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Coverage Repair Strategies for Wireless Sensor Networks using Mobile Actor Based on Evolutionary Computing

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Abstract
A standard traveling salesman problem(TSP) under dual-objective strategy constrained is proposed in this paper, characterized by the fact that the demand of both as many as possible the numbers of nodes be visited in time and minimum trajectory distance. The motivation for this TSP problem under dual-objective strategy constrain stems from the coverage repair strategies for wireless sensor networks using mobile actor based on energy analysis, wherein a mobile robot replenishes sensors energy when it reaches the sensor node location. The Evolutionary Algorithm (EA) meta-heuristic elegantly solves this problem by the reasonable designed operators of crossover, mutation and local search strategy,which can accelerate convergence of the optimal solution. The global convergence of the proposed algorithm is proved, and the simulation results show the effectiveness of the proposed algorithm.

Keywords: *coverage repair strategies, wireless sensor networks, mobile node, evolutionary computing, dual-objective strategy constrained, traveling salesman problem (TSP)*

1. Introduction

Wireless sensor networks have been attracting the interest of computer scientists and engineers recently due to their potential to impact our everyday lives and because of their numerous applications in areas such as health care, national security, inventory tracking, surveillance, and environmental monitoring. They are collections of autonomous sensing devices, belong to the domain of wireless ad hoc networks [1] and face many design and realization challenges, e.g., [2]-[4]. Recently, an emergent research area coined as “wireless sensor and robot networks” [5]-[6] has stemmed from the integration between WSN and multi-robot systems. They consist of an ensemble of sensor and robot nodes that communicate via wireless links to perform distributed sensing and actuation tasks. While sensors are highly constrained devices (i.e., they possess limited computing power, battery, memory, transmission range, etc.), robots are resource-rich, usually mobile and meant to assist, maintain and optimize sensor networks. For example, they may perform intelligent movement for data collection [7], sensor placement [8] or sensor node repair, *etc.*

Some of the literature have discussed on the mechanism how the mobile node repair static sensor nodes,but rarely involved in energy analysis considerations [7]-[9]. We are concerned with the problem of energy analysis-based coverage repair strategies in WSN, which can be defined as follows: consider a network of static sensors already deployed in some area of interest. Those will be responsible for monitoring the region. Unfortunately, network coverage (i.e., the total area monitored by the network) will be eventually degraded because of active node failures (e.g., battery depletion.), thus creating sensing holes in the area. Periodically, every sensor reports its location to a base station (by multi-hop communications) and also the current energy left (or residual survival time) to the base station too. Assume that a single mobile robot is located at the base station, it can reach each static sensor node, and replenish energy (for example, by replacing the battery or the sensor node [10]) for each node.

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Its goal is to let mobile node reach node location and repair it before node energy(or survival time) runs out , prevent the node death brings sensing holes in the area. We want to compute an 'optimal' robot trajectory so that the more number of fix node in time, the better, and also a minimum trajectory distance defined as the length total traveled.

The above scenario can be formulated as a combinatorial optimization problem. We represent the sensor network by a complete graph G = (V,E) where V = {v_1, v_2, . . . , v_n} is the vertex set and E = {e_{ij}} is the edge set, with e_{ij} being the edge between sensors *i* and *j*, $\forall$ *i, j* $\in$ {1, 2, . . . , n}. There is a single mobile node v_0 is located at the base station.

We want to find an optimal-feasible tour φ that starts and ends at the base station. The cost function for any tour φ can be computed as $\sum_{i \in V}(t_i - T_i)$ where t_i stands for the residual survival time of node v_i, T_i stands for time spent which mobile node v_0 arrive node v_i. A tour is said to be optimal -feasible if it has no repeated nodes (other than the base station as its first and last element), replenish energy (for example, by replacing battery or sensor node [10]) for each node in time.

A similar problem in the literature is that of "the traveling salesman problem (TSP)". We model the energy analysis-based coverage repair strategies as a TSP under dual-objective strategy and apply the evolutionary algorithm optimization (EA) meta-heuristic [11] to solve it.

