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Optimal Node Placement of Industrial Wireless Sensor Networks Based on Adaptive Mutation Probability Binary Particle Swarm Optimization Algorithm

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Abstract. Industrial Wireless Sensor Networks (IWSNs), a novel technique in industry control, can greatly reduce the cost of measurement and control and improve productive efficiency. Different from Wireless Sensor Networks (WSNs) in non-industrial applications, the communication reliability of IWSNs has to be guaranteed as the real-time field data need to be transmitted to the control system through IWSNs. Obviously, the network architecture has a significant influence on the performance of IWSNs, and therefore this paper investigates the optimal node placement problem of IWSNs to ensure the network reliability and reduce the cost. To solve this problem, a node placement model of IWSNs is developed and formulized in which the reliability, the setup cost, the maintenance cost and the scalability of the system are taken into account. Then an improved adaptive mutation probability binary particle swarm optimization algorithm (AMPBPSO) is proposed for searching out the best placement scheme. After the verification of the model and optimization algorithm on the benchmark problem, the presented AMPBPSO and the optimization model are used to solve various large-scale optimal sensor placement problems. The experimental results show that AMPBPSO is effective to tackle IWSNs node placement problems and outperforms discrete binary Particle Swarm Optimization (DBPSO) and standard Genetic Algorithm (GA) in terms of search accuracy and the convergence speed with the guaranteed network reliability.

Keywords: industrial wireless sensor networks, node placement, binary particle swarm optimization, adaptive mutation.

1. Introduction

In harsh industrial environments, a large number of hazards ranging from strong mechanical vibrations, high temperatures, fragile surfaces, noisy electrical effects and even explosive gases may occur. Although wired industrial communication systems, such as fieldbus systems and wired Highway Addressable Remote Transducer (HART), have been used successfully in the field of factory automation and process automation [1], [2] , on one hand, it is still difficult to install the wiring in these harsh industrial environments. On the other hand, the installation and maintenance of cables and sensors are much more expensive than sensors themselves for the traditional wired control systems. In recent years, wireless sensor networks (WSNs) have been applied in numerous fields, such as space exploration and border protection. By deploying wireless sensors to operate unattended in harsh industrial environments, it would be possible to avoid the risks to human lives and decrease the cost of the applications [3]. Thus, the industrial wireless communication technology has drawn increasing attention and been applied to factory automation and industrial process control [4], [5], [6], [7]. With Industrial Wireless Sensor Networks (IWSNs), engineers can collect information from where it previously has been economically or technologically infeasible, and therefore the process would be enhanced with respect to quality and quantity further. Now, IWSNs have been applied in food industry, beverages industry, pharmaceuticals industry, oil industry, gas industry, chemical industry, mining industry, refining industry, power plants, pulp industry, etc. The industrial applications of IWSNs demonstrate that wireless installation typically costs as much as 50 percent less than the wired alternative. Meanwhile, IWSNs can improve efficiency and be applied to the fields where the wired system cannot be installed.

However, there are still obstacles for the large-scale applications of IWSNs, among which the reliability of networks is the absolute requirement for most industrial systems. Thus this paper develops an optimal node placement model for the cluster-based IWSNs in which the reliability, cost and scalability of the network are taken into account. To obtain the best performance, a novel adaptive mutation probability binary Particle Swarm Optimization algorithm (AMPBPSO) is proposed to solve the optimal node placement problem of large-scale IWSNs with the model.

The rest of this paper is organized as follows. Section 2 introduces the related research work. Section 3 presents the node placement model of IWSNs where the objective function is formulated and introduced in detail. Section 4 specifies the optimization mechanism and procedure of AMPBPSO. The implementation of solving the optimal node placement based on AMPBPSO is addressed in Section 5. In Section 6, AMPBPSO and the developed model are first verified on the benchmark problem. Then AMPBPSO is utilized to solve the optimal node placement problems of IWSNs, and the results are compared with those of discrete binary Particle Swarm Optimization (DBPSO) and Genetic Algorithm (GA). Finally, the conclusions and future work are drawn in Section 7.

2. Related Work

Nowadays, Industrial Wireless Sensor Networks (IWSNs) have become a new research hotspot in industrial control technologies. To improve the performance of IWSNs and meet requirements in industrial applications, researchers developed various strategies to enhance and extend IWSNs. Heo et al. [8] proposed a new energy aware routing protocol for IWSNs in which real-time and reliable delivery as well as energy saving were considered. Park et al. [9] presented an adaptive protocol for IWSNs, called Breath, which ensured a desired packet delivery and delay probabilities while minimizing the energy consumption of network where the reliability of the packet were treated as the constraint. Bertocco et al. [10] developed a suitable testbed enlisting IEEE 802.14.5 wireless sensor nodes for studying the interference to optimize the network setup. Considering the high bit error rate characteristics of wireless channel due to harsh conditions like attenuation, noise and channel fading, Balasubramanian et al. [11] offered a novel real-time Medium Access Control (MAC) protocol that was specifically tailored to the requirement of the industrial environments. Villaverde et al. [12] introduced a route selection algorithm, named InRout, where local information was shared among neighboring nodes of IWSNs to enable efficient route selection. In their work, route selection is described as a multi-armed bandit task and Q-learning techniques are adopted to gain the best solution with low overhead, and thus it can improve the reliability and typical quality of service. Chen et al. [13] depicted a new distributed estimation and collaborative control scheme for wireless sensor and actuator networks to make up for the problems caused by the unreliable wireless and multi-hop communication among sensors and actuators in IWSNs. Yu et al. [14] discussed the use of forward error correction (FEC) codes in IWSNs to improve the link reliability and reduce the number of retransmissions in harsh industrial environments. They proposed a FEC scheme suitable for MAC level protection in which the packet was divided into groups and encoded using systematic FEC codes. Xing et al. [15] optimized the MAC protocol and presented a modified multi-channel one for IWSNs which could achieve more reliable communication in an energy and bandwidth efficient way.

