A GENETIC APPROACH TO SOLVE THE CHARGING SCHEDULING PROBLEM FOR WIRELESS RECHARGABLE SENSOR NETWORKS

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Abstract—Rechargeable wireless sensor networks get the focus of attention recently for wireless charging technology's rapid progress. Since the loading of each sensor is different, the speed of energy depletion of sensors is different too. Thus, to obtain a feasible charging route, not onlyshould the moving distance of the charging device be minimized to save its energy, but also all the sensors should be charged in time, so that the whole network can work correctly. In this paper, a genetic approach is proposed to solve this complex problem. The preliminary simulation results show that the proposed approach can get the feasible charging route as expected.

Index Terms—Recharging Wireless Sensor Networks, Genetic Approach, Charging Scheduling.

I. INTRODUCTION

In wireless sensor networks (WSN), hundreds or thousands of homogenous sensors with limited battery power are deployed in the region where information will be collected. Sensor nodes sense their nearby environment and send the information to a specific base station which has neither energy nor computing power limited. While sensors are deployed uniformly in a wireless sensor network,sensors located in different positions bear different communication responsibilities, the energy consumption of sensors in the network is heterogeneous so that some may die earlier than the others and cause the network to fail to work.

Thanks to advances in wireless charging technology, it is more feasible for charging the sensors [1-3]. In a rechargeable wireless sensor network, the network operating time can be greatly extended through charging the sensors. However, the charging scheduler must take the different loading of sensors into consideration, otherwise it will make part of the sensors deplete their energy before being charged, thus, making the network not work properly. That is, a charging vehicle has to take sensors requirements into consideration while planning an efficient charging path.

In this paper, we proposed a genetic approach to solve the charging scheduling problem. The preliminary simulation results show that, with the knowledge of the residuals of the sensors, the path of the charging vehicles of the sensors can be efficiently planned by the proposed genetic approach.

The rest of the paper is organized as follows. In Sect. 2, we review previous work in the field of rechargeable wireless sensor networks. The proposed genetic approach for solving charging scheduling problem is given in Sect. 3. Preliminary simulation results of the proposed approach will be described anddiscussed in Sect. 4. Finally, we conclude this paper and list possible future research directions in Sect. 5.

II. RELATED WORKS

Energy harvesting is an interesting issue of wireless sensor networks [4-6]. The energy of sensors can be charged through collecting ambient energy, such as solar power, vibration energy, and so on. Nevertheless, the energy that can be harvested is unstable and unpredictable. Thus, to keep a wireless sensor network working longer, proactive charging approaches seem to be more feasible.

T.S. Lin and C.C. Weng[7] used quadratic Gaussian function to describe the relation between the accumulated energy and the charging time for a lithium battery.

Some researchers used static charging devices to charge the sensors [8, 9]. The required number of charging devices was increased proportional to the area of the wireless sensor network. Surely, more charging devices cost more budget. In this paper, a movable charging device is used and referred as a charging car hereafter.

M. Pan *et. al*. [10] proposed a heuristic algorithm to sovle the charging problem. In their method, the charging cars charged the sensors and then carried the data from sensors back to the base stations.

S. Chen *et. al.* [11] indicated that the performance of a wireless sensor network would be decreased when the sensors were charged frequently. That is, the charging sequence of sensors should take the residuals of sensors into consideration.

L. Li *et al*. [12] proposed a heterogeneous rechargeable wireless sensor network combining human-mounted aircraft with unmanned aerial vehicles.As the unmanned aerial vehicleswere chargedby human-mounted aircraft, the unmanned aircraft flight range and monitoring range could be unlimited expanded.

A. Madhja *et al*. [13] divided the entire circular network into multiple slices, and usedone charging car per slice area to charge the sensors respectively. Although this paper considered the moving cost of the cars, the proposed method could not guarantee that

every sensor wascharged before their energy got exhausted.

G. Han et al. [14] discussed the amount of energy dissipation in different charging paths in the RFID environment.

H. Dai et al. [15] proved that the optimal quantity of the charging cars in the wireless sensor network was an NP problem, and they used an approximation approach to obtain a better solution.

As the optimal number of charging cars and the optimal charging route calculations are proved to be NP problems,a genetic approach to obtain a feasible solution of the charging route problem is proposed and described in the next section.

III. THE PROPOSED GENETIC APPROACH FOR SOLVING CHARGING SCHEDULING PROBLEM

In this paper, we assume that the residuals of sensors, the left working time, and the positions of sensors are already known by the server. The server has to determine the charging route for the charging car. The moving distance of the charging car should be minimized while all of the sensors are charged in time. A genetic approach to solve the charging scheduling problem is proposed here. The design of chromosome, fitness function, crossover and mutation operations are described below.

