A New Hybrid Swarm Optimization Algorithm for Power System Vulnerability Analysis and Sensor Network Deployment

Haopeng Zhang and Qing Hui

Abstract—In this paper, a new particle swarm optimization (PSO) inspired swarm intelligence optimization algorithm, so called hybrid multiagent swarm optimization (HMSO) algorithm, is proposed and investigated for mixed-binary nonlinear programming (MBNLP) problems. This new HMSO algorithm, including a continuous optimizer and a binary optimizer, is motivated by the recently developed results about multiagent coordination for network systems. Specifically, the new HMSO algorithm not only shares the global optimal solution among the particles like the PSO algorithm, but also shares the neighboring particle’s velocity and position information for each individual particle underlying a communication topology. In this paper, we present some applications of our new HMSO algorithm for solving recently raised power system vulnerability analysis and sensor network deployment problems. The simulation illustrations are provided and compared with an improved PSO from the literature, while the numerical results reveal the high accuracy of the new HMSO when solving MBNLP problems.

I. INTRODUCTION

The mixed-binary nonlinear programming (MBNLP) problem aims to optimize the binary variables representing the structure or topology for the system and to optimize the continuous variables representing the system parameters simultaneously, which occurs frequently in many engineering fields, for instance, chemical engineering [1], [2], electric power grid [3], [4], water network [5], heat exchange network [6], gas network [7], to cite a few examples. Many deterministic methods are devoted to solving the MBNLP problem such as branch and bound [8], outer-approximation method [9], and cutting plane method [10]. Besides those deterministic algorithms, the stochastic algorithms are also studied such as the particle swarm optimization algorithm [11] and simulated annealing algorithm [12].

The particle swarm optimization (PSO) is a well developed swarm intelligence method that optimizes a nonlinear or linear objective function iteratively by trying to improve a candidate solution with regards to a given measure of quality. Motivated by a simplified social model, the algorithm is first proposed by Kennedy and Eberhart in [13]. Since the PSO algorithm requires only primitive mathematical operators and is computationally efficient in terms of both memory requirements and speed, it solves many optimization problems quite efficiently. Besides continuous variables optimization, the binary particle swarm optimization (BPSO) algorithm is also proposed in [14] by Kennedy and Eberhart. In the BPSO algorithm, particle trajectories are the changes in the probability so that one coordinate will take on a zero or one value. By combining both continuous PSO and binary PSO algorithms, [11] provides an improved PSO algorithm to solve the MBNLP problem. Alternatively, motivated by multiagent consensus problems in control theory [15]–[20], a hybrid multiagent swarm optimization (HMSO) algorithm is proposed in [21] to solve mixed-binary programming problems and the numerical evaluation of the HMSO algorithm is also provided to show the improvement of the convergence and accuracy using the proposed HMSO algorithm.

In this paper, we focus on the application of a new HMSO algorithm to some cyber-physical network problems. First, in power systems, load shedding means cutting off supply to some loads when the demand becomes greater than the supply. While its common use is for high energy-demand times, broken power lines create subregions for which the demand cannot be met with the reduced transmission capability of the grid, even though supply is available in other parts of the system [3]. Therefore how to decide the cut-off supplies minimizing change load and generation to restore feasibility to the system to avert a blackout can be formulated as a MBNLP problem. Further, identifying small groups of lines, whose removal would cause a severe blackout, is critical for the secure operation of the electric power grid, and a bilevel optimization problem is formulated in [3] where in the outer level we identify the critical lines, which corresponds to the combinatorial part of the problem, and in the inner level we measure the blackout severity by solving the load shedding problem. In this paper, a new HMSO algorithm is proposed to solve the power load shedding and vulnerability problems for the power network system numerically and compared with an improved PSO algorithm from the literature.

