Optimization of Multi-function Sensor Placement Satisfying Detection Coverage

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Abstract. Wireless Sensor Networks (WSNs) have become essential parts in Industrial Internet of Things (IIoT). However, owing to the type associated with data acquisition and the large scale of monitoring, sensors are often installed at a lot of locations and a wide variety of sensors make WSN topology more complex. To address these limitations, a complementary promising solution, known as software defined wireless sensor network (SDWSN), is proposed. SDWSN acquires desired information based on users' demands from large-scale sensor networks by dynamically customizing its function. Thanks to the SDWSN, multi-type data sensing is able to enlarge the sensing scale and reduce the cost. Existing sensor placement techniques are usually focus on simple function sensor or multi-type sensor. Witness the development of SDWSN, it is ideal to explore such abilities such that the multi-type sensing functions can be conducted in a same node. Because each area covered by different multi-function sensor nodes has different detection requirements, multi-function sensor nodes placement faces many challenges. In this paper, based on multi-objective decomposition, we study the number and function redundancy of all nodes minimization problem in multi-function sensor nodes placement. Specially, we propose an improved MOEA/D-DE algorithms based on orthogonal experiment design. Simulation and evaluations validate the efficiency of our proposal.

Keywords: WSN · Placement · Multi-objective · Optimization

1 Introduction

Nowadays, wireless sensor networks (WSNs) become more and more popular for real-time monitoring. The WSN nodes can be sensors such as magnetic, vibration, sound, and so on, that are often used to monitor humidity, temperature, pressure, and other factors. Usually, in industrial applications, a variety of types of physical factors need be measured at the same time. Therefore, multi-type sensors are placed to meet different monitoring needs in a variety of detected areas. For example, multi type sensors, including CO concentration sensor, CO_2 concentration sensor, smoke concentration sensor, air temperature/relative humidity sensor, can be placed in a forest to identify smoldering and flaming combustion phases of forest fire [1]. Additionally,

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multi type sensors are place for structural health monitoring of long-span suspension bridges [2, 3]. However, as a result of single-hop or multi-hop data transmission, the use of multi-type sensor will increase the scale of wireless network, and make the network topology more complex.

After decades of extensive study, Software Defined sensor wireless network (SDWSN) has experienced fast development, and has been another alternative technique that satisfies multi type data monitoring [4]. SDWSN actively acquires desired information based on users' demands from large-scale sensor networks by dynamically customizing its function by injecting roles into the reconfigurable multi-functional sensor nodes [5, 6]. Therefore, by optimizing the placement of the multi-function sensor nodes in the SDWSN, it is possible to effectively reduce the number of sensors required for multi-type data monitoring and make the network topology simpler. As shown in Fig. 1, detected areas (in shadow) are covered only by two multi-function sensors, which require two temperature sensors, two sulfur sensors and one carbon sensor before.

