Optimum Design of Damping Controllers Using Modified Sperm Swarm Optimization

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ABSTRACT This paper is proposed a modified sperm swarm optimization algorithm (MSSO) for numerical function optimization and optimal design of damping controller in power system. To provide a fine balance between the explorative and exploitative behavior, MSSO utilizes a chaotic velocity damping factor. In addition, the proposed method considers a reasonable velocity limitation to avoid explosion and divergence of the sperm movement. The proposed algorithm is benchmarked with a set of test functions and the results are compared with the standard sperm swarm optimization (SSO) and some other robust metaheuristic from the literature. To demonstrate the feasibility and effectiveness of the proposed method in power systems, power system stabilizers (PSS) and thyristor-controlled series capacitor (TCSC) controllers are designed for a 5-area 16-machine system. The performance of the suggested controllers on a multi-machine power system under various operating situation is evaluated using a nonlinear time-domain simulation. As results demonstrate, the MSSO is superior and could generates better optimal solutions in compared with SSO and other competitive algorithms. The numerical results reveal that, for damping oscillation problem the modified algorithm (MSSO) converges faster than the other methods.

INDEX TERMS PSS, TCSC, chaotic, sperm swarm, coordinated design.

I. INTRODUCTION

The power system stability problem is an important topic in the power system process. In interconnected power systems, especially in the deregulated paradigm, some stability issues are correlated with electromechanical oscillations. The Power System Stabilizer (PSS) for generators and the additional controllers for flexible AC transmission system (FACT) devices are effective tools for modifying the stability of power systems through oscillation modes damping. Numerous methods have been suggested for damping controller design [1], [2]. Among FACTS series devices for transient stability enhancement, Thyristor Controlled Series Capacitor (TCSC) permits quick and persistent modifications of the impedance of transmission line [3], [4]. TCSC controllers offer assistance to improve and control the power flow via a line in the steady-state and damping inter-area oscillation. Nevertheless, the ability for being useful through great disturbances such as faults to develop the transient stability of the power system is considered as other important specifications of the mentioned controllers. The conventional optimization techniques cannot be suitable for solving the problem of power system controller.

It is essential to develop the meta-heuristic algorithms that are broadly applied for the expanding problems of global optimization [5]–[10]. The interplay between FACTS and PSSs damping controllers is able to enhance or reduce the damping of the power system and may be a reason for instability when tie-line and power systems are interconnected.

Increasing characteristics of power system damping attracted the attention of many investigators [11]–[20]. Lately, a variety of publications are about some disadvantages
and limitations of metaheuristic algorithms. Although metaheuristics algorithms could provide relatively satisfactory results, no algorithm could provide superior performance than others in solving all optimizing problems. Therefore, several studies have been done to improve the performance and efficiency of the original metaheuristic algorithms in some ways and apply them for a specific purpose [21]–[27].

Sperm swarm optimization (SSO) is a recently developed metaheuristics algorithm inspired by the attitude of sperm of ovum while fertilizing the ovum [28], [29]. Compared to the other metaheuristic, SSO possess several advantages. It has a very simple structure, fast converging rate, can be easily understand and utilized. Despite of these advantages, SSO can be easily fallen into a local minimum [28].

In order to prevail this drawback, in the current research a modified version of the algorithm is proposed. The proposed modified sperm swarm optimization (MSSO) utilizes a new chaotic velocity damping factor which significantly improves the performance of the search process and could provide a well balance between exploration and exploitation. This modification improves the performance and convergences speed of the algorithm, significantly. To validate the effectiveness of the proposed method, a set of well-known standard benchmark functions from the literature are employed. In addition, the performance and efficiency of the new method is investigated through numerical experiments of design damping controller optimization. Optimal coordination of PSS and TCSC-POD is performed to damp the oscillation modes. Eigenvalue investigation and nonlinear time-domain simulation in the 5-area 16-machine system validated the efficiency of the suggested method. According to the simulation outcomes, the suggested method accomplishes great robust efficiency for damping modes within various functioning conditions.