Since power systems are of vital importance for both civil and military applications, a sensor network for detecting the possible damages to the power system is highly needed. As the second application of our new HMSO algorithm, the distributed sensor deployment is studied in this paper due to the fact that network technology has been widely applied for network damages and threats detection and dissemination in practical scenarios. In sensor network systems, each sensor has an initial value about the environment, and the network permits the allowed unidirectional communication between two nodes if and only if they are neighbors. The aim of the sensors is to distribute each individual’s value among the network to reach an equilibrium distribution and further to achieve an overall information of the place of interest. Therefore, how to locate each sensor and build the communication...
topology is of high priority. Based on the communication topology, designing a framework that rapidly distributes each individual’s value among the network is the second step [22], [23]. In [22], a two-stage hierarchical algorithm design is provided in which the first stage is a network topology design for rigidity in the network, while the second stage is an optimal weight design for network graphs characterizing efficiency based on the graph topology obtained in the first stage. In this paper, instead of using this two-step design, an MBNLP problem is formulated by introducing binary variables for topology into the weight design step. To enhance information dissemination and rapid response to damages or threats, the optimal distributed linear agreement (ODLA) problem [24] is solved by means of the new HMSO algorithm. Moreover, considering the communication cost for the sensor network, a new MBNLP problem is proposed by considering the tradeoff between distance among sensors and dissemination efficiency.

The outline of this paper is summarized as follows. First, mathematical preliminaries are provided in Section II. Then the new HMSO algorithm is introduced in Section III. In Section IV, optimal load shedding strategy and vulnerability for power systems are studied and solved numerically by using the new HMSO algorithm, and the sensor network deployment is presented in Section V. Finally, Section VI concludes the paper.

II. MATHEMATICAL PRELIMINARIES

A. Topology

In this paper, we use undirected or directed graphs to represent topologies of a network. Specifically, let \( \mathcal{G} = (\mathcal{V}, \mathcal{E}) \) be a directed graph (or digraph) denoting the network with the set of nodes (or vertices) \( \mathcal{V} = \{1, \ldots, n\} \) involving a finite nonempty set denoting the agents, and the set of edges \( \mathcal{E} \subseteq \mathcal{V} \times \mathcal{V} \) involving a set of ordered pairs \((i, j)\) denoting the direction of information flow. A graph or undirected graph \( \mathcal{G} \) is a directed graph for which the arc set is symmetric. If there is a path from any node to any other node in the graph, then we call the graph connected. The set of neighbors of node \( i \) for a graph is thus defined by \( \mathcal{N}_i = \{j \in \mathcal{V} : \{i, j\} \in \mathcal{E}\} \).

Finally, the matrix entry at the \( i \)th row and \( j \)th column of the arc-node incidence matrix \( A \) for a digraph is defined as:

\[
A(i, j) = \begin{cases} 
1 & \text{if } (j, i) \in \mathcal{E} \\
-1 & \text{if } (i, j) \in \mathcal{E} \\
0 & \text{otherwise}
\end{cases}
\]

and its Laplacian matrix \( L \) is defined as \( L = A^T A \).

B. Mixed-Binary Nonlinear Programming

Mathematically, a mixed-binary nonlinear programming problem is defined as:

\[
\begin{align*}
(P) \quad & \min f(x, y) \\
\text{s.t.} \quad & g(x, y) \leq 0, \\
& h(x, y) = 0, \\
& x \in X, \quad y \in Y
\end{align*}
\]

where \( \leq \) denotes \( \leq \) elementwise, \( X \subset \mathbb{R}^n \), \( Y \subset \mathbb{R}^m \), \( \mathbb{R}^n \) denotes the set of \( n \)-dimensional (column) vectors whose components are real numbers, and \( \mathbb{R}^m \) denotes the set of \( m \)-dimensional vectors whose components are either 0 or 1.

It follows from [11] that the optimization problem \((P)\) can be decomposed with \( x = [v^T, \xi^T]^T, y = [\omega^T, \psi]^T \) into the following problem

\[
\begin{align*}
(R) \quad & \min f(v, \omega) \\
\text{s.t.} \quad & G(v, \omega) \leq 0, \\
& v \in \Xi \cap V, \quad \omega \in \Omega \cap V
\end{align*}
\]

with \( V = \{[v^T, \omega^T]^T : h(v, \xi, \omega, \psi) = 0 \text{ for some } \xi \in \mathbb{R}^{n_x} \cap X \text{ and } \psi \in \mathbb{R}^{m_\omega} \cap Y\} \), where \( n_v \) denotes the dimension of \( v \) and \( m_\omega \) denotes the dimension of \( \omega \). This decomposition implies that \( \xi \) and \( \psi \) can be written as an implicit function of \( v \) and \( \omega \).