Chromosome design

Assuming that there are *N* sensors that need to be charged on the entire wireless sensor network, each chromosome has *N* genes each of which is the serial number of the sensor. The position in a chromosome stands for the charging order of a gene. In the case that $N = 7$, the following is a possible chromosome. This chromosome represents the order in which seven sensors are charged, i.e., 1-> 5-> 3-> 2-> 7-> 6-> 4.

1	5	3	2	7	6	4

Fitness function

The goal of this article is to charge all the sensors before their energy are exhausted and minimize the energy consumption of the charging car. Since no matter what the charging sequence is will not change the amount of electricity required to a sensor,to save the energy of a charging car is to minimize the moving distance of it.

Fitness

$$f(g_n) = D_{car-g_0} + D_{g_0-g_1} + \cdots + D_{g_{n-1}-g_n} \quad (1)$$

Where

D_{car-g_0} indicates the distance from the charging car to the firstsensor to be charged.$D_{g_i-g_{i+1}}$ is the distance betweenthe *i*-th and *i*+1-th sensorsto be charged.

Subject to:

$$\frac{D_{car-g_0}}{Speed_{car}} \leq timeleft_{g_0} \quad (2)$$

$$\frac{D_{car-g_0}+D_{g_0-g_1}+\cdots+D_{g_{n-1}-g_n}}{Speed_{car}} \leq timeleft_{g_n} \quad (3)$$

Where $timeleft_{g_i}$ represents the remaining time of the *i*-th sensorto be charged before its energy is exhausted.

The remaining time of a sensor can be estimated using its residual energy and the average energy consumption speed. In this paper, it is assumed that the remaining time of each sensor is already known. Furthermore, to simplify the problem, the time required for charging is also assumed to be 0 and omitted in equation (3).The charging time will be taken into account in future studies.

Selection

In order to make the better chromosome have a higher probability of being selectedto generate new chromosomes, the chromosome pool is sorted in descending order according to the fitness value (because the fitness value is the smaller the better) firstly. Then, let*n*chromosomes be in the pool, a random number *s* is selected from 0 ton^2-1 and the $\lfloor\sqrt{s}\rfloor$-th chromosome is the selection result. To sum up, the algorithm to select a chromosome fromthe chromosome pool is listed below.

Step 1: Select two random number *s* from 0 to n^2-1.

Step 2: Choose the $\lfloor\sqrt{s}\rfloor$-th chromosome from the sorted chromosome pool to be the selection result.

Crossover

At first, two chromosomeC_a and$C_b$are randomly selected from the chromosome pool using the selection method mentioned above, and a cutting point *k*is randomly generated. Let *C*[*i*] represent for the gene at the position *i* of the chromosome *C*, and *C*[*i*, *j*] represent for a subsequence of the chromosome *C* from the position *i* to *j*. Then the content of the crossover result chromosome $C_c$is composed of C_a[0, *k*-1] and C_b[*k*, *n*-1].However, the contents of C_a[0, *k*-1] and C_b[*k*, *n*-1]may be duplicated, so the crossover steps are modified as below.

Step 1: Set C_c [0, *k*-1] = C_a [0, *k*-1].

Step 2: Set $C_c[i] = \begin{cases} C_b[i], & if\ C_b[i] \in C_c[0, k-1] \\ -1 & , otherwise \end{cases}$ where $k \leq i \leq n-1$.

Step 3: Find the elements from $C_b$that have not yet been placed in C_c, and fill in the positions of -1s in $C_c$sequentially.

Mutation

The mutation operation is set to swap the values of two random selected genes in a chromosome. The algorithm to mutate a chromosome $C_m$is listed below.

Step 1: Select two random number x and y from 0 to n-1.
Step 2: Swap the values of $C_m[x]$ and $C_m[y]$.

IV. RESULTS AND DISCUSSIONS

The simulation program was coded with Visual Studio c#and executed on a personal computer running Microsoft Windows 10. The simulation environment was specified by a 600 × 600m rectangular region with 7 sensors that need to be charged. These sensors were distributed randomly inside the region as shown in Fig. 1. The speed of charging car was set to be 0.5m per second. Two testing scenarios were used to demonstrate the feasibility of the proposed genetic approach. In Fig. 1, the charging car's position is marked as a red box and the positions of sensors are gray circles. The coordinates of the charging car and sensors are listed in the Table 1.