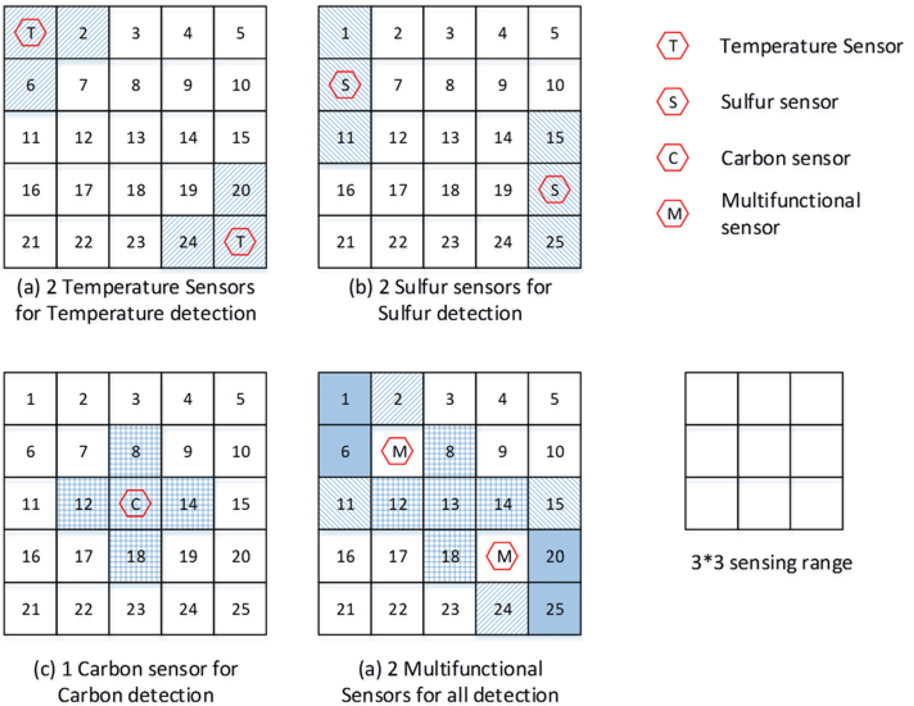

Fig. 1. Replacing multi-type sensors with multi-function sensors

Detected areas, workload capacity of each node, and number of available nodes should be considered to optimizing multi-function sensor placement. Therefore, essentially, we shall seek how to optimize multi-function sensor placement according to different monitoring requirements. The main contributions of this work exist in three folds.

Firstly, the optimizing placement problem of multi-function sensor nodes is modeled as a bipartite graph problem model in which a power set with the maximum position correlation will be found with the goal of minimizing the redundancy of the function and the number of nodes.

Secondly, because the two optimization goals proposed in the modeling are mutually exclusive, an improved MOEA/D-DE algorithm is proposed to solve this problem where the initial population generation strategy is improved by orthogonal method.

Thirdly, virtual-world trace based simulations are conducted after compared with the benchmark functions. Experiment results validate the efficiency of our proposals. The advantage of our algorithm verifies the equitable function redundancy in sensor nodes placement decisions.

2 Related Work

The problem of sensor nodes placement has been extensive studied in health monitoring [7], water distribution system [8], and so on. Moreno-Salinas et al. [9] offer a solutions to the problem of optimal acoustic sensor placement for underwater target positioning with the goal of maximizing the range-related information available for positioning. Eliades and Polycarpou [2] considers the problem of water quality sensor placement in drinking water distribution networks such that the presence of any contaminant substance in the network is detected as effectively as possible, and formulate it in a fault detection framework with which a computational solution methodology is presented based on the iterative deepening of Pareto solutions. However, most of these solutions are based on single functional sensor which can not be directly applied to the multi-functional sensors placement due to the combination relationship of functions.

Moreover, multi-type sensor WSN are playing increasing role on multi-source data sensing. Placing multi-type sensors to satisfy heterogeneous monitoring demands refers from many factors, such as cost, communication capability, number of sensors. Zeng et al. [10] consider a water quality monitoring sensor network consisting of two kinds of sensors with different prices. The cost-efficient sensor deployment problem is investigated on how to deploy these two kinds of sensors in a given water distribution system to minimize the deployment cost, without violating the quality-of-sensing requirement. Furthermore,sensor placement problem will be more complex when more types of sensors are considered. Xu et al. [11] use the updated finite element (FE) model to select the sensor types, which include fiber Bragg grating (FBG) sensors, laser displacement transducers, and accelerometers, numbers, and locations for structural health monitoring of long-span suspension bridges, while Soman et al. [3] place multi-type sensors with integer Genetic Algorithm (GA) to maximize a common metric to ensure adequate Modal Identification (MI) and Accurate Mode Shape Expansion (AMSE). Unfortunately, when all kinds of sensors are integrated in a multi-functional sensor node, these above methods will be never suitable to multi-functional sensors placement because of different functional limit. We are motivated to address this issue in this paper.

3 System Model and Constraints

3.1 System Model

In this paper, a graph model is used to describe the combinatorial optimization problem of multi-function sensor placement problem. As shown in Fig. 2, all the observed areas are regarded as an observation area set A. All the necessary detection functions are regarded as a set F. The sensor nodes are treated as a power set S representing the set F.

