

Optimal Power Flow in Deregulated Power Systems by Using Optimization Techniques

M.Sindhu¹; G.V. Nagesh Kumar²; Vempalle Rafi^{3*}; B. Sravan Kumar⁴; M. Aruna Bharathi⁵ ¹PG Student, Department of Electrical and Electronics Engineering, JNTUA College of Engineering Pulivendula, Kadapa, India.

²Professor, Department of Electrical and Electronics Engineering, JNTUA College of Engineering Pulivendula, Kadapa, India.

^{3*}Assistant Professor (A), Department of Electrical and Electronics Engineering, JNTUA College of Engineering Pulivendula, Kadapa, India.

^{3*}vempallerafi@gmail.com

⁴Assistant Professor, Department of Electrical and Electronics Engineering, GITAM University, Vishakhapatnam, India.

⁵Professor, Department of Electrical and Electronics Engineering, Geethanjali College of Engineering and Technology, Hyderabad, India.

Abstract

An independent system operator tasked with providing equitable and fair transmission services in an open-market context has a challenging job in dynamic security-constrained dispatch of an electric power network. This study proposes a new methodology based on the optimal flow of power and swarming mode, which is restricted by iterative stability. In addition to the static and dynamic functional constraints, dynamic margin needs in relation to normal condition and contingencies, particle swarm and moth swarm optimizations are used to optimize social welfare. Furthermore, because the pattern of load growth in the current market environment is difficult to forecast, a new approach for estimating the sensitive loading direction linked with a dynamic loading margin is presented. To demonstrate and test the suggested approach, an IEEE 14-bus test system with both supply and demand bids is utilized.

Key-words: Current Market Environment, Load Growth, Particle Swarm Optimization, Moth Swarm Algorithm.

1. Introduction

The functioning of the power system has been meticulously studied with the deregulation of the power flow process. With ever-increasing demand, the majority of industrialized countries are constructing new transmission lines. System operators who provide market players with sufficient, realistic methods for evaluating, maintaining, and pricing system security in order to consider transactions in a secure market. However, load demand rose as a result of the requirement to operate the power system, including economic concerns, resulting in several considerations surrounding the power system's operation and security.

Charges include stability, safety and dependable grid electricity operation in an autonomous system with distinct environmental operators (ISOs). Complex simulations and models are included through suitable system pricing with security limitations and diverse concerns. The different models, including security [1, 2], were proposed on the market.

The likelihood of bifurcation relies on the loading level of the system. In severely loaded systems, the attraction region is relatively tiny as the operating point approaches the maximum load point on the P-V curve [5], which makes the system unable to withstand any disturbances. For HB, the analysis includes the detection and prediction of bifurcation sites close to power systems. The index fork is a common approach. It's one way.

The prediction is suggested [6–8] utilizing HB and SNB indices. A novel method for identification for bifurcation includes the load rising step variable. For detection in accordance with the index in [9] of the Dynamic Loading Margin (DLM) method and with load-increasing steps. This technique of bifurcation detection detects the event in five or six iterations. In addition, in system management it is important to determine the sensitive load direction of the network. Comprehensive study has been carried out into the calculation of the loadability margin, given the stability of static voltage [10–14].

Continuous flow can be the most accurate approach for calculating the load-bearing margins in a particular charge direction by tracing system curves P-V that can be linked to an SNB or LB [10, 11]. In [12], a maths method for calculating an SNB closet and a worst case load capacity buffer for collapse of voltage was described. The worst loading direction for SNB is obtained by this approach. In [13] the maximum loading condition was estimated by the iterative and direct power flow method. In [14] the authors suggested a modified continuation flow for stationary comportment of power system tracking owing to variations in parameters. This method has a continuation method for tracking the solution curve using a predictor corrector. In static models all of the above strategies consider SNB alone.

The paper offers a sensitive direction of the load with an iterative load, including SSC-OPF. A novel method for the analysis of the SSC-OPF sensitive load direction. The PSO method involves optimisation. It is used. The suggested approach, which incorporates the security margin function

solution in accordance with the contingency criterion N-1. Maximize social welfare goals which cover and maintain the adequate distance with voltage parameters at bus or system stability limits, to the maximum loading situation.