Although the previous work has improved the reliability of IWSNs based on protocol modification and routing optimization, it is still necessary to carefully design and optimize the node placement scheme of IWSNs from the system point of view as it directly determines the final performance of networks especially for large-scale IWSNs. Actually, node placement has drawn increasing attention in non-industrial applications of WSNs, and various deployment strategies and algorithms have been proposed to construct sensor networks for different design goals, such as the minimum cost, highest energy efficiency, network coverage and connectivity of WSNs. However, the optimal node placement of WSNs has been proven to be an NP-hard problem [16], [17], and therefore evolutionary algorithms have been studied and applied to node deployment problems, which have shown the outstanding performance in solving a wide variety of NP-hard problems. As the most widely used evolutionary algorithm, Genetic Algorithms (GAs) have been successfully used to design the node placement of WSNs. Ferentinos and Tsiligiridis [18] used a GA to design WSNs to fulfill the existent connectivity constraints and incorporate energy-conservation to guarantee maximum life span of the network. Jia et al. [19] investigated the coverage control scheme based on a multi-objective GA in which the minimum number of sensors was selected in a densely deployed environment while preserving full coverage of networks. Hu et al. [20] developed a hybrid approach of combining a genetic algorithm with schedule transition operation to maximizing the lifetime of sensor networks. To achieve better results, various meta-heuristic algorithms, such as Particle Swarm Optimization (PSO) [21], [22], Differential Evolution (DE) [23], Harmony Search [24] and Ant Colony Optimization (ACO) [25], [26] have been applied to the optimal design of WSNs. However, the previous works mainly focus on optimizing node placement for maximizing the lifetime of networks due to the characteristics of WSN applications. Different from general WSNs in the non-industrial applications [27], the demand of energy saving in IWSNs is alleviated as the network is maintained and the battery of nodes can be replaced. But IWSNs have stringent requirement of the communication reliability because the real-time field data are transmitted to the control system through IWSNs. Therefore, the network reliability should be especially concerned in the node placement of IWSNs, and the node placement strategies for the WSNs mentioned above are unsuitable for IWSNs. Now only few attempts have been made on optimizing the node deployment in IWSNs to satisfy the network reliability needs. And as far as we know, no one has addressed this problem utilizing intelligent optimization algorithms.

3. Node Placement of IWSNs

3.1. Communication model of cluster-based IWSNs

The node placement problem of IWSNs with the two-tiered clustering architecture is addressed in this work. The lower-layer is the single-hop communication between the sensor node and its cluster-head node. The upper-layer is the routing among cluster-heads to the base station via multi-hopping. In IWSNs, each node (including the sensor node and cluster-head node) has a maximum communication range. The communication radii of the sensor node and cluster-head node are denoted as R_S and R_{CH}, respectively. Generally, the communication capacity of the cluster-head node is more powerful than that of the regular sensor node. For instance, assuming that three sensor nodes (S1, S2 and S3) and three cluster-head nodes (CH1, CH2 and CH3) placed in the field as Fig. 1, the communication radii are constant and the communication ranges of them can be determined. The distance between the sensor node S1 and the cluster-head node CH1 or CH2 is below R_S, that is, CH1 and CH2 are covered by the communication circle of S1, and thus the monitored data of S1 can be reliably transmitted to CH1 or CH2. However, the data transmitted from S2 will not be received by CH2 as the location of CH2 is beyond the maximum communication range of S2. In case of CH1 running out of its energy and the data of any sensor cannot be transmitted to the base station, which will make the whole network break down and cause the shutdown of the industry system or even hazard. Thus the extra nodes have to be deployed for redundancy to guarantee the essential reliability and robustness of IWSNs. Besides, the additional cluster-head nodes can improve the balance of load and extend the lifetime of batteries, which reduces the maintenance work of IWSNs. In summary, two questions, i.e. how many cluster-head nodes are needed at least and how to place them, should be considered carefully to satisfy the design goals of IWSNs.

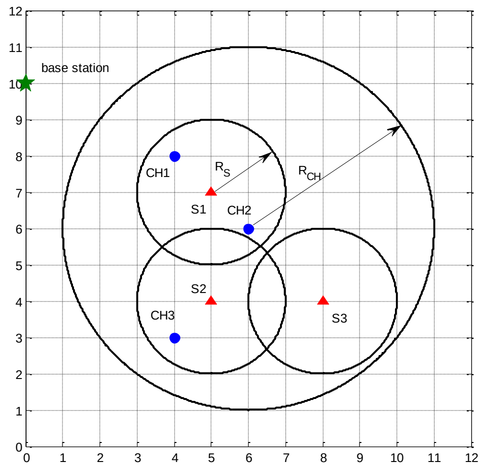

Fig. 1. A sample on the communication model of sensor nodes (▲) and cluster-head nodes (●)

3.2. Optimal node placement model of IWSNs

The main objective of designing the architecture of IWSNs is to guarantee the reliability of IWSNs as well as minimize the investment cost and the maintenance cost of networks. In addition, the maximum communication load of cluster-head nodes also need be considered for the scalability and real time of the system. Therefore, the optimal node placement model of IWSNs is a constrained multi-objective optimization problem and can be formulated as (1)-(2).

$$f = \alpha \times C + \beta \times SD_{CL} \ . \quad (1)$$

$$s.t. \quad \begin{cases} MIN_{CH}^{S} = L_{SN} \geq 2 \\ MIN_{CH}^{CH} = L_{CN} \geq 2 \\ LCH_j \leq MCL - 1 \end{cases} . \quad (2)$$

where C is the setup cost of IWSNs; SD_{CL} is the standard deviation of cluster-head communication load which indicates the maintenance cost of IWSNs; α and β are the weighting factors with $\alpha + \beta = 1$. MIN_{CH}^{S} is the minimum communicating cluster-head number of all the sensors, and MIN_{CH}^{CH} is the least communicating cluster-head number of all the cluster-head nodes. L_{SN}, L_{CN} and MCL represent the sensor node reliability constraint, the cluster-head node reliability constraint and the maximum load constraint, respectively. LCH_j is the load number of the j-th cluster-head.