The paper is structured as follows. Section II is related work. We propose coverage repair strategies as a TSP under dual-objective strategy and the EA-based algorithm for solving the problem in Sec. III. The convergence of the proposed algorithm to a globally optimal solution with probability 1 is proved in Sec. IV. Section V shows the efficiency of the proposed algorithm through simulation experimental results on modified TSP standard benchmark problems, precede the final remarks in Sec. VI.

2. Related Work

The traveling salesman problem (TSP) is one of the most challenging problems in NP-hard combinatorial optimization. It has been drawing significant research attention, probably because it arises practically in many areas, is very easy to understand and serves as a standard test bed for further algorithmic developments [12]. For example, Rafael Falcon [10] introduced 1-TSP-SELPD in the carrier-based coverage repair problem in wireless sensor and robot networks.

Improving the efficiency of the existing algorithms or designing new efficient algorithms for TSP to decrease the computation amount is a very urgent task due to both the theoretical importance and the wide range of applications of TSP.

A lot of research with Evolutionary Algorithm (EA) approach we did on the TSP problem. The quantum concept and technique are integrated into the genetic algorithm designing to result in a novel quantum genetic algorithm [13], a new evolution strategy based on clustering and local search scheme is proposed for some kind of large -scale traveling salesman problems [14], in [15] a new chromosomal encoding scheme and a new crossover operator are described and a new local search scheme is used to improve the quality of the offspring generated by the crossover.

The standard TSP is very closest to our problem, We solve the energy analysis-based coverage repair strategies (modeled as a TSP under dual-objective strategy) through an evolutionary Algorithm (EA) approach designed one population-based meta-heuristic algorithms, for their proved ability to overcome local optima through a parallel exploration of the search space and the use of social communication mechanisms to drive the population toward promising regions.

3. Evolutionary Computing For Coverage Repair Strategies

3.1. Network model

In lots of literature the wireless sensor network is represented by a complete graph $G = (V,E)$ where $V = \{v_1, v_2, \ldots, v_n\}$ is the vertex set and $E = \{e_{ij}\}$ is the edge set, with e_{ij} being the edge between sensors i and j, $\forall\ i, j \in \{1, 2, \ldots, n\}$.

In our proposed model, a collection of static nodes in wireless sensor networks correspond to the vertex set V. If the static node v_i current remaining energy value is expressed as e_i , and assume that the consumption of the node energy per time is expressed as f_i (in actual case this value will not remain the same, here in order to simplify the problem assume that the value is a constant), then this node's residual survival time is $t_i=e_i/f_i$, it means that after t_i time the node will die if is not added energy, the node monitoring area there could be a coverage hole. Supposed there is a mobile sensor node v_0. This mobile sensor node v_0 can traverse each static sensor node v_i from the initial position and return to the initial fixed position(also named the base station). When the mobile node v_0 reaches each static sensor node v_i, it can replenish energy(for example, by replacing the battery or the sensor node [10]) for node v_i, then the node v_i's current energy recovery to a maximum energy of e_{max} .

3.2. Problem formulation: Coverage Repair Strategies

In order to simplify the problem reasonably, the moving speed of mobile node v_0 is assumed constant for w, then the mobile node v_0 arrive node v_i in time $T_i=S(v_0, v_i)/w$, where $S(v_0, v_i)=|\overline{v_0 v_{j,1} \ldots v_{j,k} \ldots v_{j,m}\ v_i}|$ stands for the Euclidean length of line $\overline{v_0 v_{j,1} \ldots v_{j,k} \ldots v_{j,m}\ v_i}$ that means the mobile node v_0 through a number of intermediate nodes $v_{j,1}$, …, $v_{j,k}$, …, $v_{j,m}$ to node v_i , as shown in Figure 1.