III. NEW HYBRID MULTIAGENT SWARM OPTIMIZATION

In this section, a new HMSO algorithm is detailed in Algorithm 1, and the flow diagram is shown in Fig. 1. The aim of this algorithm is to find an optimal solution to the minimization problem \( \min_x f(x) \). The algorithm accelerates the search for the desired solution by use of the neighboring agents’ information and three search directions. The first search direction \( \sum_{j \in \mathcal{N}_i} (v_j - v_i) \) accelerates the update for the agent’s velocity. The second direction switches between local information and neighbors’ information. The third search direction \((p - x)\) accelerates the movement of agent \( i \) to its best position. Moreover, in Algorithm 1, the position update formula for continuous variables is Equation (1) while the update formula for binary variables is shown in Equation (2). \( F \) is the feasible set for the optimization problem, \( \text{sign}(x) = \frac{x}{|x|} \), and \( \text{round}(X) \) rounds the elements of \( X \) to the nearest integers. In Fig. 1, the “gbest” position refers to the agent’s best known position while the “gbest” position refers to the multiagent network’s best known position. 

\[
x_i = \begin{cases} 
  x_i + v_i & \text{if } x_i + v_i \in F \\
  x_i & \text{otherwise}
\end{cases} \quad (1)
\]

\[
x_{i,j} = \begin{cases} 
  1 & \text{if } r_{i,j} < \text{sign}(v_{i,j}), \ x_{i,j} = 1, \text{ and } x_i \in F \\
  0 & \text{if } r_{i,j} \geq \text{sign}(v_{i,j}), \ x_{i,j} = 0, \text{ and } x_i \in F \\
  x_{i,j} & \text{otherwise}
\end{cases} \quad (2)
\]

IV. OPTIMAL LOAD SHEDDING STRATEGY AND VULNERABILITY FOR POWER SYSTEMS BY HMSO

In this section, the severity of a blackout for power systems is studied as an application of our new HMSO algorithm. Power systems have been extensively studied for its crucial impact on our daily life and industrial applications. To identify small groups of lines, whose removal would cause a server blackout, is an important issue for secure operation.
of the electric power grid. Therefore, an MBNLP problem is formulated in [3] by optimizing the total volume of load shed varying from line-cut variables and the phase angle variables. A lossless power system network with \( m \) bus and \( n \) lines is considered, and the voltages at the buses are assumed to be fixed and the dependence of real power injection at buses on the phase angle variables can be fully described by active power constraints. The power system model is developed as \( A^T B \sin(A\theta) - P = 0 \), where \( P \) is a vector of power injections, \( A \) is the node-arc incidence matrix of the topology of the power system, \( B \) is a diagonal matrix whose diagonal entries correspond to line admittances, \( \theta \) is a vector of phase angle variables, and \( \sin(A\theta) \) denotes a vector whose \( i \)-th component is \( \sin((A\theta)_i) \). To further study the changes in the topology, a binary-valued line parameter \( \gamma_i \), is introduced to indicate whether the \( i \)-th line is in service, specifically, \( \gamma_i = 1 \) if the line is out of service and \( \gamma_i = 0 \) if the line is in service. Matrix \( \Gamma \) is defined as a diagonal matrix whose diagonal entries corresponding to \( (1 - \gamma_i) \), so the power flow model can be rewritten as \( A^T B \Gamma \sin(A\theta) - P = 0 \). Hence, the optimal load shedding strategy is formulated in [3] as

\[
\begin{align*}
\text{min}_{\theta,Z} & \quad e^T Z^g \\
\text{s.t.} & \quad A^T B \Gamma \sin(A\theta) - (P + Z) = 0, \\
& \quad P^d \leq P^d + Z^l \leq 0, \\
& \quad 0 \leq \frac{\pi}{\pi} \\
& \quad -\frac{\pi}{\pi} \leq A\theta \leq \frac{\pi}{2} \\
& \quad 0 \leq \frac{\pi}{\pi} \leq P^g \geq P^g,
\end{align*}
\]  

where \( e \) denotes a column vector whose elements are all ones, \( P^g \) denotes power injections in generations, \( P^l \) denotes power injections in loads, \( Z^g \) denotes changes in generations, \( Z^l \) denotes changes in loads, \( P = [(P^g)^T, (P^l)^T]^T \), and \( Z = [(Z^g)^T, (Z^l)^T]^T \).