II. MODIFIED SPERM SWARM OPTIMIZATION

Sperm Swarm Optimization (SSO) is a recently developed population-based metaheuristic inspired by the attitude of sperm of sperms while fertilizing the ovum [28]. The algorithm uses a set of potential solutions (sperms), which floating in the entire search space to explore and obtain the best solution. At the same time, the candidate solutions look at the best sperm in their path. In the other word, sperms will be considered its previous best position (sperm best solution) as well as the previous global best position of the swarm (global best solution). In the SSO algorithm, each sperm improves its location toward the optimum by considering its current location, current velocity, the distance to sperm best solution \( x_{best_i} \), and the distance to global best solution obtained so far \( x_{gbest_i} \). Mathematically, in SSO the sperms updated their position according to the following equation:

\[
x_i (t + 1) = x_i (t) + v_i (t)
\]

where, \( v_i (t) \) is the current velocity of the \( i \)th sperm which consists of three components; initial velocity, personal best solution \( x_{best_i} \) and the global best solution \( x_{gbest_i} \) as shown in Eq. (2).

\[
v_i (t) = InitialVelocity + CurrentBest + GlobalBest \tag{2}
\]

The first part of Eq. (2) presented the initial velocity of each sperm after the ejaculation in the search space (cervix area) which is affected by the \( pH \) value. This velocity can be expressed as:

\[
InitialVelocity = D \times \log_{10} (pHRand_1) \times v_i \tag{3}
\]

where, \( D \) is the velocity damping factor which is a random number between 0 and 1, \( pHRand_1 \) is a random number in the range of 7 to 14 representing the \( pH \) value of the visited location.

The second term in Eq. (2) representing the best position obtained by the sperm so far which is affected by both PH and temperature and can be described in the following form:

\[
CurrentBest = \log_{10} (pHRand_1) \times \log_{10} (TempRand_2) \times (x_{best_i} - x_i (t)) \tag{4}
\]

In which, \( TempRand_1 \) is a random numbers in the range of 35.1 to 38.5 the temperature value of the visited location.

The last term of Eq. (2) demonstrated the best position of all sperms which closest to the target and evaluated using the following expression:

\[
GlobalBest = \log_{10} (pHRand_1) \times \log_{10} (TempRand_2) \times (x_{gbest_i} - x_i (t)) \tag{5}
\]

By substituting Eqs (3 - 5) in Eq (2), the velocity of the \( i \)th sperm at iteration \( t \) can be defined as follows:

\[
v_i (t) = D \times \log_{10} (pHRand_1) \times v_i + \log_{10} (pHRand_1) \times \log_{10} (TempRand_2) \times (x_{best_i} - x_i (t)) + \log_{10} (pHRand_1) \times \log_{10} (TempRand_2) \times (x_{gbest_i} - x_i (t)) \tag{6}
\]

According to Eq. (6), the sperm velocity in the SSO algorithm is affected by two factors: the \( pH \) value and the temperature of the visited zone. The temperature is an important factor in determining the best solution for the sperm (egg location).

The SSO algorithm has a simple concept and structure and could provide acceptable solution compared with some other metaheuristics [28]. However, the algorithm is unable to converge to the global minimum and may trapped into local optima and faced premature convergence in case of complex functions.

In order to prevail the above mentioned drawback and improve the effectiveness and robustness of SSO, in the current research a modified approach of the algorithm is proposed (MSSO).

SSO as a metaheuristic algorithm requires two main phases include investigating the various promising regions in a search space (exploration) in the early iterations and the local search around the obtained promising regions (exploitation) in the late iterations. In addition, a well balance among these
two phases is needed. Therefore, in the proposed MSSO, to improve the search performance and controlling the balance between global search in early iterations and local search in late iterations, the following equation is proposed for the damping factor \( D \):

\[
D = 100 \times e^{(-20 \times \text{Iter/Iter}_{\text{Max}})}
\]  

(7)

where, \( \text{Iter}_{\text{Max}} \) is the maximum number of iterations. Actually, the proposed \( D \) is a decreasing function which provide an effective global search in the initial iterations and robust local search in the last iterations.

