of the equation may be seen when the equation speeds up or slows down. It's also becoming less accurate since the dynamic alignment is decreasing.

b) Determination of Bifurcation

After an HB event, the eigenvalues' locations change. Non-imaginary portion of complex word approaches imaginary axis with zero non-imaginary component of complex word bifurcation in the state matrix of eigenvalues.

To estimate the dynamic system stability conditions of the electric current in the buses, Depending on the load direction, the output range of a DLM oscillates between the start and finish positions.

The bifurcation point approach, which contains and depends on three steps, is the easiest way in the system to find the distance. Growing load, decreasing load, and changing load either expanding or lessening inside the limits for power framework enhancement are examples of different phases. The bifurcation approach for power flow analysis has numerous iterations.

c) SSC-OPF Market-clearing Model

The accompanying enhancement issue is utilized in this article to exhibit the OPF market clearing model with lower annoyance solidness prerequisites: This is a non-straight advancement issue with a suggested limit that can be tended to utilizing the improvement strategy. The improvement proposed in this study will be used as the basis for the PSO approach to solving the problem.

d) Load Direction Sensitivity Analysis

One of the primary factors that impacts the DLM is the load direction growth. The increase in the energy market load on electricity depends on the price, making pattern prediction impossible, and the system network is completely strained.

Overview of PSO

PSO is a multifactorial research approach that follows the flock development of birds for activities for emerging movements. It takes advantage of the number of cells that make up the group. Multidimensional search space is covered by PSO cells. As the particles fly by, they constantly adjust their positions depending on the information they get from their interactions with other nearby particles, using the optimal position found by both its neighbors and itself. Each cell searches the entire scan space for a worldwide least (or most extreme). The cell group direction is determined by the combination of neighboring cells and their past experience.

It is beneficial to determine the resolution of the search by areas that must be searched between the current and target positions. This constraint facilitates local problem space exploration. It also accurately models human learning's progressive modifications. Particles may disregard excellent solutions if Pvmax is too large.

A tiny pvmax, on the other hand, prevents particles from adequately exploring beyond local solutions. A local minimum may be recorded by the PSO as a result of the latter. In many PSO studies, Pvmax is set to 10% to 20% of the variable dynamic range in each dimension [27]. The low inertia weight was suggested and evaluated at [28, 29] to suit the algorithm initially for global search and afterward for neighborhood search. The inactivity weight is 2 if it does not change over time.

Numerous studies have provided different values for acceptable parameters for some common functions in [29].

Simulation is often used for optimization problems such as Eq. (24), limitations on both equality and inequality are imposed on the fitness function.

$$\text{Min.}\quad F(X),$$
$$\text{s.t.}\quad G(X) = 0,$$
$$\underline{H} \le H(X) \le \overline{H}$$

There is a boundary on a variable optimization vector, x. F is a scalar enhancement capacity, and G is the vector balance work expressed in the accompanying condition. (3); A vector anisotropic function, H, is also a vector function. (Low and high) terms. The PSO approach was used to calculate the process, which contains the stages below.

Step 1: To begin, establish the input system parameters, as well as the variable and constraint limits.

Step 2: There must be a random uniform distribution of particles in the population for each P_v before the population may begin.

$$p\,v^{max} = (p\,p^{max} - p\,p^{min}) * \sigma$$

P_{best} initial is an individual set with I initial positions, and Gbest is the beginning stage found with the base wellness.

Step 3: A new value for the velocity vector is calculated by using Equation (20). As you can see in Equations (20) and (22):

$$\gamma = 0.7968, \qquad ac_1 = ac_2 = 2.$$

Step 4: Considering the Positional Constraints to Modify: Eq. (21) modifies each individual location depending on its new velocity. If even a single element of a breaches its constraints, it must be substituted with a particle computed n that does not break the requirements.

Step 5: Update P_{best} and G_{best}; The Pbest for every cell in every emphasis is as per the following:

$$Pbest_i^{d+1} = pp_i^{d+1} \qquad \text{if } F_i^{d+1} \le F_i^d,$$

$$Pbest_i^{d+1} = pp_i^d \qquad \text{if } F_i^{d+1} > F_i^d,$$

Individual I is specified in Eq., and the fitness function is Fi (2). G_{best} is a collection of the assessed best places among P_{best} elements in iteration dC1.