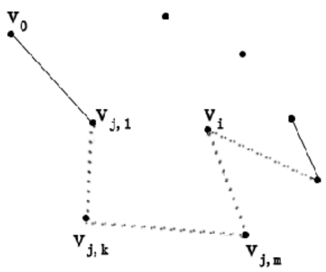

Figure 1. mobile node v_0 through a number of intermediate nodes $v_{j,1}$, …, $v_{j,k}$, …, $v_{j,m}$ to node vi from base station

Most reasonable repair strategy should satisfy that before each node v_i's survival time t_i run out , the mobile node v_0 should reach node v_i's location and repair it, prevent the node v_i death brings blind area, which requirements, $\forall\ i \in \{1, 2, \ldots, n\}$, $T_i=S(v_0, v_i)/w < t_i$, indicates that the node v_i can get timely repair.

We want to find an optimal feasible solution tour φ that starts and ends at the base station where the mobile node v_0 through all the static nodes $V = \{v_1, v_2, \ldots, v_n\}$, which can be expressed by $\varphi = v_0 v_{j,1}\ v_{j,2} \ldots v_i \ldots v_{j,n-1} v_{j,n} v_0$. A tour is said to be feasible if it has no repeated nodes (other than the base station as its first and last element). A tour is said to be optimal means the more number of static nodes fixed successfully by mobile node v_0, the better, this cost function for any tour φ can be computed as

$$\max \sum_{i \in V} sign(t_i - T_i) \quad (1)$$

where $sign(x)=\begin{cases}1, & if \quad x>0\\ 0, & if \quad x\le 0\end{cases}$ represents sign function. Considering such path may be more than one, we hope to find the path with the shortest length, this cost function can be computed as

$$\min \sum_{i=0}^{n} d(v_{j,i}, v_{j,i+1}) \quad (2)$$

where $d(v_{j,i}, v_{j,i+1})$ stands for the Euclidean length of node $v_{j,i}, v_{j,i+1}$. If we do not consider condition (1), this problem returns to the standard traveling salesman problem, one of the most classical combination optimization problems.

3.3 Evolutionary Computing Coverage for Repair Strategies

A . Encoding scheme and population initialization

A feasible solution tour φ that starts and ends at the base station where the mobile node v_0 through all the static nodes $V = \{v_1, v_2, \ldots, v_n\}$ can be expressed by vertex sequence $v_0v_{j,1}\ v_{j,2}\ldots v_i\ldots v_{j,n-1}v_{j,n}v_0$, so integer-coded schema for chromosome is designed in this paper , chromosome φ=0 $j_1j_2\ldots i\ldots j_{n-1}j_n$ 0 corresponds to a path $\varphi = v_0v_{j,1}\ v_{j,2}\ldots v_i\ldots v_{j,n-1}v_{j,n}v_0$. For example, paths $\varphi = v_0v_1v_2v_5v_4v_7v_3v_6v_0$ is uniquely obtained for the string of integer-coded '012547360'.

The initialization of the population of chromosomes can be done by a random method. Since the random approach is used in this paper, the chromosomes as many as the population size *pop* value are generated randomly. Each chromosome is represented randomly as a permutation of *n* integers between 1 and *n*. As described above, the process to generate the initial population does not yield any illegal chromosome.

B. Fitness function

The value of Formula (1) $\sum_{i\in V} sign(t_i - T_i)$ and Formula (2) $\sum_{i=0}^{n} d(v_{j,i}, v_{j,i+1})$ are both functions of the variable path $\varphi = v_0v_{j,1}\ v_{j,2}\ldots v_i\ldots v_{j,n-1}v_{j,n}v_0$. To facilitate the presentation, use

$$f_1(\varphi)=\sum_{i\in V} sign(t_i - T_i), \quad f_2(\varphi)=\sum_{i=0}^{n} d(v_{j,i}, v_{j,i+1})$$

let

$$f(\varphi) = (f_1(\varphi), f_2(\varphi))$$

denote the fitness function.

Let φ_1 , φ_2 be two individuals, φ_1 is said to be better than φ_2, if $f_1(\varphi_1) > f_1(\varphi_2)$, regardless the values of $f_2(\varphi_1)$ and $f_2(\varphi_2)$; only in the case of $f_1(\varphi_1) = f_1(\varphi_2)$, φ_1 is said to be better than φ_2, if $f_2(\varphi_1) < f_2(\varphi_2)$.