Reliability Constraint. To ensure the communication reliability of IWSNs, each node must have at least one redundant cluster-head node; that is, the cluster-head number for each node in IWSNs should be more than two as (3)

$$\begin{cases} MIN_{CH}^{S} = L_{SN} \geq 2 \\ MIN_{CH}^{CH} = L_{CN} \geq 2 \end{cases} . \quad (3)$$

where L_{SN} and L_{CN} are the pre-defined least numbers of cluster-heads for sensor nodes and cluster-head nodes, respectively.

As seen in Fig. 2, the sensor node S1 and the cluster-head node CH4 have one redundant cluster-head node, i.e. CH2 and CH6, respectively. When CH1 or CH5 fails, the data of S1 still can be transmitted to the base station successfully due to the assigned redundant cluster-head nodes, and therefore the reliability of IWSNs is improved and guaranteed.

Suppose that there are N_s sensor nodes and N_{ch} cluster-head nodes placed in the industry field and N_i (i = 1, 2,…, N_s) and M_j (j = 1, 2,…, N_{ch}) are the cluster-head node numbers of the i-th sensor node and the j-th cluster-head, respectively, MIN_{CH}^{S} and MIN_{CH}^{CH} can be calculated as (4)-(5).

$$MIN_{CH}^{S} = \min\{N_i, | \, i = 1, 2, ..., N_S\} \ . \quad (4)$$

$$MIN_{CH}^{CH} = \min\{M_j, | \, j = 1, 2, ..., N_{ch}\} \ . \quad (5)$$

However, a node need not transmit its data to every cluster-head node in its communication range. Thus, in this work every sensor node or cluster-head node only communicates with the nearest L_{SN} or L_{CN} cluster-head nodes. The nearest cluster-head node is used as the regular working one and the others are reserved as the redundant ones.

Maximum Load. Although the energy and communication capacity of cluster-head nodes are more powerful than those of sensor nodes, their load-driven capacity is still limited owing to the finite computation ability. Thus, the total load of cluster-head nodes should not be beyond the maximum communication load *MCL*. Furthermore, at least one configuration point should be reserved for the upgrading or maintenance of the system. Therefore, the maximum number of load nodes for each cluster-head node is defined as (6).

$$LCH_j \leq MCL - 1\,. \tag{6}$$

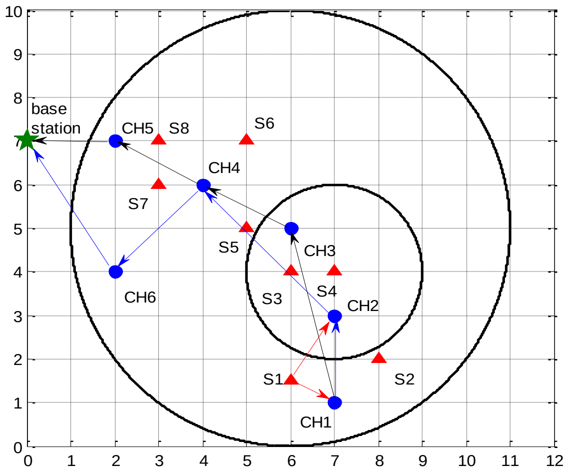

Fig. 2. An instance of the reliable IWSNs (the symbol ▲ represents the sensor node and the symbol ● represents the cluster-head node)

Setup Cost. When constructing IWSNs, the setup cost should be reduced without decreasing the performances of the system, especially in the very large-scale applications. For the node placement in IWSNs, the change of the cost mainly lies in the investment of cluster-head nodes as the sensor nodes are already determined by the requirements of monitoring. Thus, the setup cost can be defined as (7)

$$C = P_{ch} \times N_{ch}\ . \tag{7}$$

where N_{ch} is the number of the cluster-head nodes used and P_{ch} is the weight of the cluster-head node number .

Maintenance Cost. The communication load equilibration of cluster-head nodes plays a key role in balancing the energy consumption. As the communication of node needs energy supply, the high-load cluster-head node consumes energy faster than the others. To insure the normal running of IWSNs, the battery of cluster-head node need be replaced before its energy totally runs out. Thus, the unbalanced load uniformity will bring the frequent maintenance of IWSNs, which should be avoided. Therefore, the load uniformity of IWSNs is considered as the main metric of the maintenance cost to be optimized in this paper, which can be indicated by the standard deviation of the cluster-head load (SDCL) as (8)-(9),

$$SD_{CL} = \sqrt{\frac{\sum_{j=1}^{Nch}(LCH_j - ML_{CH})^2}{Nch-1}} \ . \tag{8}$$

$$ML_{CH} = \frac{\sum_{j=1}^{Nch} LCH_j}{Nch} \ . \tag{9}$$

where ML_{CH} is the mean load of all the cluster-head nodes.