Step 6. Iterations at the end are used to determine if the requirements have been met and to repeat the procedures by returning to Step 3. At the point when the greatest number of rehashes is accomplished, the method is ended.

IV. SSC-OPF with Loading Directions that are Both Sensitive and Mixed (SSC-OPF-SLD)

Fig. 1 illustrates the SSC-OPF technique with the sensitive load direction related with the best market solution. Once the DLM technique is complete, the time required to calculate and determine the sensitive load direction for each cell can be very costly for any large system. After performing SSC-OPF, the suggested technique computes the sensitive direction together with the corresponding DLM.

The following is how it works:

- In the first iteration of the DLM computation, the start and load structure define the direction of the height load. The loading parameter is set to zero, indicating that this is a simple market clearing situation.
- In this case, k might be set to the working point's most extreme burden level. The current value of parameters is used to solve the SSC-OPF issue specified in Eq. (17).

- The SSC-OPF current solution to set with load increase N, which is used to the initial direction for estimating sensitive loading direction.
- N_i is the loading direction, and the process for detecting DLM considers the solution of SSC-OPF with a starting value, operating circumstances, and sensitive direction to calculate DLM. An increase in load direction is being evaluated.
- The sensitive direction determination after SSC-OPF, which is associated with DLM sensitive direction either with or without DLMreq.
- If DLM > DLMreq, the algorithm terminates, and the method Using DLM in SSC-OPF returns to Step 1 with a gentle loading with the orientation created in Step 2. It should be noted that contingencies can be directly considered to ensure the proper security of the system. Furthermore, the iterative technique suggested in this article enables for control of the loading parameter's value.

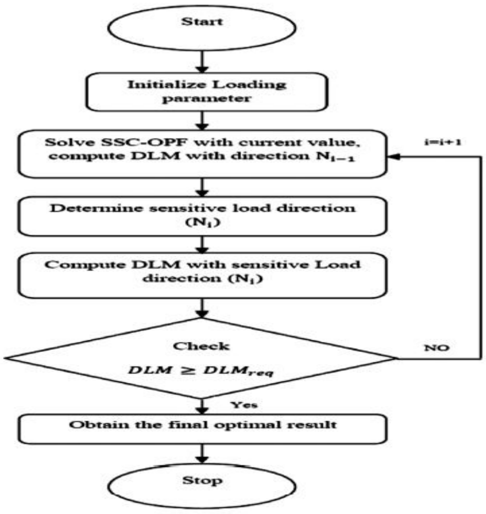


Figure 1. Flowchart of proposed SSC-OPF-SLD.

Numerical Results

It is compared to the IEEE 14-Bus Test System [30]. This section presents and discusses the IEEE 14-Bus System Test findings utilising Common OPF and SSC-OPF-SLD. The IEEE 14-bus test setup is shown in Figure 2. Receptive power is upheld by five coordinated machines with IEEE type-1 exciters; two of the machines are compensators. There are 11 payloads with a total of 259 and 81.3 MW of capacity in the system. Information on market bids may be found in Table 1. (GENCO and ESCO numbers in this table relate to the transporter number in Figure 2). Because of its ability to mimic the power market, this test system gives important data for testing the suggested procedures.

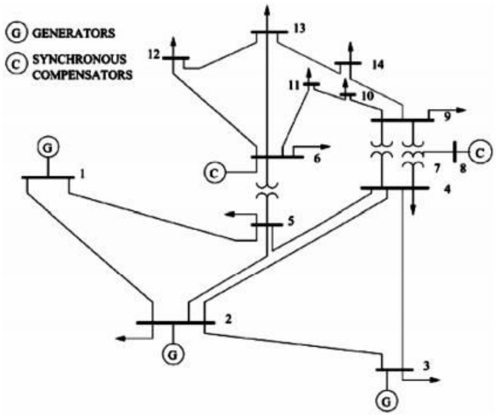


Figure 2. Single-line diagram of the IEEE 14-bus system.

The DLM, which comprises input and output data sets, is an advantage of the approach described in the power system. In the DLM detection and estimate approach, N – 1 contingencies are employed. For optimality, the PSO approach is utilized, which incorporates and eliminates the Lagrangian with complexity and multi-player computing.
Figure 5 depicts the convergence of the PSO method, which incorporates step-by-step algorithms. There are a total of 30 cells in the search. As the number of cells increases from [16] to 30 to 50, rapid fusion is obtained. The load sensitivity is set between 0.3 and 0.4 with the appropriate DLM as shown in Fig. 6. A total of seven iterations of the suggested method are required to arrive at the desired outcome. When the output changes and a DLM with an OPF operating point is needed, the sensitive loading directions must also change.