As shown in Eq. (6), in the SSO algorithm, the velocity of the sperms is a stochastic variable and may allow the sperms follows wider cycles in the problem space. To control these oscillations and avoid explosion and divergence, a reasonable damping factor \( D \) is introduced in the proposed MSSO to clamp the movement of the sperms according to:

\[
-v_{\text{imax}} \leq v_i \leq v_{\text{imax}}
\]  

(8)

where \( v_{\text{imax}} \) is a designated maximum movement allowed, which defines the maximum change one sperm can undergo in its positional coordinates during an iteration based on the following equation:

\[
v_{\text{imax}} = 0.1 \times (u_{b_i} - l_{b_i})
\]  

(9)

Finally, chaotic dynamics are integrated into the proposed MSSO to enrich the searching behavior and avoid getting locked in a local optimum. Chaos is a non-linear phenomenon that can be seen all over the place in nature [30]. Chaos has been a novel optimization technique, and chaos-based searching algorithms have piqued interest due to its ease of implementation and unique ability to avoid getting locked in local optima. As a representative chaotic system, the well-known logistic equation [31] is used in this paper. The Logistic equation is described as follows:

\[
\theta (t + 1) = \mu \times \theta (t) \times (1 - \theta (t)) \quad 0 \leq \theta \leq 1
\]  

(10)

where, \( \mu \) is a control parameter and has a real value in the range of \([0, 4]\). The behavior of the system represented by Eq. (10) is greatly changed with the variation of \( \mu \). The value of \( \mu \) determines whether \( \theta \) stabilizes at a constant size, oscillates within limited bounds, or behaves chaotically in an unpredictable pattern. Equation (10) displays chaotic dynamics when \( \mu = 4.0 \). Figure 1 shows the chaotic dynamics, where \( \mu = 4.0 \) and \( \theta(1) = 0.55 \) for 300 iterations. The new equation for chaotic damping factor (CD) obtained by multiplying Eq. (7) and Eq. (10) reads as follows:

\[
CD = \theta \times 100 \times e^{(-20 \times \text{Iter/Iter}_{\text{Max}})}
\]  

(11)

By substituting Eq. (11) in Eq. (6) the following velocity updated equation for the proposed MPSO will be obtained:

\[
v_i (t) = \theta \times D \times \log_{10} (pHRand_1) \times v_i + \log_{10} (pHRand_1) \\
\times \log_{10} (TempRand_2) \times (x_{\text{best}_i} - x_i (t))
\]  

(12)

All parameters of Eq. (12) have been defined previously. The flowchart of the proposed MSSO is depicted in Fig. 2.

### III. POWER SYSTEM MODEL

The controller design and system studies to develop the small-signal stability margin can be accepted out by applying linear models. Regularly, the standard modeling for power system has been established on a group of nonlinear differential-algebraic calculations, as follows:

\[
\dot{x} = f(x,u) \\
y = g(x,u)
\]  

(13)

where \( x \) is the state variables vector and \( u \) is the input control parameters vector. The linear state equation is obtained, as follows:

\[
\dot{x} = Ax + Bu \\
y = Cx + Du
\]  

(14)

Putting the modes of state matrix modes within the left side is the aim of the optimum design. Closed-loop matrix \( A \) can be utilized to calculate the modes of the total system.

### A. STRUCTURE OF PSS

PSS compensates the phase-lag between exciter input and machine electrical torque. In order to achieve this goal, an additional stabilizing signal is presented through the excitation system. PSS produces proper torque on the rotor of the machine. Therefore, the phase lag between the exciter input and the machine electrical torque is compensated. Speed and the supplementary stabilizing signal are proportional. This stabilizer style consists of a dynamic compensator and a washout filter as displayed in Fig. 3.

The output signal is another input to the regulator excitation system. The mean component of the output of PSS will be removed by the washout filter, which is mainly a high pass filter. Generally, the constant value of time can be ranged from 0.5s to 20s.