4. Adaptive Mutation Probability Binary Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm was first proposed by Kennedy and Eberhart in 1995 [28], which has been studied and applied to solve numerous science and engineering problems successfully. It works with a group of particles. Each particle can be considered as a candidate solution and represented by a position vector $x_i = \left(x_{i1}, \cdots, x_{ij}, \cdots, x_{iD}\right)$ in a D dimensional search space, which keeps on moving toward new points in the search space with the addition of a velocity vector $v_i = \left(v_{i1}, \cdots, v_{ij}, \cdots, v_{iD}\right)$ to facilitate the search procedure. During the search process all particles move toward the areas of potential solutions by utilizing the cognitive and social learning components. The process is repeated until any prescribed stopping criterion is reached. After any iteration, each particle updates its position and velocity to achieve a better fitness value according to (10)-(11)

$$v_{ij}^{G+1} = w \times v_{ij}^{G} + c_1 \times r_1 \times (P_{ij}^{G} - x_{ij}^{G}) + c_2 \times r_2 \times (Pg_j^{G} - x_{ij}^{G}) \ . \tag{10}$$

$$x_{ij}^{G+1} = v_{ij}^{G+1} + x_{ij}^{G} \ . \tag{11}$$

where v_{ij}^{G} represents the velocity of the j-th element of the i-th individual at iteration G; w is the inertia weight; c_1 and c_2 are called as the acceleration factors, usually valued as 2.0; r_1 and r_2 are the uniform random numbers between 0 and 1; x_{ij}^{G} represents the position of the j-th decision variable of the i-th individual at iteration G; P_i^{G} and Pg^{G} denote the local best position of the *i*-th individual and the global best position of the group until iteration *G*, respectively.

However, the standard PSO and majority of its variants are developed for optimization problems in continuous space, which cannot be used to solve discrete binary optimization problems directly. To extend its application fields, Kennedy and Eberhart proposed a discrete binary PSO (DBPSO) algorithm in 1997 [29]. DBPSO reserves the velocity updating formula (10), but the velocity vector is transformed into the probability of being “1” of each bit through the sigmoid limiting function as (12). Finally, the binary solution is generated based on this probability as (13)

$$sigmoid(v_{ij}^{G+1}) = \frac{1}{1+e^{-v_i^{G+1}}} \ . \qquad (\mathbf{12})$$

$$x_{ij}^{G+1} = \begin{cases} 1, \ if \ \ rand() \le sigmoid(v_{ij}^{G+1}) \\ 0, \ else \end{cases} . \qquad (\mathbf{13})$$

where $rand()$ is a random number uniformly distributed in [0,1].

However, DBPSO is easy to be trapped in the local optima. To make up for it, a probability binary Particle Swarm Optimization (PBPSO) algorithm was presented in our previous work, which has been proven to be efficient and effective for solving various optimization problems [30], [31], [32]. Considering that the optimal node placement of large-scale IWSNs is a high-dimensional constrained multi-objective NP-hard problem and its fitness evaluation is very time-consuming, a novel adaptive mutation PBPSO (AMPBPSO) is proposed in this paper into which an adaptive mutation operator is introduced to improve the search ability and convergence speed of the algorithm.

4.1. Initialization

AMPBPSO adopts the binary encoding. Assume the population size of AMPBPSO and the dimension of solutions are *N* and *D*, respectively. The *i*-th individual, i.e. a candidate solution, is denoted as $bx_i = \left(bx_{i1}, \cdots, bx_{ij}, \cdots, bx_{iD}\right)$, where $i = 1, 2, \cdots, N$; $j = 1, 2, \cdots, D$; $bx_{ij} \in \{0,1\}$ .The local best position of the *i*-th individual and the global best position of the group are denoted as $bP_i = \left(bP_{i1}, \cdots, bP_{ij}, \cdots, bP_{iD}\right)$ and $bPg = \left(bPg_1, \cdots, bPg_j, \cdots, bPg_D\right)$, respectively. In the search process, the whole updating mechanism of PSO is reserved. However, the original position vector $x_i = \left(x_{i1}, \cdots, x_{ij}, \cdots, x_{iD}\right)$ of PSO is redefined as the pseudo-probability of being “1” in AMPBPSO, and the velocity $v_i = \left(v_{i1}, \cdots, v_{ij}, \cdots, v_{iD}\right)$ represents the change of the pseudo-probability x_i.

bx_{ij}, v_{ij} and x_{ij} of AMPBPSO is initialized as (14)-(16),

$$bx_{ij}^{0}=\begin{cases}1, & \text{if } rand()\le 0.5\\ 0, & \text{otherwise}\end{cases}. \quad (\mathbf{14})$$

$$v_{ij}^{0}=(v_{\max}-v_{\min})\times rand()+v_{\min}\ . \quad (\mathbf{15})$$

$$x_{ij}^{0}=(x_{\max}-x_{\min})\times rand()+x_{\min}\ . \quad (\mathbf{16})$$

where $rand()$ is a random number uniformly distributed in [0,1]; $v_{\min}$ and $v_{\max}$ are the lower and upper velocity bound; $x_{\min}$ and $x_{\max}$ are the pre-defined lower and upper pseudo-probability bound, respectively.

4.2. Population Updating

Like PSO, the velocity v_i and the pseudo-probability x_i of AMPBPSO is dynamically updated according to (17)-(18),

$$v_{ij}^{G+1}=w\times v_{ij}^{G}+c_1\times r_1\times(bP_{ij}^{G}-bx_{ij}^{G})+c_2\times r_2\times(bPg_j^{G}-bx_{ij}^{G})\ . \quad (\mathbf{17})$$

$$x_{ij}^{G+1}=v_{ij}^{G+1}+x_{ij}^{G}\ . \quad (\mathbf{18})$$

Note that the binary solution bx_{ij}^{G}, bP_{ij}^{G} and bPg_j^{G} are used here instead of x_{ij}^{G}, P_{ij}^{G} and Pg_j^{G} in the standard PSO. If $x_{ij}^{G+1}>x_{\max}$ or $x_{ij}^{G+1}<x_{\min}$, we fix x_{ij}^{G+1} to $x_{\max}$ or $x_{\min}$, respectively. After the updating of the pseudo-probability, the real probability pr_{ij} is calculated and adopted to generate a new binary solution through the probability estimation operator as (19)-(20).

$$pr_{ij}^{G+1}=(x_{ij}^{G+1}-x_{\min})/(x_{\max}-x_{\min})\ . \quad (\mathbf{19})$$

$$bx_{ij}^{G+1}=\begin{cases}1, & if\ \ rand()\le pr_{ij}^{G+1}\\ 0, & otherwise\end{cases}. \quad (\mathbf{20})$$