Next, the power network vulnerability analysis problem is formulated as a bilevel mixed-binary nonlinear optimization problem [3], where in the outer level we look for the critical lines, which corresponds to the combinatorial part of the problem, and in the inner level we measure the

---

**Algorithm 1 New Hybrid Multiagent Swarm Optimization Algorithm**

```plaintext```
for each agent \( i = 1, \ldots, q \) do
  Initialize the agent’s position with a uniformly distributed random vector: \( x_i \sim U([x, \bar{x}], \Gamma) \), where \( x \) and \( \bar{x} \) are the lower and upper boundaries of the search space;
  Update the agent’s velocity: \( v_i \sim U([y, \bar{y}], \Gamma) \), where \( y \) and \( \bar{y} \) are the lower and upper boundaries of the search space;
end for
repeat
  \( k \leftarrow k + 1 \);
  Choose random parameters: \( \eta, \lambda, \kappa \sim U(0, 1) \);
  Let \( n_v \) denote the number of continuous variables in the optimization problem;
  for each agent \( j = 1, \ldots, n_v \) do
    for \( f(\sum_{i \in N} x_i) < f(p_i) \) do
      Update the agent’s best known position: \( p_i \leftarrow f(\sum_{j \in N} x_j) \);
      If \( f(p_i) < f(p) \) update the multiagent network’s best known position: \( p \leftarrow p_i \);
      Update the agent’s velocity: \( v_i \leftarrow v_i + \eta \sum_{j \in N} (v_j - v_i) + \lambda (p_i - x_i) + \kappa (p - x_i) \);
    end for
  end for
  for each agent \( j = n_v + 1, \ldots, q \) do
    for \( \text{round}(f(\sum_{i \in N} x_i)) < f(p_i) \) do
      Update the agent’s best known position: \( p_i \leftarrow \text{round}(\sum_{j \in N} x_j) \);
      If \( f(p_i) < f(p) \) update the multiagent network’s best known position: \( p \leftarrow p_i \);
      Update the agent’s velocity: \( v_i \leftarrow v_i + \eta \sum_{j \in N} (v_j - v_i) + \lambda (p_i - x_i) + \kappa (p - x_i) \);
    end for
  end for
  Update the agent’s position component using (2);
  for \( f(x_i) < f(p_i) \) do
    Update the agent’s best known position: \( p_i \leftarrow x_i \);
    If \( f(p_i) < f(p) \) update the multiagent network’s best known position: \( p \leftarrow p_i \);
  end for
until \( k \) is large enough or the change of \( f \) is small
return \( p \)
```

---

Fig. 1. Flow diagram for the new HMSO algorithm
blackout severity by solving the load shedding problem, which corresponds to the nonlinear part of the problem. To formally state this problem, let $\mathcal{L}(A, B, \Gamma, \theta, P)$ denote an instance of the load shedding problem in (3)–(7), and let $\arg\min \mathcal{L}(A, B, \Gamma, \theta, P)$ denote an optimal solution to this problem. Then the power system vulnerability problem can be defined as follows.

$$
\min_{\theta, Z, \gamma} - e^T \gamma
$$

s.t. $Z = \arg\min \mathcal{L}(A, B, \Gamma, \theta, P)$,

$$-e^T Z^g \geq S,$$

$\gamma_i \in \{0, 1\}$ for $i = 1, 2, \cdots, m$

where $S > 0$ is a specified severity. Clearly this is a bilevel, mixed-binary optimization problem which is hard to solve practically. Here we will use the proposed new HMSO algorithm to solve this problem numerically.