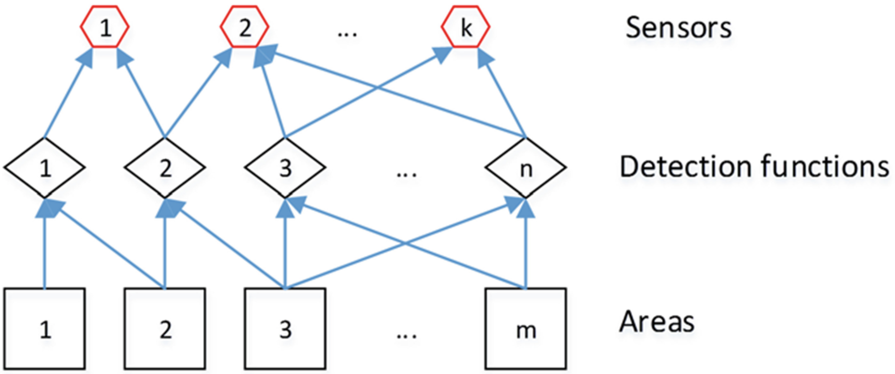

Fig. 2. Mapping relationship between functions assigned to sensors and areas

We assume the system holds the following assumptions:

The sensor node has multi software defined functions. So that, according to the observation area requirements, it can be programmed to different detection functions, such as perception of temperature, light, carbon dioxide and so on. When the detection function is not required, the sensor node can turn it off.

To satisfy the coverage of all observed areas, the sensing range of the sensor node can be increased or reduced.

The observed areas are irrelevant, so the detecting results from the different observation areas do not affect each other. Moreover, all observed areas that have a variety of detecting functional requirements must be satisfied.

All the sensor nodes do not communicate with each other, and send data to the server directly.

In order to simplify the problem model, the detection range of the sensor is represented by a matrix, such as that a sensor with range of 3 can cover the detection range is around 3 * 3 of the matrix area.

Regardless of the energy and storage capacity limit of the sensor, it is assumed that each sensor has enough energy and storage capacity to complete monitoring tasks and record all the detection data.

It can be seen that the final model of the multi-function sensor placement problem is a constraint combinatorial optimization model of a bipartite graph mapping functions of sensors to the observed areas. Therefore, in this paper, the multi-function sensor placement problem is solved to achieve the following objectives:

Under the premise of satisfying the coverage of all observed areas, the number of sensor nodes is the least to reduce the entire network construction costs.

The detection functions of all sensors have the least redundancy in detecting requirements relative to the covered observed areas to improve the utilization of the sensor.

3.2 Problem Statement

The objective of the multi-function sensor placement optimization is to minimize the number of sensors required and the function redundancy of all sensor nodes. An optimal placement scheme allows the detection functions with the same observation area to be assigned centrally on as few sensor nodes as possible. In another word, the detection functions detecting the same observation area are allocated as much as possible to a same node. The objective of minimization the sensors' number can be expressed in an integrated and weighted count Z, as following formula 1.

$$Z = (1 - \alpha) * S + \alpha * \sum_{i=0}^{n} f(x_i) \tag{1}$$

Where α $(0 < \alpha < 1)$ is the weight parameter, and n is the total number of observed areas. Function $f(x_i)$ indicates the total number of sensor nodes required for the observed area x_i, and S is the total number of sensors required in this scheme.

Another objective is minimization the function redundancy. The the function redundancy is defined as follows.

Definition 1 (Function redundancy): The function redundancy of the sensor placement is represented by the difference between the number of areas covered by all the detection functions minus the total number of detection requirements in the actual observation area. There are M observation areas, and the number of detection requirements of the i-th area is t_i. For the placement of N multi-function sensors, the number of functions of the j-th sensor is f_j, and the number of coverage areas is s_j. Then, the function redundancy can be expressed as formula 2.

$$R = \sum_{j=1}^{N} f_j * s_j - \sum_{i=1}^{M} t_i \tag{2}$$

When the number of sensor nodes is less, the detection functions required by the observation areas are more likely to be arranged on a same sensor node leading to higher function redundancy after increasing number of coverage areas of the sensor node. To reduce function redundancy, the number of sensor nodes will increase due to reduce the number of coverage areas of a single sensor. Therefore, there are two optimization objectives, such as minimizing the weighted count Z of sensor nodes required and the sensor node function redundancy R.

