PSO based Algorithm for Wireless Rechargeable Sensor Networks

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ABSTRACT
Wireless energy transfer is a recent emerging technology in wireless sensor network. This technology is a promising alternative to the power constraint problem in wireless sensor networks. Energy is the important constraint in sensor network which can be improved by different technology. Energy harvesting techniques can scavenge some amount of energy but still it's not enough. Lots of researchers put effort to solve this problem which results in wireless energy transfer. With the development in the technology, multiple nodes can be charged simultaneously by wireless charging vehicle.

Scheduling of wireless charging vehicle helps to improve the network lifetime. In addition to optimizing the travel time of the wireless charging vehicle the cost arising from travel path of charger between the nodes must also be taken into account. In this paper a (pso) based heuristics to schedule the travel path of wireless charging vehicle that takes into account both the travel cost and travel time. The result is experiment with a sample environment by varying its travel cost and travel time. Our results show that PSO can achieve shortest travel path and cost is also saved as well as network lifetime is improved.

Keywords
Wireless energy transfer, sensor networks, Particle swarm optimization (PSO), Wireless charging Vehicle (WCV), travel path.

1. INTRODUCTION
The recent promising wireless charging technology provides a solution to sensor nodes by means of charging wirelessly. The wireless charging technology was initiated by Kurs et al [1]; By means of the two strongly coupled magnetic resonant objects he tried to transfer energy from one storage device into other device wirelessly. In Wireless power charging Technology [2], power can be transferred from the transmitting antenna of a power charger to the receiving antennas of a power charger to sensor nodes receiving antennas. The power is transferred to DC voltage for the purpose of sensor utilization or else it can be stored in batteries.

Wireless sensor networks (WSN) are mainly powered by batteries. The battery storage capacity is limited and so a WSN can only remain operational for a limited amount of time. To extend the lifetime of sensor networks lot of efforts are put by various researchers, But still it remains as a bottleneck. This area of research leads to the growth of wireless energy in fields of electronics, health care, electrical vehicles, etc. For example, wireless charging pads is used to charge mobile devices without connecting charging cables whenever they are placed on the pad [3]. In case of health care applications wireless charging of implanted batteries is replaced by surgical operation to dispose old batteries. Wireless charging technology provides a new research solution to the emerging Electrical Vehicle (EV) industry. This can be introduced with high efficiency to deliver hundreds of watts of energy, where the charging system are placed at power stations, parking lots or even under the road surface to recharge EV's battery packs [4]. For the next generation WSNs, wireless charging technology has to grow up with hybrid technology to power the sensor nodes and these networks are known as Wireless Rechargeable Sensor Networks (WRSNs).

There are lots of applications that utilize commercial products from Powercast to charge the sensor nodes wirelessly [5]–[8].The Radiation-based wireless charging techniques have very low efficiency and can only transfer a small amount of energy whereas magnetic resonant coupling proposed in [9] has high efficiency and supports transferring hundreds of watts of energy over a large air gap. To implement futuristic WRSNs, this technique is adopted in mobile vehicles where resonant coils and high-density battery packs are used in very close proximity and deliver wireless energy to the nodes with high efficiency [10]–[16]. To schedule more than one vehicle to recharge all the sensors is a great challenge [15], [16].In addition to it vehicle's recharge capacity, travelling cost pose great research issue [16]. These problems are NP-hard and new algorithms arrived with good results which are more desirable [14]–[16].

In this paper, the main focus is on minimizing the total travelling cost of wireless charging vehicles to recharge the sensors. In order to achieve this fair scheduling algorithm should be implemented. This is achieved by using a meta-heuristics method called Particle Swarm Optimization (PSO).Kennedy and Eberhart introduced a self-adaptive global search based optimization technique which is called as Particle Swarm Optimization (PSO) [17]. The algorithm is similar to Genetic algorithms but, the difference is only no direct recombination of individuals of the population. It is based on the social behavior of the particles. In PSO each particle adjusts its trail based on its best position (local best) and the position of the best particle (global best) of the entire population. This increases the stochastic nature of the particle and converges quickly to a global minimum with a good solution.

The advantage of using PSO is its simplicity and its effectiveness in wide range of application with low computational cost. Some examples of PSO application are: the reactive voltage control problem [18], data mining [19], pattern recognition [20] and environmental engineering [21], Scheduling [22, 23] and task allocation [24, 25].

The works contributed in this paper are as follows:

- A model is formulated for WCV-SN mapping to minimize the overall cost of Recharging.

- Designed a heuristic that uses PSO to scheduling problem of charging vehicle based on the proposed method.

The rest of the paper is organized as follows: Section 2 presents related work. In Section 3, WCV-SN scheduling problem and its formulation is described. In Section 4, scheduling heuristic that uses PSO is described. Section 5 presents an experimental simulation of our work. Section 6 concludes the paper.