2. Normal OPF- Market

The market for OPF-hinged optimization, a restricted nonlinear issue, comprises optimization with an objective function that contains a set of equality and inequality constraints, as illustrated below:

$$Min. f(x, p, k),$$

$$s.t. g(x, p) = 0,$$

$$h_{\min} \le h(x, p, k) \le h_{\max} \qquad (1)$$

$$p_{\min} \le p \le p_{\max}$$

The f, g, and h functions were considered with the objective function including as

$$f(x, p, k) = -(C_D^T P_d - C_S^T P_S).$$
 (2)

The negative producer surplus, in addition to the consumer surplus, is represented by Eq. (2), i.e., the social net benefit.

Equality constraints: The flow of power is represented by g(x, p) = 0 using conventional formulae.

$$g(x, p, k) = g(\delta, V, Q_G, P_S, P_d) = 0.$$
 (3)

The usual steady-state depiction of system loads includes constant PQ loads with constant power factor that are supposed to increase for the purpose of stressing the system as follows:

$$P_{L} = P_{L0} + P_{d},$$

$$P_{d} \le k P_{L0},$$

$$Q_{L} = P_{L} \tan \phi,$$

$$P_{G} = P_{Go} + P_{S.}$$
(4)

Inequality constraints: Inequality limits are the system's physical and security restrictions. Transmission line thermal limitations were addressed in the physical and security limits.

$$I_{ij}(\delta, V) \le I_{ij\max}.$$
(5)

Generator Reactive power limits:

$$Q_{G\min} \le Q_G(\delta, V) \le Q_{G\max}.$$
 (6)

ISSN: 2237-0722 Vol. 11 No. 3 (2021) Received: 02.01.2021 – Accepted: 18.05.2021 1885

Voltage "Security" limits:

$$V_{\min} \le V \le V_{\max} \tag{7}$$

Power limits on Transmission lines:

$$|P_{ij}(\delta, V)| \le P_{ij\max}.$$
(8)

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

$$P_{s\min} \le P_s \le P_{s\max},$$

$$P_{d\min} \le P_d \le P_{d\max}.$$
(9)

3. OPF with Small Perturbation Stability Constraints

a. Modelling

To analyze accurately in order to bifurcate for a particular system, including the use of correct dynamical models. In order to assess tiny signal stability in power networks, load flow and dynamical equations are required. With the speed of the equation, the dynamic state varies and increases/decreases. Dynamic order, on the other hand, is diminishing, which may result in low accuracy.

b. Determination of Bifurcation

The bifurcation occurrence in power system of Eigen values in state matrix depends on its position with the pair of Eigen values, which reaches the imaginary axis with non-zero imaginary part of complex term when HB occurs.

The DLM is considered in power system with different loadings and the range of output varies between initial and final position of loading directions for estimating the dynamic stability states of the system for power flow in the buses.

To determine the distance the simplest way in the system is bifurcation point method, which includes and depend on three stages. Different stages include by increasing load, by decreasing load, by varying load either increasing or decreasing within the limits for the optimization in the power system. There are many iterations in the bifurcation method for power flow study.

c. Market-clearing Model SSC-OPF

The following optimization model is used to describe an OPF market clearing model with minor perturbation stability requirements in this article: it is a non-linear optimization problem with an implicit constraint that is solved using an optimization approach. The PSO approach is utilized as the foundation to solve the given optimization issue in this study.

d. Sensitivity Analysis for Load Direction

This article represents an OPF marketing clearance model, with the inclusion of modest stability restrictions, with the following optimization issue: non-linear optimization fundamentally with an implied restriction; this problem is addressed by a technique of optimization. The PSO approach is utilized as the foundation to solve the given optimization issue in this study.

Overview of PSO

Multi-agent search technology is PSO which follows the progress of a birds' flock in the emerging movement in the quest for food. It employs a variety of swarming particles. In a PSO system, particles fly into a multifaceted search area. During the flight, each particle changes its location through its own neighbouring particle experiences and uses the best place its neighbours find themselves in. Each particle passes through the search space to find the smallest world (or maximum). With the historical experience of a set of its surrounding particles and of itself, the swarm direction of a particle is determined.

Each particle's new velocity and position is given in equations. (10) and (11):

$$pv_{d+1} = cf * [\gamma * pv_d + ac_1 rand() * (p_{best} - pp_d) + ac_{2rand}() * (G_{best} - pp_d)], \quad (10)$$

$$pp_{d+1} = pp_d + pv_{d+1} \quad (11)$$

Here, rand() is a uniform random value lies between [0,1], and cf is the constraint factor given as Eq. (12):

$$cf = \frac{2}{\left|2 - ac - \sqrt{ac_2 - 4ac}\right|},$$
(12)

Where $ac=ac_1+ac_2$ and $ac\geq 4$.