4.3. Adaptive Mutation

Although the standard PBPSO is efficient and effective, the performance of PBPSO is not quite satisfactory on high-dimensional problems. To improve the search ability and avoid premature convergence, an adaptive mutation operator is adopted which operates as (21)-(22)

$$if\ \ rand() < p_m,\ bx_{ij}^G = \begin{cases} 1,\ if\ \ bx_{ij}^G = 0 \\ 0,\ if\ \ bx_{ij}^G = 1 \end{cases}. \quad (\mathbf{21})$$

$$p_m = \frac{1}{D} \times (0.05 + \frac{1.45}{G_{\max}} \times G). \quad (\mathbf{22})$$

where p_m is the mutation rate of each bit. In AMPBPSO, p_m adaptively varies based on the solution dimension D and the iteration number G; that is, p_m linearly increases from $\frac{0.05}{D}$ to $\frac{1.5}{D}$ in the search process. The introduction of the dimension D is to enhance the scalability of the algorithm, and the linear increment of p_m can retain the diversity of the population. The final value of p_m, i.e. $\frac{1.5}{D}$, is adopted to ensure the accuracy of local search.

The evolutionary mechanism of AMPBPSO can be described as Fig. 3. Unlike DBPSO discarding the position updating formula and using the velocity as the probability to generate solutions, AMPBPSO reserves the original position of PSO by re-defining it as the pseudo-probability and therefore the entire updating mechanism of PSO is inherited. All the binary individuals of AMPBPSO have the pseudo-probability states as well as velocity states, which are updated following the framework of PSO and adopted to yield new candidate solutions using the probability estimation operator. For one thing, as the pseudo-probability of each individual is updated from generation to generation according to the information from its historical and global best individuals, AMPBPSO has the strong global exploration ability. For another, AMPBPSO adopts the pseudo-probability vector to create the new solution, thus it can maintain population diversity effectively. Moreover, the adaptive mutation operator enhances further the capability of local search as well as escaping from the local optima. Therefore, AMPBPSO can achieve an appropriate balance between exploration and exploitation.

After the offspring solutions are generated, the fitness of each individual is calculated and the local best position as well as the global best position is replaced if the fitness value of the new one is better. In summary, the procedure of AMPBPSO can be depicted as Fig. 4.

5. Implementation of AMPBPSO for the Node Placement in IWSNS

5.1. Solution Representation

For industrial applications, the sensor nodes are deployed for monitoring and their locations are already determined. Thus, the variables included in the optimal node placement of IWSNs are the number and positions of the cluster-head nodes used. Each individual of AMPBPSO specifies the number and positions of cluster-head nodes encoded as a binary vector, where a bit “1” indicates that a cluster-head node is placed at the corresponding grid conjunction while a bit “0” denotes the opposite. Fig. 5 displays an example individual, which represents a grid with four rows and four columns. The grid junctions are encoded row by row into the binary vector, and therefore a 16-bits binary solution can be used to delineate a corresponding candidate deployment scheme.

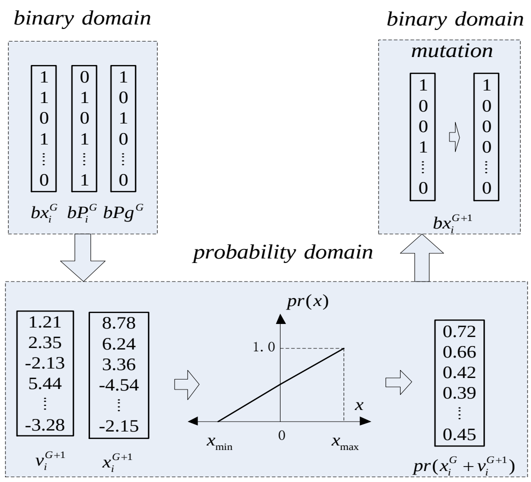

Fig. 3. Evolutionary mechanism of AMPBPSO

5.2. Fitness Function

As mentioned above, the optimal node placement of IWSNs is a constrained optimization problem. To deal with the constraints, the penalty function method is introduced to fix the fitness and lead the algorithm to search in the feasible areas effectively as (23)-(26).

$$f_p = f + p_1 + p_2 + p_3 \ . \tag{23}$$

$$p_1 = \sum_{i=1}^{Ns} \max\{0, c_1 \times (L_{SN} - N_i)\} \ . \tag{24}$$

$$p_2 = \sum_{j=1}^{N_{CH}} \max\{0, c_1 \times (L_{CN} - M_j)\} \ . \tag{25}$$

$$p_3 = \sum_{j=1}^{N_{CH}} \max\{0, c_2 \times (LCH_j + 1 - MCL)\} \ . \tag{26}$$

where f_p is the final fitness value; p_1, p_2 and p_3 are the penalty items of the sensor node reliability constraint, the cluster-head node reliability constraint and the maximum load number constraint, respectively. c_1 is the penalty coefficient of the reliability constraints, and c_2 is the penalty coefficient for violating the limitation of the communication load.

5.3. Optimal node placement of IWSNs based on AMPBPSO

Based on the pre-defined fitness function, AMPBPSO iteratively generates new candidate solutions to search the optimal node placement scheme of IWSNs. The whole procedure of designing the optimal node placement with AMPBPSO can be described as follows:

Step 1: Set the model parameters of IWSNs, such as R_S, R_{CH} and MCL.

Step 2: Initialize AMPBPSO including weight factor w, learning factors c_1 and c_2, the maximum velocity v_{max} , the binary population bx, the local best individual bP_i, the global best individual bP_g, the velocity v, the pseudo-probability x and its lower/upper bound x_{min} /x_{max}.

Step 3: Update the velocity vector and pseudo-probability vector of each individual according to (17)-(18).

Step 4: Generate offspring individuals, i.e. new binary solutions, by performing the probability estimation operator as (19)-(20) and the adaptive mutation operator as (21)-(22).