C. Crossover Operator

We adopt the order crossover operator (OX, a kind of two-point crossover operator) [16] for the evolution of individuals. Select two individuals P_1 and P_2, generate two random integers *X*, *Y*∈ {1,2,…, n} as the crossover points. interchange part between two cut point, list the original order from the first gene after the second cut point Y, remove the existing gene, and then fill these no duplicate numbers from the first position after the second point Y, specific process is shown in Figure 2.

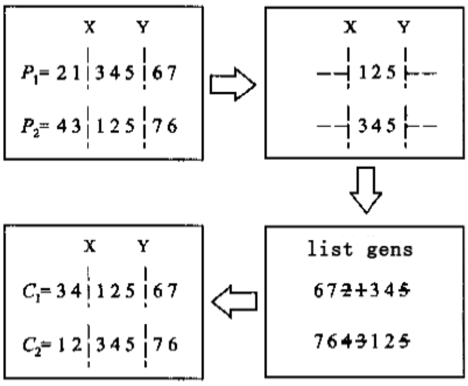

Figure 2. Example of the order crossover operator process

This crossover operator can be a good way to solve the difficulty that the general two-point crossover operation produces illegal individual as repeated integer gene, meanwhile, it can retain the adjacent relationship and the precedence relationship between nodes, meet the problem needs.

D. Mutation operator

Select individuals from crossover offspring according to the mutation probability $p_m \in (0,1)$ to take part in mutation. For each selected individual, say $\varphi=0\ j_1j_2\ldots j_i\ldots j_k\ldots j_{n-1}j_n\ 0$, randomly generate two integers $i,k \in \{1, 2, \ldots, n-1,n\}$, swap the two integer j_i and j_k , thus generates a new offspring individual $\varphi'=0\ j_1j_2\ldots j_k\ldots j_i\ldots j_{n-1}j_n\ 0$.

E. Local search operator

Considering the possibility that a node less residual survival time needs to repair first of greater, a local search operator we are proposing is developed. For selected individual, say $\varphi=0\ j_1j_2\ldots j_i\ldots j_{n-1}j_n\ 0$, randomly generate integer $i \in \{1, 2, \ldots, n-1,n\}$, considered the nodes $v_{j,i}, \ldots, v_{j,n-1}, v_{j,n}$ corresponding to the following integers $j_i, \ldots, j_{n-1}, j_n$ after the ith location, sort their residual survival time $t_{j,i}, \ldots, t_{j,n-1}, t_{j,n}$ in ascending order , get their ascending sequence $t_{j,i}', \ldots, t_{j,n-1}', t_{j,n}'$, then the local search result for $\varphi=0\ j_1j_2\ldots j_i\ldots j_{n-1}j_n\ 0$ is $\varphi'=0\ j_1j_2\ldots j_i'\ldots j_{n-1}'\ j_n'\ 0$.

After reassigned, if the new generated individual φ' is better than the current one φ, according to their fitness function value, update the current one and continue to the next iteration, otherwise,dose not.

F. Selection operator

Selection strategy is concerned with choosing chromoso mes from population space. It may create a new population for the next generation based on either parent and offspring or part of them.

For all the individual members including parents and offspring, according to their fitness function value, select the best *pop* individuals directly to form the next generation population.

G. Termination criterion

If the algorithm execution reaches the maximum evolutionary generations, then stop, and keep the best solution obtained as the approximate global optimal solution of the problem.

3.4 Coverage Repair Algorithm Based on Evolutionary Computing

ALGORITHM

Step 1. (Initialization) Choose population size *pop*(this population size number may be odd), proper mutation probability p_m, *etc*. Randomly generate initial population *P(0)*. Let the generation number $t = 0$.

Step 2. (Crossover) Choose two parents in *P(t)* with probability p_c, and use the proposed crossover operator to generate two offspring. This procedure is repeated *pop*/2 times and results a total of generating *pop* individual.

Step 3. (Proposed local search) For each offspring generated by crossover, the proposed local search scheme is used to generate an improved offspring. All these improved offspring constitute a set denoted by O_1.