Moth Swarm Algorithm (MSA):

New high-level algorithm inspired by word preference for Moonlight. There have been two new optimization operators proposed:

(1) A dynamic crossover point selection technique in light of populace variety to oversee contrast vectors Lévy-transformation and boost reconnaissance exploring capabilities.
(2) The Instant Memory Associative Learning Process mimics the moth's short-term memory, reducing memory requirements and solving the classic start-up speed-PSO problem. In the astronomical navigation phase, this method is used to take advantage of the limited range.

Simulation Results

a) PSO algorithm
0.05 to estimate the K factor
Best = 0.040601, PRO: 1/20 repeat
Best = 0.034799, PRO: 20/20 iterations

Bus voltages are as follows:
1.0043 1.0027 1.0042 1.0007 1.0073 1.0066 1.0027 1.0026 1.0040 1.0096
1.0050 1.0074 1.0082 1.0098

The following are the bus power values: 2.5035
0.4051
0

0.0372
0.1435
1.0017
0.0808
0.2307
0.1191
0.5083
0.1584
0.0648
0.0957
0.3136

SocialWelfare = 26.2075

K Factor Rating: 0.1
GBest = 0.081207, PSO: 1/20 repeat
GBest = 0.069603, PSO: 20/20 iterations
Values of voltage on buses columns 1–7

1.0038 1.0050 1.0061 1.0000 1.0068 1.0036 1.0009 1.0002 1.0030 1.0094
1.0015 1.0029 1.0055 1.0077

Power values at buses are:
2.6519
0.4051
0
0.0390
0.1504
1.0494
0.0847
0.2417
0.1248
0.5325
0.1660
0.0680
0.1003
0.3286

57.1332 = SocialWelfare

Considering the K-Factor: 0.15
GBest = 0.1218, PSO: 1/20 iterations
GBest = 0.1044, PSO: 20/20 iterations

Columns 1 through 7 show the voltage values on buses.
1.0070 1.0070 1.0011 1.0036 1.0085 1.0096 1.0077 1.0078 1.0068 1.0032
1.0042 1.0026 1.0005 1.0055
The following are the bus power values: 2.7904
0.4051
0

0.0407
0.1572
1.0971
0.0885
0.2527
0.1304
0.5567
0.1735
0.0710
0.1048
0.3435

88.1811 SocialWelfare

When evaluating the K factor 0.2.
PSO: 1/20 repeat, GBest = 0.1624
PSO: 20/20 iterations, GBest = 0.1392.

Levels of effort on buses

1.0087 1.0094 1.0046 1.0098 1.0036 1.0003 1.0059 1.0017 1.0097 1.0010
1.0096 1.0017 1.0048 1.0016
The following are the bus power values: 2.8351
0.4051
0.0993
0.0425
0.1641
1.1448
0.0924
0.2637
0.1361
0.5809
0.1811
0.0741
0.1094
0.3585

114.4853 SocialWelfare

Considering the K-Factor: 0.25
PSO: 1/20 iterations, GBest = 0.203
PSO: 20/20 iterations, GBest = 0.17399

Bus voltages are as follows:
1.0086 1.0034 1.0061 1.0005 1.0051 1.0043 1.0064 1.0027 1.0092 1.0088
1.0033 1.0038 1.0099 1.0098
The following are the bus power values:
2.8790
0.4051
0.1912

0.0443
0.1708
1.1925
0.0962
0.2747
0.1418
0.6051
0.1886
0.0772
0.1139
0.3734

141.3997 SocialWelfare

0.3 when evaluating for the K-Factor
PSO: 1/20 iterations, GBest = 0.2436
PSO: 20/20 iterations, GBest = 0.20879

Bus voltages are as follows:
1.0087 1.0002 1.0008 1.0018 1.0036 1.0095 1.0022 1.0060 1.0057 1.0049
1.0064 1.0025 1.0030 1.0030

The following are the bus power values:
2.9224
0.4051
0.2834
0.0461
0.1777
1.2402
0.1001
0.2857
0.1475
0.6293
0.1962
0.0803
0.1185
0.3884