### B. TCSC DAMPING CONTROLLER

A reactor in series with a bi-directional thyristor valve is fired from 0.5s to 20s. The mean component of the output of PSS will be removed by the washout filter, which is mainly a high pass filter. Generally, the constant value of time can be ranged from 0.5s to 20s.
the voltage of the capacitor to shape a fixed series capacitor in parallel with a Thyristor Controlled Reactor (TCR) (Figure 4). For the load flow investigations and stability analysis, TCSC can be modeled as a variable reactance. In the present research, TCSC is considered as a reactance in both dynamic stability and load flow. The dynamic equation of TCSC is as follows:

\[
\dot{X}_{TCSC} = \frac{1}{T_{S}} \left( K_{S} \left( \Delta X_{TCSC} + \Delta U_{TCSC} \right) - \Delta T_{TCSC} \right) \tag{15}
\]

To create an electrical torque in phase with the speed deviation based on the phase compensation method, the damping controller is designed. TCSC based damping controller which is regarded as a lead-lag compensator and comprises two stages of the lead-lag compensator, signal-washout block, and gains block is illustrated in Figure 5. The rapid advance in means of communication has permitted the speed deviation utilization as the input signal of TCSC.

\[
v(i) = \frac{\Delta P_{Li}}{\Delta X_{j}} \tag{16}
\]

where \(\Delta P_{Li}\) and \(\Delta X_{j}\) are the active power flow variation in \(i\)th line and the tie-line \(j\)th reactance, respectively.

The sensitivity indices \(v(i)\) is presented as follows:

\[
\|v\| = \sum_{i=1}^{M} \|v(i)\| \tag{17}
\]

where \(M\) shows the number of transmission lines. The best placement of TCSC device is the tie-line related with the largest norm.

C. PLACEMENT OF TCSC

Enhancing the power transfer capability of the transmission lines is the major purpose of TCSC installation in the power system. Therefore, the placement of TCSC has a significant function in achieving this major feature. A novel technique according to the sensitivity indices of real power is used to placement of TCSC [11], [23]. In the mentioned approach, the sensitivity vector \(v(i)\) is written as:

\[
\Delta Y_{TCSC} = \frac{1}{T_{S}} \left( K_{S} \left( \Delta X_{TCSC} + \Delta U_{TCSC} \right) - \Delta T_{TCSC} \right) \tag{15}
\]
IV. PSSS AND TCSC-POD COORDINATION DESIGN BY USING MSSO

In the suggested technique, the optimum parameters are obtained under various operating conditions and disturbances. First, an appropriate objective function should be presented for tuning design. In this research, MSSO is employed to better optimize synthesis and finding the global optimum extent of the fitness function. A multi-objective function according to the damping ratio and damping factor is considered to enhance the damping of the modes, and the objective function is obtained as follows [32], [33]:

\[
F(X) = F_1 + \alpha F_2 = \sum_{i \geq i_0} (\sigma_i - \sigma_0)^2 + \alpha \sum_{i \geq i_0} (\xi_i - \xi_0)^2
\]  

where \(\sigma_i\) and \(\xi_i\) are the damping factor and the damping ratio of the \(i\)th eigenvalue. The weighting parameter \(\alpha\) for combining both two objective functions \((F_1\) and \(F_2\) functions) at the same time. By minimizing the \(F(X)\), the system modes are changed to a \(D\)-shape area (Fig. 6).

Additionally, \(\alpha\) is derived from different experiments performed on this problem to achieve the appropriate answer from both dynamic and small-signal views. The design problem may be defined as the following constrained optimization problem, where the limitations are the bounds of POD controller parameter:

subject to

\[
\begin{align*}
K_{\text{imin}} & \leq K_i \leq K_{\text{imax}} \\
T_{\text{imin}} & \leq T_i \leq T_{\text{imax}}
\end{align*}
\]  

(19)

The PSS and TCSC controller parameters optimization is performed by investigating the objective function (Eq. 19) which takes into regard many operating conditions. Figure 7 indicates the flowchart for calculating \(F(X)\). The controller gain \((K)\) and the lead/lag time constants \((T_1, T_2, T_3,\) and \(T_4)\) are defined by MSSO.

The presented approach applies MSSO to solve the optimization problem. In addition, it searches for the desirable set of PSSs and TCSC parameters. It is emphasized that with this process, robust stabilizers, enable to function favorably over a wide range of the operating conditions, are achieved. The target function is minimized to move the specific mode to the \(D\)-shape by using the MSSO algorithm.