2. RELATED WORK

After energy information has been collected, a global energy map can be visually analyzed by SenCars. Then the next important objective is to schedule a number of SenCars to keep all the nodes alive and minimize the traveling distance of SenCars. This is referred to as perpetual operation of the network and one of the primary goals in the designs of WRSNs. Seeking an optimal solution to schedule a fleet of SenCars for recharge is usually an NP-hard problem whereas traditional efforts of standard optimization techniques are not cost effective given limited computation resources on the SenCar. Thus, heuristic algorithms are usually proposed in practice to achieve a reasonable balance between optimality and computation complexity.

In [14], the problem to schedule a SenCar for emergency recharge is studied. In order to resolve as many emergent nodes as possible before the next emergency occurs, the SenCar needs to maximize the energy replenished back into the network within a limited time threshold. The problem is formulated into an Orienteering Problem. In the Orienteering Problem, a set of control points associated with scores are visited by competitors before a time expiration, and the competitor collecting the highest score wins the game. The problem aims to find the highest score in limited time durations. The problem is NP-hard. However, it has been shown in [14] by utilizing the fact that traveling time is negligible compared to recharge time since traveling time is usually 1-5 mins whereas recharge time requires more than 60 mins. Therefore, the traveling time of SenCar can be ignored and the Orienteering Problem can be closely approximated by a Knapsack problem. Then classic dynamic programming method is applied to solve the problem in polynomial time.

In [15], a more general case with multiple SenCars and dynamic battery deadlines is considered. Based on the energy information, an on-line algorithm that aims to select the next node with the minimum weighted sum of traveling time and node lifetime is proposed. The weighted sum method is used to balance conflicting factors in the problem. That is, on one hand, to minimize SenCars' traveling cost, it is desired to move to the nearest node requesting recharge, which may be far away from SenCar's location. On the other hand, to meet node's battery deadline, SenCars should prioritize nodes with shorter estimated lifetime. The algorithm runs in polynomial time with acceptable performance compared to the optimal case. Additionally, bringing more practical aspects would be beneficial for real applications and design the network but it certainly complicates the algorithm designs. For example, if the SenCar's own battery capacity is not considered in algorithm design, it may be stranded during operation and unable to return to the base station for battery replacement. In addition, the moving cost of SenCar should be also considered to avoid long distance movements.

In [16], a set of practical constraints of SenCar's own recharge capacity, moving cost and nodes' battery deadlines are considered. With the needs of better route plans and desires to meet sensors' battery deadlines, **we** need to coordinate the activities among the SenCars. To tackle these challenges, a 3-step adaptive algorithm is proposed in [16].

The operation of the algorithm is illustrated through an example in Fig. 4. Fig. 4(a) gives a snapshot of energy request during the operation. To keep the movement of SenCars in their confined scopes, the network is partitioned adaptively according to the recharge requests (Fig. 4(b)). The well-known K-means algorithm can be used [26].

The K-means algorithm aims to minimize the total square of sum of distance to a set of centroid positions. The centroid position is chosen as the starting position of each SenCar. After each SenCar has been assigned a working region, they compute Capacitated Minimum Spanning Trees (CMST) independently as shown in Fig. 4(c). The CMST is a minimum spanning trees with capacity threshold so it can naturally capture the recharging capacity of the SenCar and indicate from which subset of nodes the SenCar should choose to minimize the traveling cost. Finding the CMST first can also ensure the nodes on the same tree are placed in the same recharge route later. After the CMSTs are formed, the SenCar needs to further capture the sensors' battery deadlines.

To improve the previous weighted-sum algorithm from [15], the SenCar categorizes nodes according to their lifetime. If a node's lifetime is enough to last for the total recharging time of the entire recharge sequence, it can be placed at any arbitrary position in the sequence. **We** denote these nodes "non-prioritized nodes". On the other hand, if a node's lifetime is not enough, it needs to be inserted at advantageous locations in the sequence and each insertion should retain the battery deadlines of all the nodes in the recharge sequence.

These nodes are denoted as "prioritized" nodes. The algorithm first computes the recharging route of the non-prioritized nodes using a classic Traveling Salesmen Problem algorithm, e.g. the nearest neighbor or Christofides algorithm [27]. Then it inserts prioritized nodes into the recharge sequence iteratively while maintaining the time feasibility and minimizing the moving cost of the SenCar for each insertion. The final recharge routes are shown in Fig. 4(d). The aforementioned works have provided initial attempts to solve complicated recharge scheduling problems. For future works on this topic, a more general problem that encompasses stochastic energy demands should be considered.

In [28], theoretical results for on-demand wireless charging have been studied. A queuing model has been established and important characteristics have been proposed such as throughput and charging latency. Based on the analysis in [28], stochastic recharge policies can be developed in future.