168.7674 SocialWelfare

Using the K-Factor as a criterion: 0.35
GBest = 0.28419, PSO: 1/20 iterations
GBest = 0.24359, PSO: 20/20 iterations

The voltage levels on buses are
1.0087 1.0074 1.0046 1.0076 1.0085 1.0085 1.0026 1.0061 1.0034 1.0045
1.0098 1.0098 1.0057 1.0018

The following are the bus power values:

2.9649
0.4051
0.3763
0.0478
0.1845
1.2879
0.1039
0.2967
0.1531
0.6534
0.2037
0.0833
0.1229
0.4033

196.6277 SocialWelfare

——WHAT HAPPENS IF THE LINE 1-5 IS DOWN ——

Using the K-Factor as a criterion: 0.15

GBest = 0.12181, PSO: 1/20 repeat
PSO: 20/20 iterations, GBest = 0.1044 welfare value = 0.00000 dollars PSO: 20/20 iterations, GBest = 0.1044
The value of a DLM is 0.34992 USD.

0.2 while evaluating for the K-Factor

PSO: 1/20 iterations, GBest = 0.16242
GBest = 0.13921, PSO: 20/20 iterations
Value of Social Welfare = 23.86645 dollars
GBest = 0.13921, PSO: 20/20 iterations

The value of a DLM is 0.33374 USD.
Using the K-Factor as a criterion: 0.25

PSO: 1/20 repeat, GBest = 0.20301
GBest = 0.174, PSO: 20/20 iterations
welfare value = $ 48.00707
GBest = 0.174, PSO: 20/20 iterations

The value of a DLM is 0.31869 USD.

0.3 when evaluating for the K-Factor

GBest = 0.24363, PSO: 1/20 repeat
PSO: 20/20 Frequency, GBest = 0.20881 Welfare Value = $ 69.77609 PSO: 20/20 Frequency, GBest = 0.20881
The value of a DLM is 0.26386 USD.

Using the K-Factor as a criterion: 0.35

GBest = 0.28419, PSO: 1/20 repeat
PSO: 20/20 Frequency, GBest = 0.24359 Welfare value = $ 91.96020 PSO: 20/20 Frequency, GBest = 0.24359
The value of a DLM is 0.23164 USD.

—SSC-OPF Sensitive Load Direction with SSC-OPF Sensitive Load Direction with SSC-OPF (SLD)

———————————-

0.3 while evaluating for the DLM

G Best = 0.28421, PRO: 1/20 repeat
G Best = 0.2436, PRO: 20/20 iterations
The following are the bus power values: 2.2199
0.9094
0.4136
0.0445
0.1777
1.2402
0.1002
0.2854
0.1309
0.6293
0.1962
0.0803
0.1185
0.3884

The value of social welfare is 151.24479 dollars. 0.4 while evaluating for the DLM

GBest = 0.28421, PSO: 1/20 iterations
GBest = 0.2436, PSO: 20/20 iterations
The following are the bus power values: 1.8498
1.0127
0.5007
0.0401
0.1777
1.2402
0.0770
0.2857
0.1134
0.5248
0.1932
0.0803
0.1185
0.3884

The value of social welfare is 116.80279 dollars.
—-WHEN THE LINE 1-5 IS DOWN ——-
0.3 while evaluating for the DLM

GBest = 0.28423, PSO: 1/20 iterations
GBest = 0.24362, PSO: 20/20 iterations
The following are the bus power values:

1.9445
1.0127
0.6076
0.0461
0.1777
1.2402
0.0818
0.2857
0.1322
0.6228
0.1962
0.0803
0.1185
0.3884

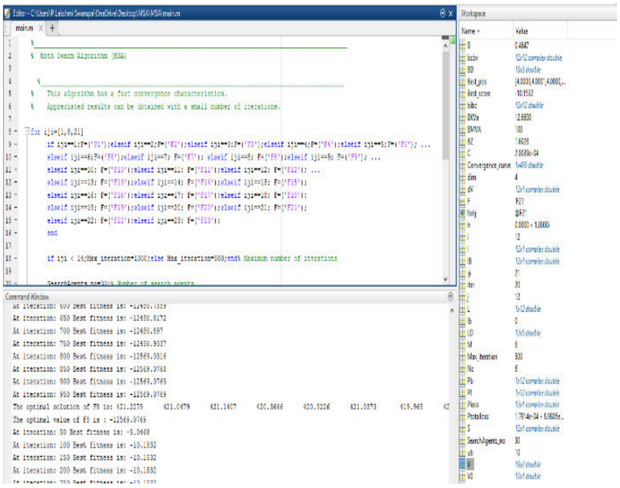
Social assistance worth $ 64.12333.
When evaluating a DLM, use 0.4.