V. MODEL VERIFICATION

In this study, the performance of MSSO is evaluated on a set of 8 benchmark functions from literature [34], [35] against standard version of the algorithm as well as some well-known state of the art metaheuristic algorithms. All of these functions are minimization problems which are useful for evaluating the search efficiency and convergence rate of optimization algorithms. The mathematical formulation and characteristics of these test functions are available in Tables 1. This benchmark set covers include both unimodal functions \((F_1\) - \(F_4))\) with unique global best for testing the convergence speed and exploitation ability of the algorithms and multimodal functions \((F_5\) - \(F_8))\) with multiple local optimum for testing local optima avoidance and exploration capability of the algorithm. The proposed algorithm is coded in MATLAB R2020b programming software.

The results and performance of the proposed MSSO is compared with SSO and other well-established optimization algorithms such as the Gravitational Search Algorithm (GSA) [36], Sine-Cosine Algorithm (SCA) [37], and Grey Wolf Optimizer (GWO) [38]. These algorithms have been proved their effectiveness and robustness in compared with other well-established methods like Particle Swarm Optimization, Genetic Algorithm, Firefly Algorithm and so on [36]–[39].
TABLE 1. Description of unimodal benchmark functions.

| Function | Range | \( f_{\text{min}} \) | \( n \) (Dim) |
|----------|-------|-----------------|--------------|
| \( F_1(X) = \sum_{i=1}^{n} x_i^2 \) | \([-100, 100]^n\) | 0 | 30 |
| \( F_2(X) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \) | \([-10, 10]^n\) | 0 | 30 |
| \( F_3(X) = \sum_{i=1}^{n} \left( \sum_{j=1}^{i} x_j \right)^2 \) | \([-100, 100]^n\) | 0 | 30 |
| \( F_4(X) = \max \{ |x_i|, 1 \leq i \leq n \} \) | \([-100, 100]^n\) | 0 | 30 |
| \( F_5(X) = \sum_{i=1}^{n} -x_i \sin(\sqrt{|x_i|}) \) | \([-500, 500]^n\) | 0 | 30 |
| \( F_6(X) = \sum_{i=1}^{n} [x_i^2 - 10 \cos(2\pi x_i) + 10] \) | \([-5.12, 5.12]^n\) | 0 | 30 |
| \( F_7(X) = -\sum_{i=1}^{n} [(X - a_i)(X - a_i)^T + c_i]^{-1} \) | \([0, 10]^n\) | -10.1532 | 4 |
| \( F_8(X) = -\sum_{i=1}^{n} [(X - a_i)(X - a_i)^T + c_i]^{-1} \) | \([0, 10]^n\) | -10.4028 | 4 |

TABLE 2. Parameter setting of the selected algorithms.

| Year | Algorithm | Parameter | Specifications |
|------|-----------|-----------|---------------|
| 2009 | Modified Sperm Swarm Optimization (MSSO) and Sperm | Number of objects | 30 |
|      | Gravitational Search Algorithm (GSA) | Maximum iteration | 1000 |
|      | | Search agents | 50 |
|      | | Gravitational constant | 100 |
|      | | Alpha coefficient | 20 |
|      | | Number of generations | 1000 |
| 2014 | Grey Wolf Optimizer (GWO) | Search agents | 80 |
|      | | Control parameter (\( \mu \)) | Number of generations | [2.0] | 1000 |
| 2016 | Sine Cosine Algorithm (SCA) | Search agents | 80 |
|      | | Number of elites | 2 |
|      | | Number of generations | 1000 |

It should be noted that the performance and convergence of these metaheuristic methods are completely depend on the internal parameters of the algorithms. MSSO and SSO have a simple structure and needs only two main parameters, \( N \) (number of sperms) and \( \text{Iter}_{\text{max}} \) (maximum number of iteration). It is found through experiments that lower value of \( N \) results in premature convergence and higher value improves exploration but increase elapsed time significantly. The appropriate value of \( N \) is considered as 30 and the maximum number of iteration is equal to 1000. In Table 2, the key parameters of the selected methods are presented. These values have been determined using the reference-based parameter identification process according to the previously published research papers. Because of stochastic nature of the metaheuristics methods, the results of single run might be unreliable and the algorithms may obtain better or worse solutions than the previously reached one. Therefore, statistical analysis should be applied to have a fair comparison and effectiveness evaluation of the algorithms. Regarding to this issue, for the selected algorithms, 30 independent runs are performed and statistical results are collected and reported in Tables 3.