Step 5: Calculate the fitness value of each individual according to (23)-(26).

Step 6: Update the local best individual bP_i and the global best individual bP_g.

Step 7: Stop the iteration and output the optimal solution if the termination criteria are met, otherwise go to Step 3.

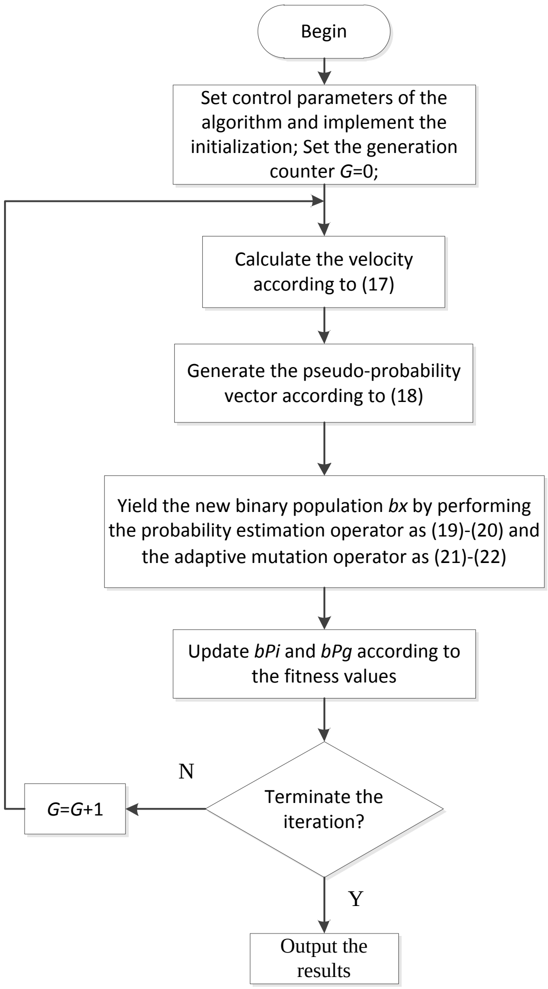

Fig. 4. The flowchart of AMPBPSO

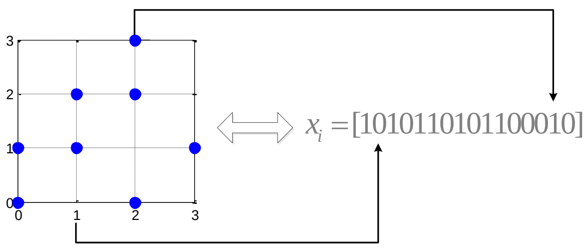

Fig. 5. Binary encoding for the node placement of IWSNs

6. Experiments and Analysis

6.1. Node Placement Benchmark Problem of IWSNs

To test the effectiveness of the developed node placement model for IWSNs, a small-scale node deployment benchmark problem is designed as Fig. 6. The gird of this problem is 10×10 and the positions of the sensor nodes are pre-placed and represented as the triangles in the figure. The communication radii of the sensor node and the cluster-head node are set as R_S=2 and R_{CH}=5, respectively. The reliability constraints are L_{SN}=2 and L_{CN}=2. Therefore, the optimal solution of this benchmark is unique, and the corresponding positions of the deployed cluster-heads are marked as the circles. AMPBPSO, DBPSO [29] and GA [18] with the recommended parameters in Table 1 were adopted to tackle the benchmark problem. The population size and the maximum generation of each algorithm were set as N=200 and G_{max}=100, respectively.

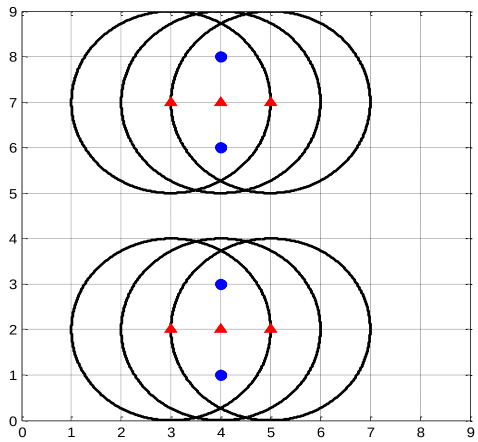

Fig. 6. The optimal placement scheme of the standard benchmark problem (▲ represents the sensor node, ● represents the cluster-head node, the circles are the communication ranges of the sensor nodes)

The experiments were run 10 times independently. The experimental results, i.e., the best fitness (Best), the mean fitness (Mean) and the standard deviation (Std_Dev) are listed in Table 2. "+" of the t-test results indicates that AMPBPSO is significantly better than the compared algorithm at the 95% confidence; "-" represents that AMPBPSO is significantly worse than the compared algorithm; and "≈" denotes that the difference is not significant. Table 2 indicates that the proposed model as well as AMPBPSO is effective for the node placement of IWSNs as the unique optimal solution of the problem was found out successfully. However, AMPBPSO did not find the best solution with 100% success rate while DBPSO and GA totally failed to reach the global best solution, which illustrates that the optimal sensor placement problem is very complicated. The t-test results show that AMPBPSO is significantly superior to GA and DBPSO on this benchmark which demonstrates that AMPBPSO has the better global search ability and the adaptive mutation operator effectively enhances the performance of the algorithm.