There are two constraints in this model. One is the maximum number of detection functions that the sensor node can run, and the other is the maximum number of sensor nodes covering a same observed area.

Although all functions can be configured on the node, the load capacity of each node is not sufficient to run more than a certain number of functions. Therefore, a strong constraint is added in the placement problem that the number of any sensor nodes in the placement scheme does not exceed the upper limit of the sensor load. This can be expressed as the formula 3.

$$\bigcap_{i=0}^{S} (Counts(S_i) \leq Up_i) = true \tag{3}$$

Where $Counts(S_i)$ represents the number of functions that the i-th sensor node S_i has, and Up_i is the upper limit of the load capacity of the sensor node S_i.

In a placement scheme, the number of sensor nodes covering a same observed area is less, the utilization of the sensor nodes is higher for the smaller detection function redundancy. According to this constraint, the maximum number of nodes covering a same area should be limited. This constraint condition can be expressed as the formula 4.

$$\bigcap_{j=1}^{n} (L_j \leq Sum(T_j) \leq U_j) = true \tag{4}$$

Where $Sum(T_j)$ represents the total number of nodes covering the j-th area T_j, and L_j and U_j denote the maximum and minimum values of the number of sensor nodes covering the T_j area, respectively.

4 An MOEA/D-DE Algorithm for Multi-function Sensor Node Placement

Because this multi-function sensor arrangement optimization is a multi-objective optimization problem, in this paper, an improved multi-objective evolutionary algorithm based on decomposition (MOEA/D) algorithm is used to solve it. The whole Pareto Frontier (PF) approximation of this problem is about to decompose into a certain number of single-objective optimization problems, and then the evolutionary algorithm is used to solve these single-objective optimization problems at the same time. The algorithm maintains a population composed of the optimal solution of each subproblem. The neighborhood relation between subproblems is defined as the distance between the weight vectors of the subproblems. The optimization process of each subproblem is carried out by the evolution between the subproblems. MOEA/D-DE uses a differential evolution method in the MOEA/D hybridization process and generates a new solution by polynomial mutation. It is better than MOEA/D to maintain the diversity of the population.

In this paper, orthogonal experiment design method is used to improve the population initialization process of the MOEA/D-DE algorithm. This method selects the most representative test combination from the complete test based on the experimental factors and the level orthogonality. Because the selected test combinations are evenly dispersed and neatly comparable, the conclusion can basically replace the conclusion of the complete testing design for improving the efficiency of the algorithm.

In the implementation process, selecting the orthogonal tests from the complete tests is completed in accordance with the orthogonal array. The orthogonal array is generated following probability statistics and certain principles, which can be regarded as $L_m(q^n)$, where m is the number of combinations of levels, n is the number of factors, and q is the number of levels. In this paper, a relatively simple special orthogonal array is used in which q is a prime number and $m = q^2$, $p = q + 1$.

The population initialization process based on the orthogonal test design is done by operations shown in algorithm 1.

Algorithm 1: orthogonal test design for population initialization

Input: $X \in R^{[a_i,b_i]}(i = 1,2,\cdots,n)$

Output: $X = \{x_1, x_2, \cdots, x_n\}$

Select q according to X;

m = q * q;

p = q + 1;

for row i from 1 to m do:

a[i,1] = int((i-1)/q) mod q;

a[i,2] = (i-1) mod q;

for row i from 1 to m and column t from 3 to p do:

a[i,t+2] = (a[i,1]*t + a[i,2]) mod q;

for each x_i with range $[a_i, b_i]$ in vector X do:

for column j from 1 to q - 1 step 2 do:

calculate $\{a_i + j * (b_i - a_i)/q, \cdots, b_i\}$;

for row k from 1 to m do:

$x_k = \left(a_1 + \partial_{k,1} * (b_1 - a_1)/q, \cdots a_i + \partial_{k,i} * (b_i - a_i)/q, \cdots, a_n + \partial_{k,n} * (b_n - a_n)/q\right)$