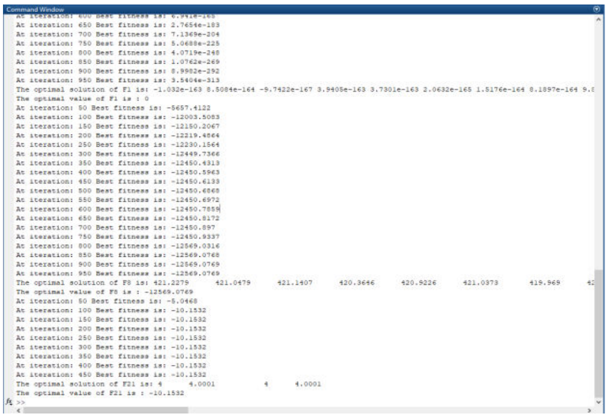
GBest = 0.28424, PSO: 1/20 repeat
GBest = 0.24362, PSO: 20/20 iterations
The following are the bus power values:

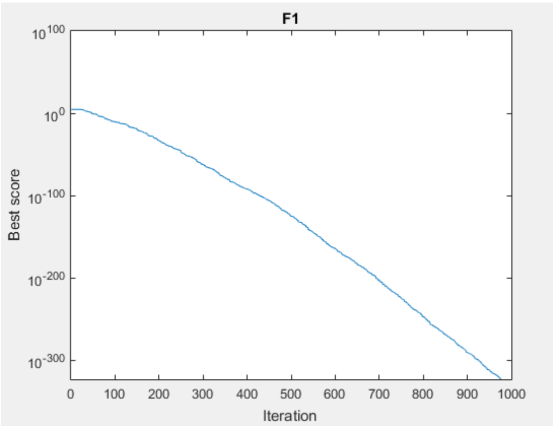
1.7026
1.0127
0.6076
0.0354
0.1777
1.2402
0.0982
0.2857
0.1134
0.4841
0.1960
0.0803
0.1185
0.3354

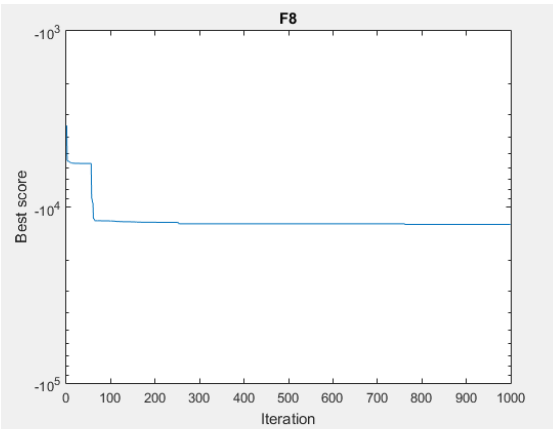
Value of Social Welfare = $ 36,82892

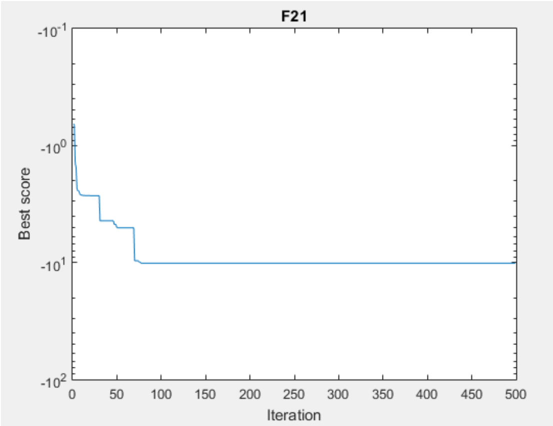
b) Moth Swarm Algorithm (MSA):