Results of Table 3 show the Best (Minimum), Worst (Maximum), Mean (Average), Median and Standard Deviation (Std) of the solutions obtained from experiments using the selected optimization algorithms. The best results among the five algorithms are shown in bold face. The results of this table show that, for all unimodal function, MSSO could provide global best solution which means that the new algorithm has a large potential search space compared with the standard SSO and also other optimization algorithms. Moreover, in case of multimodal functions, the results of the proposed algorithm are significantly better than the other methods. From the standard deviation point of view, which indicate the stability of the algorithm, the results show that MSSO is a more stable method when compared with the other techniques. From the analysis, it can be concluded that MSSO outperforms the standard algorithm and other methods.

An effective optimization algorithm should converge to the global optimum rather than a local optimum. In Fig. 8, the convergence progress curves of MSSO for benchmark test functions are compared to those of SSO, GSA, SCA, and GWO. The curves are plotted against the iteration count, which is in the hundreds. According to the graph, MSSO outperforms the other algorithms in all cases. Because of its effective modifications, the curves of test functions show that MSSO is capable of thoroughly exploring the search space and identifying the most promising region in fewer iterations.
TABLE 3. Comparison of different methods in solving test functions.

| Function | Statistics | MSSO | SSO | GSA | SCA | GWO |
|----------|------------|------|-----|-----|-----|-----|
|          | Best       | 6.23e-123 | 1.0013e-17 | 1.5523e+07 | 2.4915e-61 |
|          | Worst      | 9.29e-183  | 3.1868e-17 | 0.0043   | 3.8647e-58 |
|          | Mean       | 3.097e-184 | 2.1148e-17 | 2.3458e-04 | 4.9162e-59 |
|          | Median     | 7.63e-219  | 2.0077e-17 | 1.9737e-05 | 1.0534e-59 |
|          | Std.       | 3.48e-189  | 5.8150e-18 | 7.9295e-04 | 1.0230e-58 |
|          | Best       | 4.21e-147  | 1.5282e-08 | 1.5050e-09 | 8.3621e-36 |
|          | Worst      | 7.24e-122  | 3.3313e-08 | 9.8446e-06 | 5.3488e-34 |
|          | Mean       | 7.35e-123  | 2.3935e-08 | 1.6828e-06 | 8.3658e-35 |
|          | Median     | 6.92e-128  | 2.3469e-08 | 5.4006e-07 | 5.9294e-35 |
|          | Std.       | 2.29e-122  | 4.0025e-09 | 2.4046e-06 | 9.8594e-35 |
|          | Best       | 2.51e-123  | 102.9550  | 70.8285   | 1.2533e-19 |
|          | Worst      | 8.92e-90   | 468.6160  | 2.6762e+03 | 3.5572e-13 |
|          | Mean       | 9.82e-91   | 245.4694  | 789.1620  | 1.5096e-14 |
|          | Median     | 1.83e-98   | 221.1150  | 619.4506  | 2.0740e-17 |
|          | Std.       | 2.81e-90   | 100.1024  | 746.2287  | 6.5547e-14 |
|          | Best       | 5.24e-96   | 2.2499e-09 | 1.2610    | 9.8174e-16 |
|          | Worst      | 1.75e-73   | 5.0857e-09 | 35.6743   | 2.4431e-13 |
|          | Mean       | 1.78e-73   | 3.3030e-09 | 9.3080    | 1.9487e-14 |
|          | Median     | 3.18e-81   | 3.2020e-09 | 6.9806    | 6.3817e-15 |
|          | Std.       | 5.53e-73   | 7.4424e-10 | 8.0720    | 4.9595e-14 |
|          | Best       | -1.045e+04  | -5.94e+03 | -3.6279e+03 | -5.2993e+03 |
|          | Worst      | -9.39e+03  | -5.66e+03 | -2.0033e+03 | -3.5321e+03 |
|          | Mean       | -1.032e+04 | -5.79e+03 | -2.7826e+03 | -4.0769e+03 |
|          | Median     | -1.029e+04 | -5.79e+03 | -2.7464e+03 | -3.9726e+03 |
|          | Std.       | 65.76     | 91.04    | 365.4671  | 336.8249  |
|          | Best       | 0.00       | 8.9546   | 1.0566e-06 | 0.00      |
|          | Worst      | 0.00       | 21.8891  | 51.4451   | 10.0548   |
|          | Mean       | 0.00       | 15.6209  | 5.9694    | 0.8853    |
|          | Median     | 0.00       | 15.9193  | 9.3391e-04 | 0.00      |
|          | Std.       | 0.00       | 3.1043   | 12.2476   | 2.4438    |
|          | Best       | -10.123    | -3.74    | -10.153   | -8.1370   |
|          | Worst      | -9.54      | -2.49    | -2.6829   | -0.8802   |
|          | Mean       | -10.146    | -3.09    | -6.3969   | -4.3187   |
|          | Median     | -10.123    | -3.06    | -3.9547   | -4.9053   |
|          | Std.       | 0.043      | 0.425    | 3.5901    | 2.0785    |
|          | Best       | -10.4028   | -3.26    | -10.4009  | -9.0513   |
|          | Worst      | -10.2345   | -2.21    | -10.4029  | -9.0704   |
|          | Mean       | -10.4012   | -2.59    | -10.4029  | -5.4154   |
|          | Median     | -10.4011   | -2.56    | -10.4028  | -5.0380   |
|          | Std.       | 0.004      | 0.309    | 4.6649e-06 | 1.7315    |