Table 1. Parameters of AMPBPSO, DBPSO AND GA

Algorithms	Parameters
AMPBPSO	$w=0.8, c_1=c_2=2.0, v_{\max}=6.0, x_{\min}=-20, x_{\max}=20,$ $p_m=\frac{1}{D}\times(0.05+\frac{1.45}{G_{\max}}\times G)$
DBPSO [29]	$w=0.8, c_1=c_2=2.0, v_{\max}=6.0$
GA [18]	$p_s=1.0, p_c=0.8, p_m=0.005$

Table 2. Results of AMPBPSO, DBPSO and GA on the node placement benchmark problem

Algorithm		AMPBPSO	DBPSO	GA
Best	fp	3.32	12.90	15.30
	p1	0	0	0
	p2	0	0	0
	p3	0	0	0
Mean± Std_Dev	fp	4.01±0.51	14.18±1.13	17.93±1.61
	p1	0±0	0±0	0±0
	p2	0±0	0±0	0±0
	p3	0±0	0±0	0±0
Suceess rate		90%	0%	0%
t-test		/	+	+

6.2. Large-scale Node Placement of IWSNs

The number and positions of sensor nodes in IWSNs are designed and determined for monitoring industrial systems, and therefore they depends on the specific application and vary for the different systems. Thus, without loss of generality, sensor nodes are assumed to be randomly distributed in the industrial field, that is, the positions of sensor nodes are generated randomly in this paper. Six large-scale node placement problems, i.e. 200m×200m, 400m×400m and 600m×600m with nodes densities $\delta=0.2$ and $\delta=0.5$, were yielded and adopted as the benchmarks. The communication radii of the sensor node and the cluster-head node were set as R_S=50m and R_{CH}=100m, respectively. The reliability constraints were L_{SN}=2 and L_{CN}=2. The required accuracy of the node location information is application-dependent. On the one hand, the communication reliability is extremely important for industrial applications and the radius of wireless sensors is not exact due to various kinds of interferences in the industry environment. Thus, the high accurate location of cluster-head nodes for IWSNs is unnecessary. On the other hand, with the improvement on the accuracy of the grid onto which the industrial field is mapped, the search space of the node placement problem will increase exponentially. Based on the above factors, the grid cell was set as 10m in this paper.

Table 3. Results of AMPBPSO, DBPSO and GA on the 200m×200m node placement problems

Density		0.2			0.5		
Algorithm		AMPBPSO	DBPSO	GA	AMPBPSO	DBPSO	GA
Best	fp	16.15	72.06	78.48	27.27	36.91	40.96
	p1	0	0	0	0	0	0
	p2	0	0	0	0	0	0
	p3	0	0	0	0	0	0
Mean ± Std_Dev	fp	18.18 ±1.77	74.55 ±2.36	85.13 ±2.77	27.26 ±0	39.09 ±2.16	46.44 ±2.39
	p1	0±0	0±0	0±0	0±0	0±0	0±0
	p2	0±0	0±0	0±0	0±0	0±0	0±0
	p3	0±0	0±0	0±0	0±0	0±0	0±0
t-test		/	+	+	/	+	+

Table 4. Results of AMPBPSO, DBPSO and GA on the 400m×400m node placement problems

Density		0.2			0.5		
Algorithm		AMPBPSO	DBPSO	GA	AMPBPSO	DBPSO	GA
Best	fp	200.09	397.70	422.50	112.90	228.89	246.50
	p1	0	0	0	0	0	0
	p2	0	0	0	0	0	0
	p3	0	0	0	0	0	0
Mean± Std_Dev	fp	209.52 ±7.20	404.02 ±4.22	430.34 ±12.57	118.90 ±3.35	235.77 ±3.23	254.34 ±9.38
	p1	0±0	0±0	0±0	0±0	0±0	0±0
	p2	0±0	0±0	0±0	0±0	0±0	0±0
	p3	0±0	0±0	0±0	0±0	0±0	0±0
t-test		/	+	+	/	+	+

AMPBPSO, DBPSO and GA with the recommended parameters were used to solve the large-scale node placement problems for a fair comparison. All the algorithms were repeated 10 times on each problem independently. Tables 3-5 list the experimental results which show that AMPBPBO surpasses DBPSO and GA on all the problems and the average results of AMPBPSO are even better than the best ones of DBPSO and GA. The t-test results also demonstrate that AMPBPSO is significantly superior to GA and DBPSO.

Table 5. Results of AMPBPSO, DBPSO and GA on the 600m×600m node placement problems

Density		0.2			0.5		
Algorithm		AMPBPSO	DBPSO	GA	AMPBPSO	DBPSO	GA
Best	fp	662.47	969.70	1009.70	359.28	580.90	600.10
	p1	0	0	0	0	0	0
	p2	0	0	0	0	0	0
	p3	0	0	0	0	0	0
Mean± Std_Dev	fp	671.83 ±13.28	986.10 ±5.36	1026.74 ±13.04	366.59 ±6.62	591.14 ±4.11	611.94 ±8.18
	p1	0±0	0±0	0±0	0±0	0±0	0±0
	p2	0±0	0±0	0±0	0±0	0±0	0±0
	p3	0±0	0±0	0±0	0±0	0±0	0±0
t-test		/	+	+	/	+	+

The average convergence curves of each algorithm on the six problems are drawn in Fig. 7-12. From Fig. 7-12, we can clearly observe that AMPBPSO has the best search ability and outperforms DBPSO and GA in terms of solution quality and the convergence speed for the optimal node placement of IWSNs.

7. Conclusions and Future Work

In this paper, we have investigated the optimal node placement problem of IWSNs. Different from the non-industrial applications of WSNs, the reliability of the wireless communication has to be guaranteed as IWSNs are utilized to monitor the manufacturing process. To meet the specific need on the reliability of IWSNs, a node placement model of IWSNs is developed and formulized in which the reliability, the setup cost, the maintenance cost and scalability of the system are taken into account. Given the high dimension and NP-hard characteristic of the large-scale IWSNs node placement, an improved adaptive mutation probability binary Particle Swarm Optimization algorithm (AMPBPSO) is proposed to solve the problems where the adaptive mutation operator is introduced to keep the diversity of the population as well as enhance local search. The presented algorithm and model were firstly verified on the small-scale node placement benchmark problem. The results of the benchmark demonstrate the effectiveness and efficiency of the model and algorithm. Finally, the proposed model and AMPBPSO were used to tackle the large-scale node placement problems of IWSNs. DBPSO and GA were also applied to all the problems for a comparison. The simulation results indicate that AMPBPSO can effectively solve the optimal node placement problems with the guarantee of the reliability and outperforms DBPSO and GA in terms of search accuracy and the convergence speed.