The resolution will be defined by areas between the current location and the target position to be looked for. This restriction improves local problem space exploration. The progressive changes of

human learning are likewise simulated realistically. When P_{Vmax} is excessively large, it is possible that particles overlook suitable solutions.

However, a modest P_{Vmax} prevents particles from exploring local solutions adequately. Lastly, the PSO can be reduced to local minimum. P_{Vmax} was frequently set at 10–20% of the dynamic range of the variable on every dimension in numerous encounters with PSO [27]. The declining weight of the inertia in [28, 29] is presented and tested for global search at the beginning of the algorithm, followed by local searches. If the weight of inertia is not lowered with time, a value 2 is advised.

Numerous parameters deemed acceptable for some of the common functions in many research suggest different values [29].

The simulating process is generally utilized for optimization issues, including equality (13) and inequality restrictions with the fitness function:

$$Min. \quad f(x),$$

s.t.
$$g(x) = 0,$$

$$h \le h(x) \le \overline{h}$$
 (13)

Where x is vector of variables optimisation i.e. with limits. 'f' is the function for scalar optimisation; 'g' is the vector equality function given in Eq. (3); and 'h' is a vector inequality with 'h' limits (lower and upper). The calculated process is PSO, with the following stages.

Step 1. Input system specifications that define the bounds of each variable and constraint.

Step 2. For each Pv, the particles must be randomly started with population from a random uniform distribution in the interval.

$$pv^{\max} = (pp^{\max} - pp_{\min})^* \sigma.$$
(14)

The P_{best} initial individual set consists of I initial locations of is individual, and G_{best} is the initial position found with the least amount of fitness.

Step 3. Eq.(10) is used to update the velocity vector. The parameters in Equations (10) and (12) are chosen as follows:

$$\gamma = 0.7968, \ ac_1 = ac_2 = 2.$$
 (15)

Step 4. Considering the position limitations to change: each position is altered by Eq.(11) depending on their current speed. If the individual element of a certain element exceeds its restrictions and has to be replaced by n particles which meet its limitations.

Step 5. P_{best} and G_{best} updates; the P_{best} of every particle is updated as follows throughout the system:

$$P_{best_{i}}^{d+1} = pp_{i}^{d+1} \qquad if \quad F_{i}^{d+1} \le F_{i}^{d}, P_{best_{i}}^{d+1} = pp_{i}^{d} \qquad if \quad F_{i}^{d+1} > F_{i}^{d}.$$
(16)

The fitness function is Fi and is defined in Eq (2). for individual i. Gbest in dC1 is a collection of the best locations among Pbest elements that has been assessed.

Step 6.end iterations must be used as a stop condition and repeated steps shall be fulfilled through step 3. The operation is halted if the maximum number of iterations is reached.

4. Mixed Sensitive Loading Direction SSC-OPF

The technology proposed for SSC-OPF with a sensitive loading direction linked with an ideal market solution is shown in Figure 1. Flowchart If the DLM method for calculating and detecting the sensitive load direction is completed for each particle, the time required to execute this operation is too costly for any bigger system. The sensitive direction of the related DLM is calculated after SSC-OPF is executed in the suggested technique.

The following is the technique:

- In the first iteration, the initial generation and load specify the increased load direction of the DLM computation. The loading parameter, the basis case or pure market clearing problem, will be initialized.
- The maximum loading level for the operating point can be set to k in this situation. SSC-OPF is solved with the current parameter value as outlined in Eq. (17).

$$\begin{array}{ll} \textit{Min.} & f(x, p, k) = -(C_D^T P_d - C_s^T P_s), \\ \textit{s.t.} & g(\delta, V, Q_G, P_s, P_d, k) = 0, \\ & k = \hat{k}, \\ & h_{\min} \leq h(x, p, k) \leq h_{\max}, \\ & p_{\min} \leq p \leq p_{\max}, \end{array}$$

- The present SSC-OPF load-enhancing N solution, utilized for estimation of sensitive loading direction, in the starting direction.
- Ni means the direction of loading with the DLM method which, by considering the SSC-OPF solution with its beginning value, operating circumstances and sensible direction, determines the DLM. The direction of load increases is taken into account.
- Definition of sensitive direction following SSC-OPF, either with or without DLMreq, related with the DLM sensitive direction.