VI. PRACTICAL APPLICATIONS

The desirable parameters of PSS and TCSC-POD controller will be obtained using MSSO method. The New England 16-machine, 68-bus system is applied to show the function of the suggested technique. The system diagram and its relevant information are shown in Figure 9. The studied test system contains 68 buses, 16 machines for five interconnected areas and also has eight tie-lines and the test system can be divided into five areas as shown in Fig. 9. The implementation process of the suggested MSSO algorithm for evaluation of desirable parameters of controllers is presented in Fig. 7 as a flowchart. The active power sensitivity approach is used to determine the desired placement of TCSC. The active power sensitivity index and the tie-line data of the test system are reported in Table 4. The tie-line 40–41 has the largest sensitivity index (Table 4). [1], [9]. Therefore, this line is the best placement for installing the TCSC controller in the present study. The application of the TCSC controller in the line 40–41 will increment the power transfer ability in comparison to the non-compensated case.

In this part, MSSO, and SSO have been used in the research system to obtain the desired parameters for PSS and TCSC-POD controller. The ranges of the optimized parameters are [0.1, 100] for K, and [0.05, 2] for T1-T4. These ranges decrease the computational times significantly based on previous studies [40], [41]. The TCSC-POD controller and PSS, which the PSS is placed in machine 9 (G9) and TCSC is located in line 40–41, should be designed simultaneously using the MSSO. The D-shape sector limits are $\sigma = -0.17$, and $\zeta = 0.1$. In this study, the optimum value for $\alpha$ is considered equal to 2. These contents are obtained

TABLE 4. Values of active power sensitivity index[11].

| Tie-line | Resistance (pu) | Reactance (pu) | Line charging (pu) | $|p|$ |
|----------|----------------|----------------|-------------------|-----|
| 18–42    | 0.0040         | 0.0600         | 2.2500            | 1.16280 |
| 18–49    | 0.0076         | 0.1141         | 1.1600            | 4.15654 |
| 18–50    | 0.0006         | 0.0144         | 1.0300            | 2.18882 |
| 53–54    | 0.0035         | 0.0411         | 0.6987            | 1.76581 |
| 41–42    | 0.0040         | 0.0800         | 2.2500            | 2.44633 |
| 40–41    | 0.0050         | 0.0840         | 3.1500            | 5.69488 |
| 27–53    | 0.0320         | 0.3200         | 0.4100            | 0.33261 |
| 60–61    | 0.0023         | 0.0363         | 0.3804            | 2.23336 |
Figure 8. Comparison of convergence curves of MSSO and selected algorithms for F1-F8.
from several investigations of the eigenvalues of the case system.