In this paper, an IEEE 14-bus system shown in Fig. 2 is considered as an numerical illustration of the new HMSO algorithm, and the fitness values for both the new HMSO and improved PSO algorithms at each step are calculated by the objective function. There are 14 nodes and 20 lines in the system. For the optimal loading shedding problem, the convergence between the new HMSO and improved PSO is compared in Fig. 3 and the statics results are listed in Table I. The optimal solution is shown graphically in Fig. 4. It follows from this figure that Lines 4, 10, 11, 13, 15, and 20 are not in service to minimize change load and to keep the power system restore feasibility.

Further, the comparison between the new HMSO and improved PSO solving the power system vulnerability problem is shown in Fig. 5, and the statics results are listed in Table II and the optimal solution is shown graphically in Fig. 6, in particular, Lines 2, 3, 4, 8, 10, 17, and 20 are the source of all significant vulnerabilities in this system. From the simulation results, one can conclude that our new HMSO algorithm is superior to the improved PSO for MBNLP problems.
TABLE I

COMPARISON BETWEEN THE NEW HMSO AND IMPROVED PSO BY 15 EXECUTIONS FOR POWER SYSTEM LOAD SHEDDING

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Min</th>
<th>Max</th>
<th>Median</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>New HMSO</td>
<td>0.5002</td>
<td>0.7528</td>
<td>0.3551</td>
<td>0.5120</td>
</tr>
<tr>
<td>Improved PSO</td>
<td>0.5159</td>
<td>1.1387</td>
<td>0.6713</td>
<td>0.6300</td>
</tr>
</tbody>
</table>

TABLE II

COMPARISON BETWEEN THE NEW HMSO AND IMPROVED PSO BY 20 EXECUTIONS FOR POWER SYSTEM VULNERABILITY

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Min</th>
<th>Max</th>
<th>Median</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>New HMSO</td>
<td>-17</td>
<td>-9</td>
<td>-14</td>
<td>-13.25</td>
</tr>
<tr>
<td>Improved PSO</td>
<td>-18</td>
<td>-8</td>
<td>-11.5</td>
<td>-12</td>
</tr>
</tbody>
</table>

V. SENSOR NETWORK DEPLOYMENT BY HMSO

In this section, the sensor network deployment for load balancing in networks is considered. Each sensor has an initial value about the environment, and the network permits the allowed unidirectional communication between two nodes if and only if they are neighbors. The aim of the sensors is to distribute each individual’s value among the network to reach an equilibrium distribution, and further to achieve an overall information of the place of interest. Therefore, how to locate each sensor and build the communication topology is of high priority. Based on the communication topology, designing a framework that rapidly distributes each individual’s value among the network is the second step. In [22], a two-stage design is provided in which the first stage is a network topology design for rigidity in the network, while the second stage is an optimal weight design for network graphs characterizing efficiency based on the graph topology obtained in the first stage. In this section, instead of using the two-step design, an MBNLP problem is formulated by introducing binary variables for topology into the weight design stage, and converting the two-stage design into an MBNLP problem.

The system we consider in this paper is given by

\[ x(t + 1) = Wx(t) \]  

where \( x(t) = [x_1(t), \ldots, x_q(t)] \in \mathbb{R}^q \) is the state vector for the sensor and the constraints on matrix \( W \) can be expressed as \( W \in \mathcal{W} \), where \( \mathcal{W} = \{ W \in \mathbb{R}^{q \times q} : W_{i,j} = 0 \text{ if } (i, j) \notin \mathcal{E} \} \).

The original optimal distributed linear agreement (ODLA) problem is stated in [24]:

\[
\min_W \quad J(W, x(0)) \\
\text{s.t.} (8) \text{ holds, } W \in \mathcal{W}, \text{ rank}(W - I) = q - 1, \\
W \text{ is semistable, } e^T W = e^T, \text{ } W e = e
\]

where \( I \) denotes the identity matrix, \( W \) is semistable if and only if \( \lim_{k \to \infty} W^k \) exists, rank denotes the rank operator,

\[
J(W, x(0)) = \sum_{t=0}^{\infty} [(x(t) - x_e)^T Q (x(t) - x_e) + (Wx(t) - W x_e)^T R \times (Wx(t) - W x_e)] 
\]

\( x_e \) is the equilibrium point for the system (8), and \( Q, R \) are the positive definite matrices.