 If the process is stopped by DLM > DLMreq, the procedure will then resume to step 1 by utilizing the DLM for SSC-op calculation with the sensible loading with direction acquired in step 2. Note that contingencies may be considered directly to allow for effective handling of system security. Furthermore, this repeated procedure allows the value of the loading parameters to be controlled.

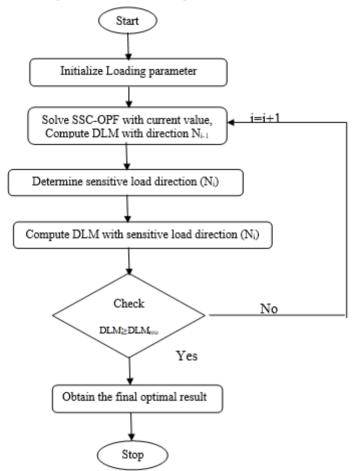


Fig. 1 - Flow Chart of Proposed SSC-OPF-SLD

Numerical Results

If the process is stopped by DLM > DLM req, the procedure will then resume to step 1 by utilizing the DLM for SSC-op calculation with the sensible loading with direction acquired in step 2. Note that contingencies may be considered directly to allow for effective handling of system security. Furthermore, this repeated procedure allows the value of the loading parameters to be controlled. Table 1 shows the market bidding data (the GENCO and ESCO numbers in this table correspond to

the bus number in Figure 2). This system has the capacity to mimic a market in power, producing relevant results that enable analyzing the strategies suggested.

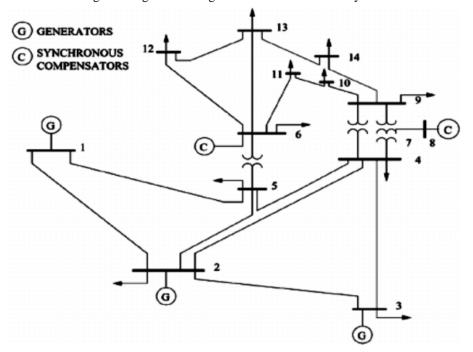


Fig. 2 - Single Line Diagram of the IEEE 14 Bus System

The advantage of method proposed in power system with the DLM, which includes input and output data sets. N - 1 contingency are used in DLM detection and estimation method. The PSO method for optimization is used for optimality which includes and abolishes the Lagrangian with complexity and computation of multi-player.

PSO convergence, including step by step algorithms in Figure 5. PSO convergence. The study comprises a collection of 30 particles. In [16], the number of particles improved from 30 to 50 leads to quicker convergence. In the range of 0.3 and 0.4, the load sensitivity with the DLM needed is shown in Figure 6. The suggested approach for identifying the sensitive load direction converges in around seven iterations. When the DLM with the OPF operating point is needed when the output changes, different direction of load is necessary.

Moth Swarm Algorithm (MSA)

A novel algorithm of high standard, inspired by moth orientation to moonlight. Two new operators were suggested for optimization:

- 1. Dynamic crossover approach for the management of vectors of difference based on population diversity Lévy-mutation improves exploration capacity in the recognition phase.
- 2. Immediate memory associated learning process. Simulate a moth short-term memory, decrease the memory required and overcome the classical-initial PSO's speed issue. In the celestial navigation stage this technology is utilized for small-scale operation.

5. Simulation Results

a) PSO Algorithm

Evaluating for the K-Factor: 0.05 PSO: 1/20 iterations, GBest = 0.040601 PSO: 20/20 iterations, GBest = 0.034799

Voltage values at buses are:

Columns 1 through 7:	1.0043	1.0027	1.0042	1.0007	1.0073	1.0066	1.0027
Columns 8 through 14:	1.0026	1.0040	1.0096	1.0050	1.0074	1.0082	1.0098

Power values at buses are:

Columns 1 through 7:	2.5035	0.4051	0	0.0372	0.1435	1.0017	0.0808
Columns 8 through 14:	0.2307	0.1191	0.5083	0.1584	0.0648	0.0957	0.3136

Social Welfare = 26.2075 dollars

Evaluating for the K-Factor: 0.1 PSO: 1/20 iterations, GBest = 0.081207 PSO: 20/20 iterations, GBest = 0.069603

Voltage values at buses are:

Columns 1 through 7:	1.0038	1.0050	1.0061	1.0000	1.0068	1.0036	1.0009
Columns 8 through 14:	1.0002	1.0030	1.0094	1.0015	1.0029	1.0055	1.0077

Power values at buses are:

Power values at buses at	re:							
Columns 1 through 7:	2.6519	0.4051	0	0.0390	0.1504	1.0494	0.0847	
Columns 8 through 14:	0.2417	0.1248	0.5325	0.1660	0.0680	0.1003	0.3286	
SocialWelfare = 57.13	32 dollar	s						
Evaluating for the K-Fa	ctor: 0.1	5						
PSO: 1/20 iterations, GI	Best = 0.1	1218						
PSO: 20/20 iterations, C	Best = 0	.1044						
Voltage values at buses	are:							
Columns 1 through 7:	1.0070	1.0070	1.0011	1.0036	1.0085	1.0096	1.0077	
Columns 8 through 14:	1.0078	1.0068	1.0032	1.0042	1.0026	1.0005	1.0055	
Power values at buses at	re:							
Columns 1 through 7:	2.7904	0.4051	0	0.0407	0.1572	1.0971	0.0885	
Columns 8 through 14:	0.2527	0.1304	0.5567	0.1735	0.0710	0.1048	0.3435	
SocialWelfare = 88.181	1 dollars							
Evaluating for the K-Fa	ctor:	0.2						
PSO: 1/20 iterations, GI	Best = 0.1	1624						
PSO: 20/20 iterations, C	Best = 0	.1392						
Voltage values at buses	are:							
Columns 1 through 7:	1.0087	1.0094	1.0046	1.0098	1.0036	1.0003	1.0059	
Columns 8 through 14:	1.0017	1.0097	1.0010	1.0096	1.0017	1.0048	1.0016	
Power values at buses are:								
Columns 1 through 7:	2.8351	0.4051	0.0993	0.0425	0.1641	1.1448	0.0924	
Columns 8 through 14:	0.2637	0.1361	0.5809	0.1811	0.0741	0.1094	0.3585	

SocialWelfare = 114.4853 dollars

Evaluating for the K-Factor: 0.25 PSO: 1/20 iterations, GBest = 0.203PSO: 20/20 iterations, GBest = 0.17399 Voltage values at buses are: Columns 1 through 7: 1.0086 1.0034 1.0061 1.0005 1.0051 1.0043 1.0064 Columns 8 through 14: 1.0027 1.0092 1.0088 1.0033 1.0038 1.0099 1.0098 Power values at buses are: Columns 1 through 7: 2.8790 0.4051 0.1912 0.0443 0.1708 1.1925 0.0962 Columns 8 through 14: 0.2747 0.1886 0.0772 0.1139 0.3734 0.1418 0.6051 SocialWelfare = 141.3997 dollars Evaluating for the K-Factor: 0.3 PSO: 1/20 iterations, GBest = 0.2436PSO: 20/20 iterations, GBest = 0.20879Voltage values at buses are: Columns 1 through 7: 1.0087 1.0002 1.0008 1.0018 1.0036 1.0095 1.0022 Columns 8 through 14: 1.0060 1.0057 1.0049 1.0064 1.0025 1.0030 1.0030 Power values at buses are: 0.4051 0.2834 0.0461 1.2402 0.1001 Columns 1 through 7: 2.9224 0.1777 Columns 8 through 14: 0.2857 0.1475 0.6293 0.1962 0.0803 0.1185 0.3884 SocialWelfare = 168.7674 dollars Evaluating for the K-Factor: 0.35 PSO: 1/20 iterations. GBest = 0.28419PSO: 20/20 iterations, GBest = 0.24359Voltage values at buses are: Columns 1 through 7: 1.0085 1.0087 1.0074 1.0046 1.0076 1.0085 1.0026

Columns 8 through 14: 1.0061 1.0034 1.0045 1.0098 1.0098 1.0057 1.0018

Power values at buses are:

Columns 1 through 7:	2.9649	0.4051	0.3763	0.0478	0.1845	1.2879	0.1039
Columns 8 through 14:	0.2967	0.1531	0.6534	0.2037	0.0833	0.1229	0.4033