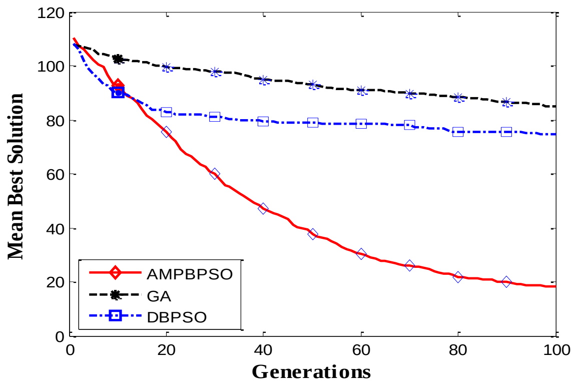

Fig. 7. Convergence curves of the 200m×200m node placement problem with $\delta = 0.2$

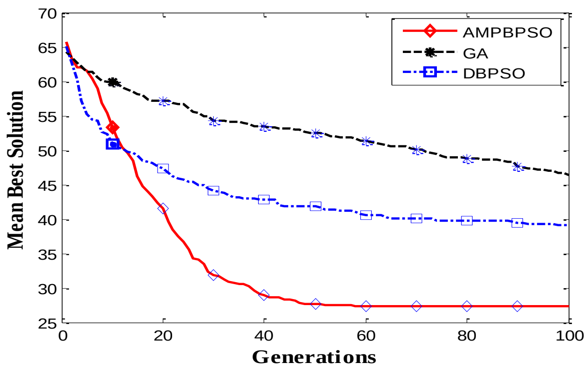

Fig. 8. Convergence curves of the 200m×200m node placement problem with $\delta = 0.5$

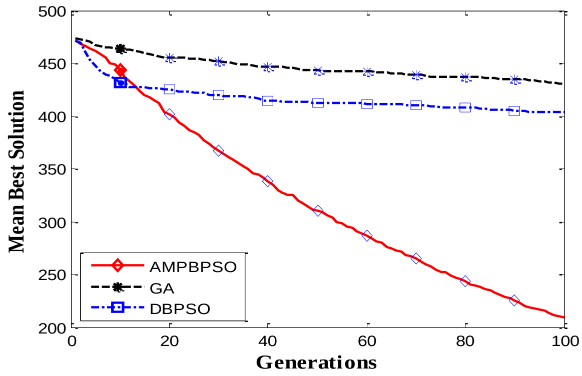

Fig. 9. Convergence curves of the 400m×400m node placement problem with $\delta = 0.2$

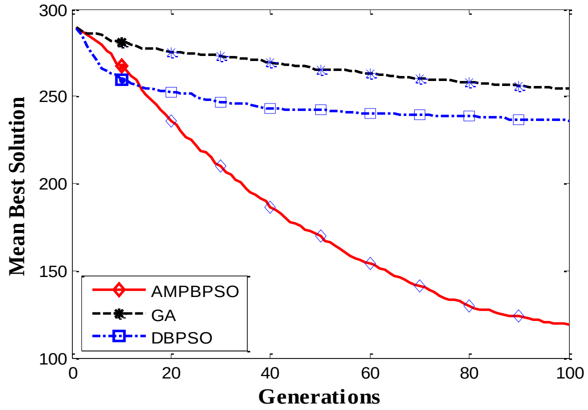

Fig. 10. Convergence curves of the 400m×400m node placement problem with $\delta = 0.5$

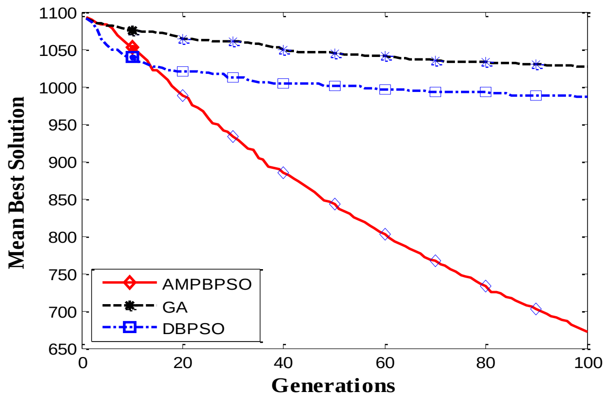

Fig. 11. Convergence curves of the 600m×600m node placement problem with $\delta = 0.2$

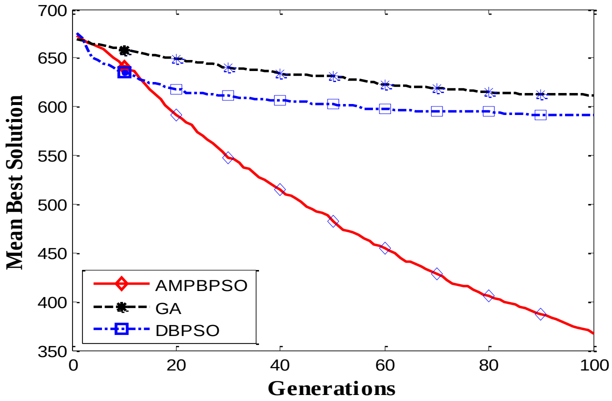

Fig. 12. Convergence curves of the 600m×600m node placement problem with $\delta = 0.5$

The optimal node placement of IWSNs is a multi-objective optimization problem, and the setting of weighting factors of each optimization goal is a challenge for real applications. Thus, the Pareto-based approach has the advantage, which is a direction for the future research. Another direction of the future research is to improve the optimization model to meet the more requirements of industrial applications.

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