% Moth Swarm Algorithm (MSA)
Command Window
At iteration: 650 Best fitness is: -12450.8172
At iteration: 700 Best fitness is: -12450.897
At iteration: 750 Best fitness is: -12450.9337
At iteration: 800 Best fitness is: -12569.0316
At iteration: 850 Best fitness is: -12569.0768
At iteration: 900 Best fitness is: -12569.0769
At iteration: 950 Best fitness is: -12569.0769
The optimal solution of F8 is: 421.2279 421.0479 421.1407 420.3646 420.9226 421.0373 419.969
The optimal value of F8 is : -12569.0769
At iteration: 50 Best fitness is: -5.0468
At iteration: 100 Best fitness is: -10.1532
At iteration: 150 Best fitness is: -10.1532
At iteration: 200 Best fitness is: -10.1532
Workspace
SearchAgents_no 30


Command Window
At iteration: 650 Best fitness is: 2.7654e-183
At iteration: 700 Best fitness is: 7.1369e-204
At iteration: 750 Best fitness is: 5.0688e-225
At iteration: 800 Best fitness is: 4.0719e-248
At iteration: 850 Best fitness is: 1.0762e-269
At iteration: 900 Best fitness is: 8.9982e-292
At iteration: 950 Best fitness is: 3.5404e-313
The optimal solution of F1 is: -1.032e-163 8.5084e-164 -9.7422e-167 3.9405e-163 3.7301e-163 2.0632e-165 1.5176e-164 8.1897e-164
The optimal value of F1 is : 0
At iteration: 50 Best fitness is: -5657.4122
At iteration: 100 Best fitness is: -12003.5083
At iteration: 150 Best fitness is: -12150.2067
At iteration: 200 Best fitness is: -12219.4864
At iteration: 250 Best fitness is: -12230.1564
At iteration: 300 Best fitness is: -12449.7366
At iteration: 350 Best fitness is: -12450.4313
At iteration: 400 Best fitness is: -12450.5963
At iteration: 450 Best fitness is: -12450.6133
At iteration: 500 Best fitness is: -12450.6868
At iteration: 550 Best fitness is: -12450.6972
At iteration: 600 Best fitness is: -12450.7859
At iteration: 650 Best fitness is: -12450.8172
At iteration: 700 Best fitness is: -12450.897
At iteration: 750 Best fitness is: -12450.9337
At iteration: 800 Best fitness is: -12569.0316
At iteration: 850 Best fitness is: -12569.0768
At iteration: 900 Best fitness is: -12569.0769
At iteration: 950 Best fitness is: -12569.0769
The optimal solution of F8 is: 421.2279 421.0479 421.1407 420.3646 420.9226 421.0373 419.969
The optimal value of F8 is : -12569.0769
At iteration: 50 Best fitness is: -5.0468
At iteration: 100 Best fitness is: -10.1532
At iteration: 150 Best fitness is: -10.1532
At iteration: 200 Best fitness is: -10.1532
At iteration: 250 Best fitness is: -10.1532
At iteration: 300 Best fitness is: -10.1532
At iteration: 350 Best fitness is: -10.1532
At iteration: 400 Best fitness is: -10.1532
At iteration: 450 Best fitness is: -10.1532
The optimal solution of F21 is: 4 4.0001 4 4.0001
The optimal value of F21 is : -10.1532
>>


F1
10^100
10^0
10^-100
10^-200
10^-300
Best score
0
100
200
300
400
500
600
700
800
900
1000
Iteration


F8
-10^3
-10^4
-10^5
Best score
0
100
200
300
400
500
600
700
800
900
1000
Iteration



GBest = 0.26324, MSA: 1/500 iterations
GBest = 0.23362, MSA: 500/500 iterations
The following are the bus power values:

1.6014
1.1011
0.7021
0.0321
0.1657
1.2201
0.0912
0.1834
0.1134
0.3713
0.1673
0.0513
0.1081
0.3251

Value of Social Welfare = $ 10.1532

Analysis: The mothsworm algorithm (MSA) is a meta-heuristic algorithm optimization approach that was inspired by moths' natural navigational style. The goal of this study is to offer a unique modified MSA with an arithmetic crossover (MSA-AC) with the goal of increasing the search for a global optimum, the speed of convergence to an optimal solution, and the performance of the classic MSA.