Step 4. (Mutation) Select the parents for mutation from set O_1 with probability p_m. For each chosen parent, the proposed mutation operator is used to generate a new offspring. These new offspring constitute a set denoted by O_2.

Step 5. (Selection) Select the best *pop* individuals among the set $P(t) \cup O_1 \cup O_2$ as the next generation population *P(t+1)*. Let $t = t+1$.

Step 6. (Termination) If termination conditions hold, then stop, and keep the best solution obtained as the approximate global optimal solution of the problem; otherwise, go to **step 2**.

4. Global Convergence Analysis Of The Algorithm

A brief and general framework of the designed algorithm based on EA is described as follows: during each iteration, the population is modified by a number of successive probabilistic transformations. The resulting new population depends only on the state of the current population in a probabilistic manner. This property reveals that the designed algorithm is of a stochastic nature. Notice that the deterministic concept of "convergence to the optimum" is not appropriate, to define exact stochastic convergence as followed.

DEFINITION 1 Let φ^* denote the chromosome which corresponds to an optimal tour. If

$$\Pr ob\{\lim_{t\to\infty} \varphi^* \in P(t)\} = 1$$

then the proposed algorithm based on EA is called to converge to the global optimal solution with probability 1, where Prob{} represents the probability of random event {}.

To prove the global convergence of the algorithm with probability 1, it is required to introduce the following concept.

DEFINITION 2 For two chromosomes φ_a and φ_b, if

$$\text{Prob}\{\text{MC}(\varphi_a) = \varphi_b\} > 0$$

then chromosome φ_b is called to be reachable from chromosome φ_a by crossover and mutation, where MC(φ_a) represents the offspring that were generated from chromosome φ_a by crossover operator and mutation operator.

Bäck [17] and Rudolph [18] have proved that if a genetic algorithm with a finite search space S satisfies the following conditions, it will converge to global optimal solution with probability 1.

• for any two chromosomes a, b $\in$ S, b is reachable from a by crossover and mutation;

• the population sequence P(0), P(1), . . . , P (t), . . . is monotone, *i.e.* for $\forall$t :

$\min\{f(x) \mid x \in P(t+1)\} \le \min\{f(x) \mid x \in P(t)\}$

For the proposed algorithm, the following conclusion applies.

THEOREM 1 The proposed coverage repair algorithm converges to the global optimal solution with probability 1.

Proof First, it is proved that for any two chromosomes φ_a and φ_b , φ_b is reachable from φ_a by crossover and mutation. In fact, note that the probability of choosing φ_a to take part in crossover is $p_c > 0$. Suppose that φ_c is any offspring generated from a by crossover and φ_e is the individual generated from φ_c by the proposed local search , then the probability of φ_e being chosen to take part in mutation is $p_m > 0$. Thus, the probability of φ_b being generated from a by crossover and mutation satisfies

$$\text{Prob}\{MC(\varphi_c) = \varphi_b\} \geq p_c \bullet p_m \bullet \text{Prob}\{M(\varphi_e) = \varphi_b\}$$

It is only necessary to prove that φ_b is reachable from φ_e by mutation , *i.e.* to prove

$$\text{Prob}\{M(\varphi_e) = \varphi_b\} > 0$$

where $M(\varphi_e)$ represents the offspring of φ_e by mutation . Suppose that φ_e and φ_b have the following form

$$\varphi_e = (e_1, e_2, \ldots, e_{n-1}, e_n)\ , \varphi_b = (b_1, b_2, \ldots, b_{n-1}, b_n)$$

It is known from the mutation operator that the probability of generating b_i from e_i by mutation is 1/(n-i+1). Therefore,

$$\text{Prob}\{\ M(\varphi_e) = \varphi_b\} = \frac{1}{n-1} \cdot \frac{1}{n-2} \cdots \frac{1}{2} \cdot \frac{1}{1} = \frac{1}{n!} > 0$$

Thus,

$$\text{Prob}\{\ MC(\varphi_c) = \varphi_b\} \geq p_c \cdot p_m \cdot \text{Prob}\{M(e) = b\} = p_c \cdot p_m / n! \ > 0$$

This proves that φ_b is reachable from φ_a by crossover 、the proposed local search and mutation.