SocialWelfare = 196.6277 dollars

----WHEN IINE 1-5 OUTAGE HAPPENS ----

Evaluating for the K-Factor: 0.15 PSO: 1/20 iterations, GBest = 0.12181 PSO: 20/20 iterations, GBest = 0.1044 Social Welfare value = 0.00000 dollars DLM value= 0.34992 dollars

Evaluating for the K-Factor: 0.2 PSO: 1/20 iterations, GBest = 0.16242 PSO: 20/20 iterations, GBest = 0.13921 Social Welfare value = 23.86645 dollars DLM value = 0.33374 dollars

Evaluating for the K-Factor: 0.25 PSO: 1/20 iterations, GBest = 0.20301 PSO: 20/20 iterations, GBest = 0.174 Social Welfare value = 48.00707 dollars DLM value = 0.31869 dollars

Evaluating for the K-Factor: 0.3 PSO: 1/20 iterations, GBest = 0.24363 PSO: 20/20 iterations, GBest = 0.20881 Social Welfare value = 69.77609 dollars DLM value = 0.26386 dollars

Evaluating for the K-Factor: 0.35 PSO: 1/20 iterations, GBest = 0.28419 PSO: 20/20 iterations, GBest = 0.24359 Social Welfare value = 91.96020 dollars DLM value = 0.23164 dollars

The sensitive load direction for SSC-OPF (SLD) ------

Evaluating for the DLM : 0.3 PSO: 1/20 iterations, GBest = 0.28421 PSO: 20/20 iterations, GBest = 0.2436 Power values at buses are: Columns 1 through 7: 2.2199 0.9094 0.4136 0.0445 0.1777 1.2402 0.1002 Columns 8 through 14: 0.2854 0.1309 0.6293 0.1962 0.0803 0.1185 0.3884

Social Welfare value = 151.24479 dollars Evaluating for the DLM: 0.4 PSO: 1/20 iterations, GBest = 0.28421PSO: 20/20 iterations, GBest = 0.2436Power values at buses are: Columns 1 through 7: 1.8498 1.0127 0.5007 0.0401 0.1777 1.2402 0.0770 Columns 8 through 14: 0.2857 0.1134 0.5248 0.1932 0.0803 0.1185 0.3884

Social Welfare value = 116.80279 dollars

---WHEN IINE 1-5 OUTAGE HAPPENS -----

Evaluating for the DLM : 0.3 PSO: 1/20 iterations, GBest = 0.28423PSO: 20/20 iterations. GBest = 0.24362Power values at buses are: Columns 1 through 7: 1.9445 1.0127 0.6076 0.0461 0.1777 1.2402 0.0818 Columns 8 through 14: 0.2857 0.1322 0.6228 0.1962 0.0803 0.1185 0.3884

Social Welfare value = 64.12333 dollars

PSO: $1/20$ iterations, GBest = 0.28424								
PSO: 20/20 iterations, GBest = 0.24362								
Power values at buses are:								
0.6076	0.0354	0.1777	1.2402	0.0982				
0.4841	0.1960	0.0803	0.1185	0.3354				
	0.6076	0.6076 0.0354	0.6076 0.0354 0.1777	0.6076 0.0354 0.1777 1.2402 0.4841 0.1960 0.0803 0.1185				

Social Welfare value = 36.82892 dollars

b) Moth Swarm Algorithm (MSA):

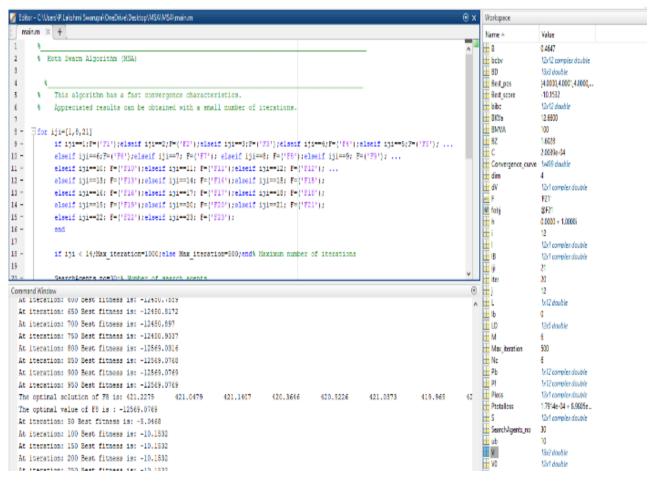
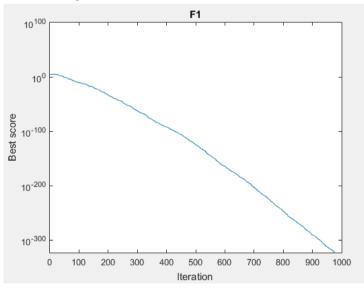