Addressing the ODLA problem directly seems quite difficult due to the facts that (9) is the infinite horizon and \( W \) satisfies semistability constraints. Hence, it is much easier to solve the original ODLA problem if we can convert it into the following semidefinite programming problem [24].

**Proposition 5.1:** The ODLA problem can be recast as follows:

\[
\min_W \quad x^T(0) Z x(0) \\
\text{s.t.} (8) \text{ holds, } W \in \mathcal{W}, \text{ rank}(W - I) = q - 1, \\
e^T W = e^T, \text{ } W e = e, \\
Z > 0, \quad Z = W^T Z W + (I - W)^T (Q + W^T R W) (I - W)
\]

In this section, a binary matrix is introduced into the ODLA problem by considering the sensor network distance between neighbors. Before processing to the problem formulation, we let \( L \circ W \) denote the Hadamard product between matrices \( L \) and \( W \). The new sensor network deployment problem can be formulated as

\[
\min_{W, L} \quad x^T(0) Z x(0) \omega_1 + e^T (L \circ D) e \omega_2 \\
\text{s.t.} (8) \text{ holds, } L \in \mathbb{B}^q, \text{ } L \circ W \in \mathcal{W}, \\
\text{rank}(L \circ (W - I)) = q - 1, \\
e^T L \circ W = e^T, \text{ } L \circ W e = e, \\
Z > 0, \quad Z = (L \circ W)^T (Q + (L \circ W)^T R (L \circ W)) (I - L \circ W)
\]

where \( D \) is the distance matrix for the sensor network, and \( \omega_1 \) and \( \omega_2 \) are positive weights.

![Figure 6](image-url)  

The optimal solution for power system vulnerability problem obtained by the new HMSO, in which the lines are not in service are heightened.
Since the optimization objective is a matrix based problem, and the new HMSO algorithm optimizes vector based problems, some transformations between matrices and vector are needed for practical implementation. Here the rand command denotes the rand function in MATLAB where rand(N) returns an N-by-N matrix containing pseudorandom values drawn from the standard uniform distribution on the open interval (0,1) and rand(M,N) returns an M-by-N matrix.

The first transform function is called \( v = M2V(L) \), which is shown in Algorithm 2, converting matrix \( L \) into vector \( v \). Since the matrix \( L \) is symmetric, only triangular part of the matrix is needed, and in here, the upper-triangular part is considered. Another property of the matrix \( L \) is that the summation of each row of the matrix is 1. To satisfy this condition, the diagonal elements can be assigned as the difference between 1 and the summation of the other element in the same row. So the upper-triangular part without diagonal elements is transformed to a vector.

The second transform function is called \( L = V2M(v) \), which is shown in Algorithm 3, transforming vector \( v \) to matrix \( M \). This function is the inverse of the function \( v = M2V(L) \), the matrix \( L \) generated by this function satisfies the symmetric property and the summation of each row and column of \( L \) is 1.

Algorithm 2 Function \( v = M2V(L) \)

Step 1. Initialize vector \( v = \text{rand}(\sum_{i=1}^{n-1} (n - i), 1) \)

Step 2. \( v(1, n - 1) = L(1, 2 : n) \)

\( v(n, 2n - 3) = L(2, 3 : n) \)

return \( v \)

The procedure of using these algorithms with HMSO is given by the following steps.

- Transform the matrix into a vector by \( v = M2V(L) \) for both \( L \) and \( W \).
- Use Algorithm 1 to optimize \( y = \text{obj}(v) \) and find the optimal solution \( p \) which is a vector, where \( \text{obj} \) denotes the vectorized form of (10).
- Transform vector \( p \) to matrix \( L \) by \( L = V2M(p) \) and \( L \) is the optimal matrix for our optimization problem.