Now, the population sequence *P(0)*, *P(1)*, . . . , *P (t)*, . . . is proved to be monotone. In fact, it can be seen from the selection scheme at step 5 of the proposed algorithm that *P(t + 1)* consists of the best *pop* chromosomes chosen from $P(t) \cup O_1 \cup O_2$ for $t = 0, 1, \ldots$. Thus, *P(0)*, *P(1)*, . . . , *P (t)*, . . . is monotone.

The proof is completed.

5. Simulation Studies

We have conducted experiment to test the feasibility of our EA-based proposal for Coverage Repair Strategies. Simulation was run in C language with an Intel(R) Pentium(R) Dual Core CPU at 2.0 GHz and 2 GB of memory under Windows XP(SP3). The instance is very similar to burma14 [19] (one standard benchmark problem, a 14-city TSP problem for which the optimal distance value is 30.8785, available from TSPLIB, a library of TSPs http://www.iwr.uni-heidelberg.de/iwr/comopt/soft/TSPLIB95/TSPLIB.html). These 2D coordinates for 14 points correspond to the 14 static nodes position in the graph. The base station is placed at point B<16.47, 96.10>, the same as node v_1 position. The travel cost $d(v_i, v_j)$ was computed as the Euclidean distance between node v_i and node v_j . On this basis, each node is randomly assigned a node residual survival time value of t_i . The mobile node v_0 starts and ends at the base station through all the 14 static nodes. The experimental parameters are as follows: mutation probability p_m=0.12,max evolutionary generations *GenMax*=1200, population size *pop*=50, Moving speed of the mobile node v_0 respectively takes different values w=0.4、0.5、0.6、0.7、0.8、0.9、1.0 , node residual survival time of each node is assigned a random number between 20 and 40. A specific group values are shown in the Table 1.

TABLE 1. THE INSTANCE SPECIFIC GROUP VALUES BASE ON BURMA14 BENCHMARK PROBLEM

Node id	Static node	Coordinate <x,y>	residual survival time
1	v_1	<16.47, 96.10>	39
2	v_2	<16.47, 94.44>	27
3	v_3	<20.09, 92.54>	36
4	v_4	<22.39, 93.37>	23
5	v_5	<25.23, 97.24>	39
6	v_6	<22.00, 96.05>	37
7	v_7	<20.47, 97.02>	35
8	v_8	<17.20, 96.29>	37
9	v_9	<16.30, 97.38>	39
10	v_{10}	<14.05, 98.12>	35
11	v_{11}	<16.53, 97.38>	36
12	v_{12}	<21.52, 95.59>	33
13	v_{13}	<19.41, 97.13>	23
14	v_{14}	<20.09, 94.55>	24

Table 2 is the result of using the designed algorithm on the energy analysis-based coverage repair problem when the moving speed of the mobile node v_0 takes different values w=0.4、0.5、0.6、0.7、0.8、0.9、1.0, Statistics of the maximum number of repaired node in time $f_1(\varphi)$ and the shortest length of the path $f_2(\varphi)$.

TABLE 1. STATISTICS OF THE MAXIMUM NUMBER OF REPAIRED NODE IN TIME $f_1(\varphi)$ AND THE SHORTEST LENGTH OF THE PATH $f_2(\varphi)$

moving speed w	optimal feasible solution φ	$f_1(\varphi)$	$f_2(\varphi)$
0.4	0-1-10-9-11-13-7-12-6-5-4-3-14-2-8-0	9	31.208772
0.5	0-1-9-11-8-13-7-14-4-12-6-5-3-2-10-0	11	36.416057
0.6	0-1-10-9-11-8-13-7-14-3-12-6-5-4-2-0	12	34.921118
0.7	0-1-2-10-9-11-8-13-7-14-3-4-12-6-5-0	13	35.651916
0.8	0-1-2-14-3-4-5-6-12-7-13-8-11-9-10-0	13	30.878501
0.9	0-1-13-7-12-6-5-4-3-14-2-8-11-9-10-0	14	31.958275
1.0	0-1-2-14-3-4-5-6-12-7-13-8-11-9-10-0	14	30.878501