Fig. 3 - MSA Algorithm in MATLAB

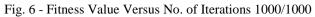
Fig. 4 -	Simulation	of MSA	in Comma	nd Prompt
----------	------------	--------	----------	-----------

The simulation of Morrin Community	
Command Window	\odot
At iteration: 600 Best fitness is: 6.9410-165	^
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-1	64 9.8
The optimal value of Fl 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	42
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	
友 >>	\checkmark
	1

Fig. 5 - Fitness Value Versus No. of Iterations



ISSN: 2237-0722 Vol. 11 No. 3 (2021) Received: 02.01.2021 – Accepted: 18.05.2021



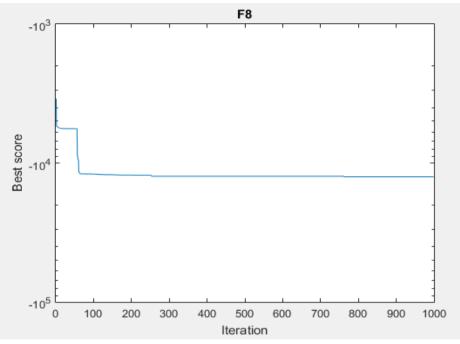
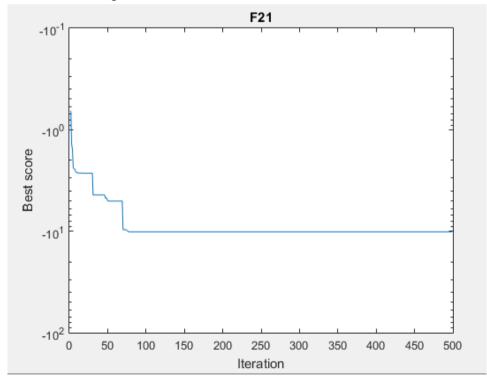


Fig. 7 - Fitness Value Versus No. of Iterations 500/500



MSA: 1/500 iterations, GBest = 0.26324 MSA: 500/500 iterations, GBest = 0.23362 Power values at buses are:

Columns 1 through 7:	1.6014	1.1011	0.7021	0.0321	0.1657	1.2201	0.0912
Columns 8 through 14:	0.1834	0.1134	0.3713	0.1673	0.0513	0.1081	0.3251

Social Welfare value = 10.1532 dollars

6. Analysis

The Moth Swarm Algorithm (MSA) is a novel method for meta-heuristic optimisation inspired on moth navigation. This work provides a new modified MSA with an arithmetic crossover (MSA-AC) to enhance the global search for the best solution, the speed of convergence and the performance of a classical MSA.

7. Conclusion

This study proposes a strategy based on the iterative SSC-OPF-SLD that incorporates a stability constraint together with the sensitive direction of loading into the energy system. The sensitive direction of loading is based on normal vector calculation. The results show the advantages of the technology suggested to give an ideal solution for the market, depending on system safety and the innovative Moth Swarm Algorithm (MSA) which is inspired by moth direction towards moonlight, in order to tackle limited optimal power flow (OPF) problems. In addition to adaptive Gaussian walks and spiral motion, the associational mechanism for the development of instantaneous memory and population diversity crossover for Lévy-mutation has been suggested. The MSA technique therefore enables system operators to study the influence of system safety on the process of market clearance. In addition, the PSO approach is used to optimize this issue. Compared to several previous studies OPF methods based on PSO, the efficacy and superiority of MSA has been shown to be straightforward to implement and to discover optimal solutions to the non-linear, restricted issue.

References

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.

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.

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.

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.

Canizares, C.A., "On bifurcation voltage collapse and load modeling," *IEEE Trans. Power Syst.*, Vol. 10, No. 1, pp. 512–522, February 1995.

Canizares, C.A., Mithulananthan, N., Milano, F., and Reeve, J., "Linear performance indexes to predict oscillatory stability problems in power system," *IEEE Trans. Power Syst.*, Vol. 19, No. 2, pp. 1023–1031, May 2004.

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.

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.

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.

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.

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.

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.

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.

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.

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.*, 1(3), pp. 466–475, May 2007.