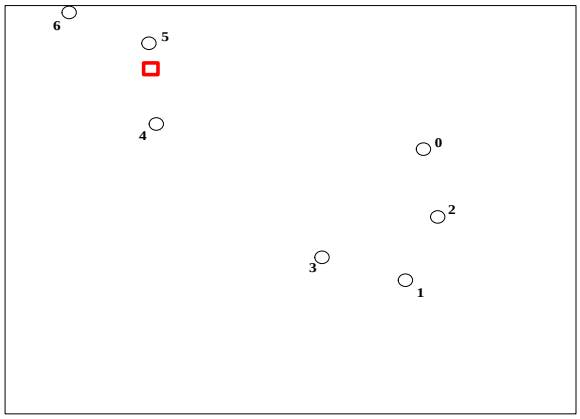


Fig. 1 The sensors deployment of the testing scenarios

Table 1 The coordinates of the charging car and sensors, and the *Timeleft* values of sensors used in two testing scenarios

Charging car/ sensors No.	x coordinate	y coordinate	Timeleft values in the first test scenario (sec.)	Timeleft values in the second test scenario (sec.)
Charging car	151	76		
Sensor#0	437	171	9989351.746	998.7462953
Sensor#1	418	330	2351446.226	2351446.226
Sensor#2	452	254	1092411.646	1092411.646
Sensor#3	330	302	5834561.91	5834561.91
Sensor#4	155	141	8261655.955	8261655.955
Sensor#5	148	44	8404243.42	8404243.42
Sensor#6	64	7	9792574.017	9792574.017

In the first testing scenario, the *Timeleft* values of sensors were large enough;therefore, the proposed genetic approach successfully found out the shortest path as the charging route as shown in Fig. 2. The length of the charging route was about 815.79 meters. However, in the second testing scenario, the *Timeleft* value of sensor #0 was small, so it needed to be charged quickly. Nevertheless, the sensor #5 was nearby the charging car, the time left for the sensor #0 allowed the charging car to charge the sensor #5 first. Finally, the charging route found by the proposed approach was shown in Fig. 3. The length of the charging route was about 1039.68 meters. Though the charging route found in Fig. 3 was longer than the shortest path shown in Fig. 2, the sensor #0 could be charged in time and keep working. Thus, the proposed genetic approach does have the potential to make a wireless sensor network work longer.

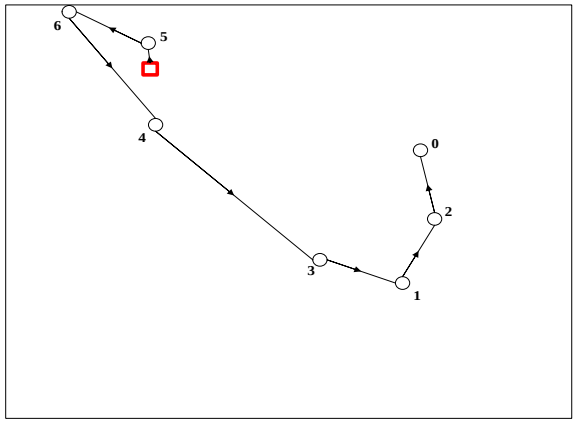


Fig. 2 The charging sequence of the first testing scenario.

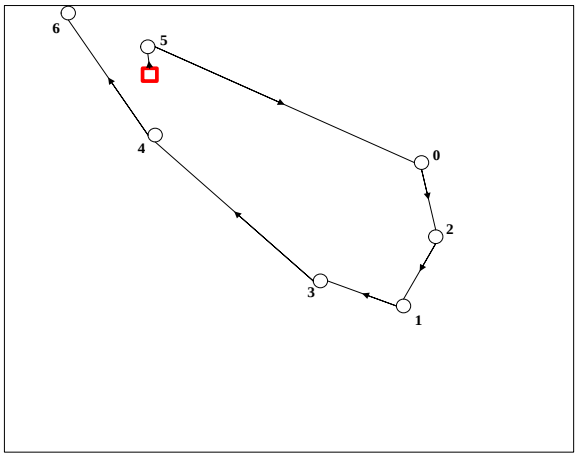


Fig. 3 The charging sequence of the second testing scenario.

CONCLUSIONS

In this paper, a genetic approach to solve the charging scheduling problem for rechargeable wireless sensor networks is proposed. Through a novel designed chromosome structure, the proposed approach can find an efficient routing path while keeping all the sensors being charged in time. However, only preliminary simulation results are shown in this paper. More sensors, more charging requirements, and more efficient genetic approach will be our future working directions.

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