In this paper, we provide two cases for our new HMSO algorithm to solve the new ODLA problem for sensor network deployment. In here, we consider a 10-node sensor network which is geospatially distributed by the distance matrix \( D \), and the fitness values for both the new HMSO and improved PSO algorithms at each step are calculated by the objective function. First, the original ODLA problem with \( \omega_1 = 1 \) and \( \omega_2 = 0 \) for (10) is solved by both the new HMSO and improved PSO algorithms which means that the topology between the sensors are fixed before and only the weight need to be designed. Table III provides the results about the comparison between the new HMSO and improved PSO by running 20 executions. Moreover, the convergence comparison is shown in Fig. 7, and the optimal \( W \) obtained by the new HMSO is given by the following matrix.

The graphical representation of this matrix is shown in Fig. 8. Under this framework for the sensor network system, the trajectories of the sensors’ states are shown in Fig. 9. From the optimal solution result, the topology for the sensor network is fully connected, which means the algorithm can achieve the fastest convergence rate in contrast to other topologies with the same weights. The reason lies in the fact that the communication cost is not considered in this case.

Secondly, we set \( \omega_1 = 1 \) and \( \omega_2 = \frac{1}{10} \) for (10), and hence, the topology between the sensors is also needed to be design while the weight design process. In this case, we set the distance matrix as matrix (11). Table IV provides the results about the comparison between the new HMSO and improved
The optimal solution for the ODLA problem obtained by the new HMSO and improved PSO by running 20 executions. Moreover, the convergence comparison is shown in Fig. 10.


(11)

The optimal W for the new ODLA problem is given by

\[
\begin{bmatrix}
0.6010 & 0 & 0.0236 & 0.0461 & 0.0806 & 0 & 0.0600 & 0 & 0.0174 & 0 \\
0.0045 & 0.0108 & 0 & 0 & 0.0770 & 0 & 0 & 0 & 0 & 0 \\
0.0236 & 0.0308 & 0.4120 & 0 & 0.0998 & 0.0186 & 0.0118 & 0 & 0 & 0.0808 \\
0.0461 & 0 & 0 & 0.3852 & 0 & 0.0577 & 0.0660 & 0.0623 & 0.0149 & 0.0958 \\
0.0806 & 0 & 0.0998 & 0 & 0.3504 & 0 & 0 & 0 & 0 & 0 \\
0.0660 & 0.0770 & 0.0918 & 0.0660 & 0 & 0 & 0.4764 & 0.0560 & 0.0650 & 0.0672 \\
0.0034 & 0 & 0 & 0.0623 & 0 & 0.0434 & 0.0560 & 0.5509 & 0 & 0.0187 \\
0.0034 & 0 & 0 & 0.0149 & 0 & 0 & 0.0650 & 0 & 0.5676 & 0.0329 \\
0 & 0 & 0.0808 & 0.0958 & 0 & 0 & 0.0672 & 0.0187 & 0.0329 & 0.4623 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\]

The graphical representation of this matrix is shown in Fig. 11. Under this framework for the sensor network system, the trajectories of the sensors’ states are shown in Fig. 12. In this case, the communication cost is also considered as part of the cost function, so the optimal weights and topology shown in Fig. 12 are the tradeoff between convergence rate and communication cost. For example, Sensor 1 does not communicate with Sensors 2, 6, 8, and 10 to save the communication cost but Sensor 1 has a higher weight value to achieve a faster convergence rate compared with the first case.

VI. CONCLUSION

In this paper, some cyber-physical applications of a new emerging swarm intelligence optimization algorithm, so called hybrid multiagent swarm optimization algorithm, in the areas of power system analysis and sensor network deployment, is investigated through mixed-binary nonlinear programming problems. In particular, in the area of power systems, we focus on the problems of how to decide the cut-off supplies minimizing change load and generation to restore feasibility to the system to avert a blackout, and how to identify small groups of lines, whose removal would cause a severe blackout. With the formulation of mixed-binary nonlinear programming for these problems, a new HMSO algorithm is used to solve them numerically. Moreover, a
new load balancing algorithm for the sensor network system is also numerically illustrated by means of the new HMSO algorithm.

REFERENCES