The rate of convergence for the optimum tuning of TCSC-POD and PSS are illustrated in Figure 10. The oscillation modes have been moved to the desired area. Table 5 presents the achieved PSS and TCSC controller parameters by MSSO and SSO.

In addition, the system close-loop eigenvalue and minimum damping coefficient are reported in Table 6 for both methods. By computing the eigenvalues of the linearized system model, it is found that the system has four inter-area modes. It demonstrates that the applying MSSO method is an effective approach to increase the global searching capability and improve performance stability.

Time-domain analysis with two scenarios are achieved on the case study to demonstrate the efficiency of the designed controllers. A 3-phase fault is used to line 1-2 at 0.1s and cleared after six cycles (Scenario I). The speed deviation regarding a specific machine (G13) is evaluated over the simulation period (Fig. 11 to Fig. 14). These figures show that the design of PSS and POD-TCSC controllers by MSSO creates
 TABLE 5. Results obtained by SSO and MSSO.

| Algorithm | K   | T1  | T2  | T3  | T4  |
|-----------|-----|-----|-----|-----|-----|
| SCA       | 10.10 | 0.198 | 2.00 | 0.001 | 2.00 |
| TCSC      | 11.00 | 1.081 | 1.54 | 1.438 | 0.544 |
| SSO       | 10.25 | 0.217 | 0.298 | 1.538 | 0.376 |
| TCSC      | 11.76 | 0.472 | 0.723 | 0.946 | 0.202 |
| MSSO      | 13.65 | 1.204 | 1.423 | 1.639 | 1.657 |
| TCSC      | 32.26 | 0.613 | 0.282 | 0.323 | 0.359 |

 TABLE 6. Inter-area modes and related damping ratio.

| LFO         | Damping ratio |
|-------------|----------------|
| Without Controller | 0.01128 |
|              | 0.05734 |
|              | 0.07138 |
|              | 0.05966 |
| SCA         | 0.105 |
| -0.1790 ± j1.663  | 0.061 |
| -0.1880 ± j3.072  | 0.070 |
| -0.2623 ± j3.7610  | 0.0654 |
| SSO         | 0.1240 |
| -0.1953 ± j1.5620  | 0.1033 |
| -0.2327 ± j2.2391  | 0.1064 |
| -0.2731 ± j2.6437  | 0.1000 |
| MSSO        | 0.1869 |
| -0.2803 ± j1.473  | 0.1610 |
| -0.33067 ± j2.026  | 0.1445 |
| -0.3574 ± j2.556  | 0.1364 |

 FIGURE 10. Fitness convergence with MSSO & SSO.

 good damping for the case study. Moreover, to illustrate the potential of proposed method, a 3 phase fault is used to line 29-28(at bus 29) (scenario II). The dynamic property of the system was computed for 20 seconds. The speed deviation is computed over the simulation period (Fig. 15 to Fig. 18). These results are same as the results obtained from the scenario I (Fig. 11 to Fig. 14), verifying the robustness of the proposed method for designing controllers. Simulation results display that the controllers designed by MSSO method have a better feature comparing to those designed by SSO and SCA. As it can be seen from Fig. 11 to Fig. 18 in all cases the
result of the proposed method will be converged after almost 5 seconds which is much lower than those obtained from the other methods.

VII. CONCLUSION

This research develops an effective version of sperm swarm optimization algorithm namely modified sperm swarm optimization (MSSO). MSSO’s main features are that it just has two internal parameters, it’s simple to code, and it’s simple to use. The proposed algorithm’s performance is evaluated using a set of four unimodal and four multi-modal test functions to determine the algorithm’s exploration, exploitation, and convergence rates. Moreover, the results were compared with SSO and well-known and recently developed algorithms include GSA, SCA, and GWO. As per the results and finding, it was observed and may be concluded that MSSO is capable of finding the global solution for most of the unimodal and multi-modal
benchmark functions and outperform the standard SSO and also other algorithms in a statistically significant manner. While, for most of the benchmark test functions, all the competitor methods rarely reach the global optimal solutions. The performance of the new algorithm for optimal coordinated design of PSS and TCSC controller is investigated for oscillations damping. The numerical experiments reveal that the newly proposed algorithm for oscillations damping is quite robust and efficient when compared with the others.

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