Figure 3 shows the best trajectory where the mobile node v_0 travels and visits the static nodes when w takes different values w=0.7、0.8、0.9、1.0. Table 2 shows that the energy analysis-based coverage repair problem(modeled as a TSP under dual-objective strategy) returns the standard traveling salesman problem when w=1.0 , all the 14 static nodes can be repaired, and the shortest length of the path can get 30.878501 (aslo showed in Figure 3 (a)) ; when w=0.9 , the mobile node v_0 may reach node v_{13} for it's residual survival time just has 23, in order to get more nodes be repaired timely.The price is that the shortest path length is increased from 30.878501 to 31.958275 (aslo showed in Figure 3 (b)); such similar situation occurred in the other *w* values situation. These results show that the designed of the algorithm can guarantee that the number of repaired nodes is as many as possible and the path length get shortest.

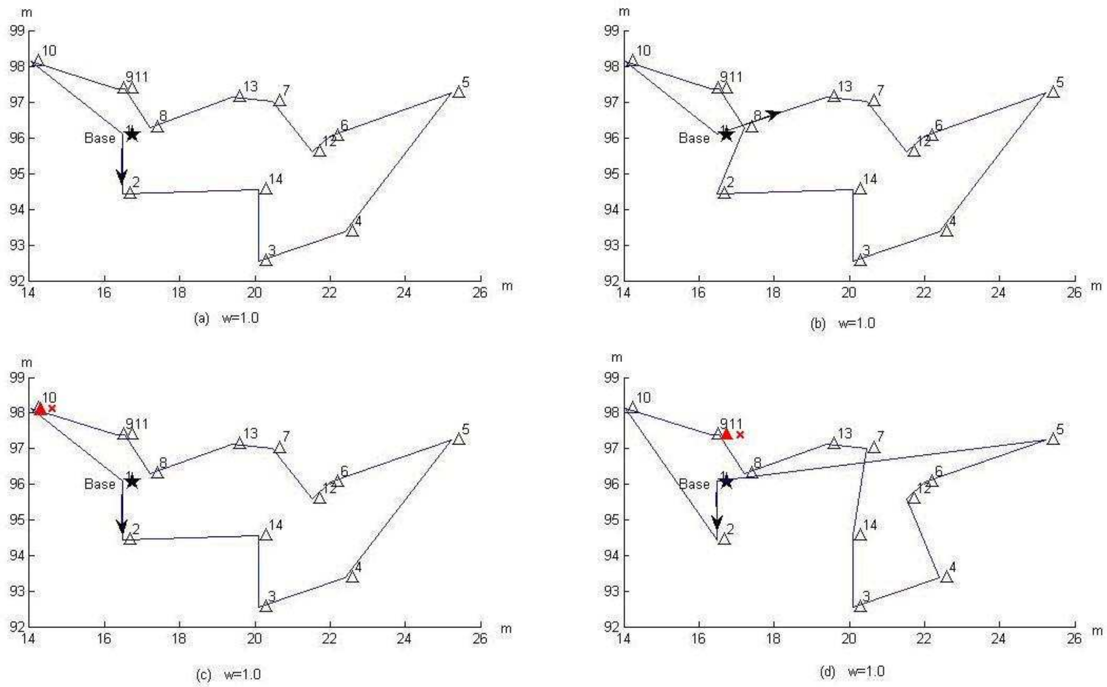

Figure 3

6. Conclusion

We modeled the energy analysis-based coverage repair strategies in WSN as a dual-objective combinatorial optimization TSP problem and solved it by the evolutionary algorithm (EA) approach. This problem keeps a great degree of resemblance with the TSP with time windows, for which every static must be served fixing within a strict period of time. Our study highlights the benefits of designing of dual-objective model and integral heuristic rules. The simulation experience results show that the designed of the algorithm can guarantee that under the condition of the number of repaired nodes is as many as possible, and the path length gets shortest.

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