Conclusion:

This paper demonstrates the repetitive SSC-OPF-SLD based strategy, which includes stability limits on the power system as well as sensitive loading direction. Simple vector arithmetic is used to determine the sensitive loading direction. The findings indicate the benefits of the suggested technology, which offers a mix of optimum market solutions based on system security, and a new moth swarm algorithm (MSA) to solve the problem of constrained optimum power flow (OPF) triggered by the moth trend. Towards the moonlight. In addition to adaptive Gaussian walking and spiral locomotion, a learning approach associated with the intersection of transient memory and population diversity has been proposed for fibrotic mutation to enhance capabilities for exploitation and exploration, respectively. As a consequence, system operators may utilise the MSA technique to examine the impact of system security on the market clearing process. PSO strategy is additionally used to defeat this issue.

The MSA's efficacy and superiority have been proved in contrast to a number of recently published OPF solutions Based on PSO. The Administrative Service Agreement is simple to implement and can find the right solutions for nonlinear restricted problems.

References

1. Milano, F., Canizares, C. A., and Invernizzi, M., "Multi-objective optimization for pricing system security in electricity markets," IEEE Trans. Power Syst., Vol. 18, No. 2 pp. 596–604, May 2003.
2. Milano, F., Canizares, C. A., and Conejo, A. J., "Sensitivity-based security-constrained OPF market clearing model," IEEE Trans. Power Syst., Vol. 20, No. 4, pp. 2051–2060, November 2005.
3. Marszalek, W., and Trzaska, Z. W., "Singularity-induced bifurcations in electrical power systems," IEEE Trans. Power Syst., Vol. 20, No. 1, pp 312–320, February 2005.
4. Yue, M., Brookhaven National Lab, "Bifurcation subsystem and its application in power system analysis," IEEE Trans. Power Syst., Vol. 19, No. 4, pp. 1885–1893, 2004.
5. Canizares, C. A., "On bifurcation voltage collapse and load modeling," IEEE Trans. Power Syst., Vol. 10, No. 1, pp. 512–522, February 1995.
6. Canizares, C. A., Mithulananthan, N., Milano, F., and Reeve, J., "Linear performance indexes to predict oscillatorystability problems in power system," IEEE Trans. Power Syst., Vol. 19, No. 2, pp. 1023–1031, May 2004.
7. Tomim, M. A., Lopes, B. I. L., Leme, R. C., Jovita, R., Zambroni de Souza, A. C., de Carvalho Mendes, P. P., and Lima, J. W. M., "Modified Hopf bifurcation index for power system stability assessment," IEE Proc. Generat. Transm. Distrib., Vol. 152, No. 6, pp. 906–912, November 2005.
8. Hasanpor Divshali, P., Hosseinian, S. H., Nasr Azadani, E., and Vahidi, B., "Modified fast indices for prediction of Hopf bifurcation by matrix reciprocal condition number," The Iranian Conference on Electrical Engineering (ICEE 2008), Tehran, Iran, May 2008.
9. Wen, X., A Novel Approach for Identification and Tracing of Oscillatory Stability and Damping Ratio Margin Boundaries, Ph.D. Thesis, Iowa State University, Ames, IA, 2005.
10. Ajjarapu, V., and Christy, C., "The continuation power flow: A tool for steady state voltage stability analysis," IEEE Trans. Power Syst., Vol. 7, No. 7, pp. 416–423, February 1992.
11. Canizares, C. A., and Alvarado, F. L., "Point of collapse and continuation methods for large AC/DC systems," IEEE Trans. Power Syst., Vol. 8, No. 1, pp. 1–8, February 1993.
12. Dobson, I., and Lu, L., "New methods for computing a closest saddle node bifurcation and worst case load power margin for voltage collapse," IEEE Trans. Power Syst., Vol. 8, No. 3, pp. 905–913, August 1993.
13. Zeng, Z.-C., Galiana, F. D., Ooi, B. T., and Yorino, N., "A simplified approach to estimate maximum loading conditions in the load flow problem," IEEE Trans. Power Syst., Vol. 8, No. 2, pp. 648–654, May 1993.
14. Chiang, H.-D., Flueck, A. J., Shah, K. S., and Balu, N., "CPFLOW: A practical tool for tracing power system steady-state stationary behavior due to load and generation variations," IEEE Trans. Power Syst., Vol. 10, No. 2, pp. 623–630, May 1995.
15. Gu, X., and Canizares, C. A., "Fast prediction of loadability margins using neural networks to approximate security boundaries of power systems," IET Proc. Generat. Transm. Distrib., Vol. 1, No. 3, pp. 466–475, May 2007.