In the algorithm 1, the number of rows and columns (m, n) is calculate firstly after selecting a suitable q according the input vector X. Then, these parameters are used to construct an orthogonal array. Thirdly, the range $[a_i, b_i]$ of each dimension $x_i(i = 1, 2, \cdots, n)$ in the input vector X , $X = \{x_1, x_2, \cdots, x_n\}$, is divided into q horizontal spaces $\{a_i + j * (b_i - a_i)/q, \cdots, b_i\}(j = 0, 2, \cdots, q - 1)$, according to the horizontal number q. The value of each dimension of the individual x_k in each factor combination a_k corresponding to each row of the orthogonal array is obtained. As a result, there are a total of m uniform and neatly scattered initial individuals in the search space $R^{[a_i,b_i]}(i = 1, 2, \cdots, n)$.

5 Performance Evaluation and Analysis

5.1 Configuration of Algorithm Parameters

In the evaluation, main parameters of the improved MOEA/D-DE algorithm are shown in Table 1.

Table 1. Configuration of algorithm parameters

Parameters	Value or Range
Prime number: q	13
Population size: N	300
Neighborhood: T	30
The probability of selecting T:δ	0.5
Crossover probability: CR	0.8
Mutation probability: P_m	0.125
Maximum number of parent individuals: n_r	3
Number of generations: Gen	500
Normal distribution mean and variance of stretching Factor F	(1,0.15)
Decomposition mode	Tchebycheff Approach

5.2 Verification of Multi-function Sensor Placement

In the experimental simulation, a test set with 15 areas and a total of 50 observation function requirements is constructed. In the constraint, the upper limit of the number of sensor nodes is 20, to ensure that each region has at least one sensor node to cover. Each sensor node's load capacity is set to 50, to ensure that all the observation requirements at least can be mapped to a same node. The number of iterations of the population is set to 1000 times. The results are as follows.

As shown in the Fig. 3, The purple dot represents the optimal solution of the Pareto, and the blue dot represents the solution reached during the algorithm iteration. In the multi-function sensor node placement scheme, the fewer the number of sensor

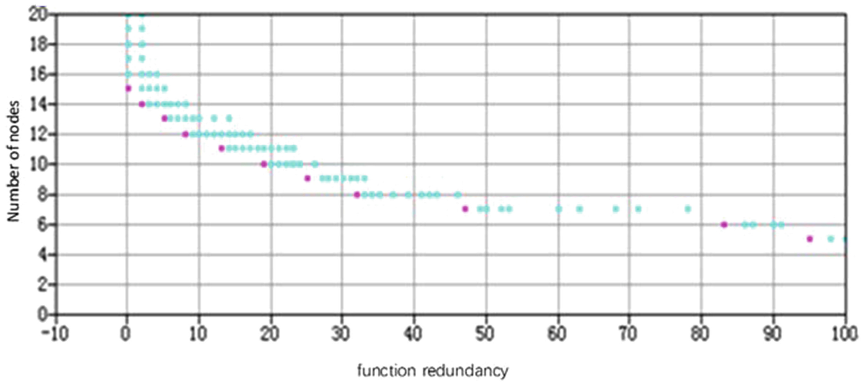

Fig. 3. Simulation of multi-function sensors placement.

nodes are used, the greater the functional redundancy is. In contrast, the more the number of sensor nodes is, the lower the functional redundancy is. This is consistent with the theoretical analysis.

6 Conclusion

In this paper, we have studied placement problem for multi-function sensor in wireless sensor networks. Our objective is to minimize the number of sensor nodes required and function redundancy of all sensor nodes. We first formally state the problem studied in this paper, with a special emphasis on the multi-function sensor node. To address the placement optimization problem, we propose an improved MOEA/D-DE algorithm. To verify the efficiency of our proposals, we conduct extensive simulations to evaluate the performance of our algorithms. The experiment results demonstrate that our algorithm has the advantages of fast convergence and strong population distribution. This validate the correctness of our algorithm design by taking the simulation of sensor application scenarios into consideration.

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