3. WCV-SN SCHEDULIGN PROBLEM FORMULATION

The scheduling of WCV to sensor nodes can have several objectives. The main focus is on minimizing the total cost of recharging the sensor nodes with maximum efficiency of the network. The optimization problem can be defined as follows.

The sensor network is denoted as a Directed Acyclic Graph (DAG) represented by G=(V, E), where V_i ($i \in N_r$) is the location of sensor node i to be visited, and E is the set of edges. Each edge E_{ij} is associated with a traveling energy cost c_{ij} , which is proportional to the distance between nodes i and j.

Given a set of SenCars $S = \{1, 2, . . . ,m\}$ and a set of recharge node list $N_r = \{1, 2, . . . , n_r\}$. A SenCar has recharge capacity

Ca that determines the maximum number of nodes it can recharge before it goes back to the base station for its own battery replacement. Different SenCars could have different recharge capacities during the run. Each sensor node *i* has lifetime *li* and demand (reward) for energy recharge *ri*. *Ai* specifies the arrival time for a vehicle at sensor node *i*.

Two decision variables xij for edge Eij and yia for vertex Vi are introduced. The decision variable xij is 1 if an edge is visited, otherwise it is 0. The decision variable yia is 1 if and only if vertex *i* is served by vehicle *a*, otherwise it is 0. *ui* is the position of vertex *i* in the path. Our objective is to maximize the total amount of energy recharged minus total traveling energy cost of the SenCars while ensuring the recharge capacities of SenCars are not exceeded and no sensor node depletes battery energy.

The problem can be given as: "Find a Route for WCV such that the total cost incurred for recharging all the The problem can be given as: "Find a Route for WCV such that the total cost incurred for recharging all the sensors and the travel time of the WCV is minimized by covering all the sensor nodes."

The total travel time of all the assigned wireless charging vehicle WCV_j is given as travel (Rechrg)_t by adding all the travel time of WCV from Base station to sensor nodes and return back to base station(Eq. 1).

The total recharging time of the sensor by WCV_i is given by the adding the time of recharging of individual sensors of individual WCVs (Eq. 2).The total cost of recharging a WCV is just the sum of total travel time and recharge time (Eq. 3).The network recharge cost is given by adding the recharge cost of all the WCV assigned for the network (Eq.4.).When estimating the total cost for all the nodes to be recharged, the largest cost for travelling to all the sensor nodes is minimized (Eq. 5).

$$c_{\text{travel}} \ (\text{Rechrg})j = \sum_k \text{WCVkj} \qquad -(1)$$

$$c_{(\text{Rechrg}(\text{WCV})} = \sum_k \text{WCVkj} \quad \sum_k \text{Snj} \qquad -(2)$$

$$c_{\text{Total (wcv)}j} = \sum_k \text{WCVkj} \ + \ \sum_k \text{WCVkj} \quad \sum_k \text{Snj} \qquad -(3)$$

$$\text{cost(Total)} = \max(\text{Ctotal(rechrg)j})\forall j€p \qquad -(4)$$

$$\text{minimize(cost(rechrg)} \qquad \forall \ \text{Ctravel} \qquad -(5)$$

4. SCHEDULING BASED ON PARTICLE SWARM OPTIMIZATION

A scheduling heuristic for dynamically scheduling the wireless charging vehicle is given here. The heuristic optimizes the cost of WCV- SN mapping based on the solution given by particle swarm optimization technique. The optimization method consist of two components: a)

the scheduling heuristic given in Algorithm 1, and b) the PSO steps for WCV-SN mapping optimization as listed in Algorithm 2.

$$v_i^{k+1} = \omega v_i^k + c_1 rand_1 \times (pbest_i - x_i^k) + c_2 rand_2 \times (gbest - x_i^k) \qquad -(6)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad -(7)$$

where

v_i^k velocity of particle i at iteration k

vik+1 velocity of particle i at iteration k + 1

ω inertia weight

cj acceleration coefficients; j = 1, 2

randi random number between 0 and 1; i = 1, 2

xik current position of particle i at iteration k

pbesti best position of particle i

gbest position of best particle in a population

xik+1 position of the particle i at iteration k + 1.

4.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a stochastically global optimization swarm-based intelligence algorithm [8] which was introduced by Kennedy and Eberhart (1995). PSO is influenced by the social behavior of animals such as a flock of birds' searches a food source or a school of fish protects from a predator or swarm of bee's searches for food sources. The particle swarm optimization algorithm solves many problems in various fields of engineering and computer science.

In PSO the particle is equivalent to a bird or fish flying through a search space. The movement of each particle is co-ordinated by a velocity which has two components i.e. magnitude and direction. The position of each particle is influenced by its best position and the best particle position in a problem space. The fitness value is used to measure the performance of a particle.

The term population is used in PSO which is the number of particles in a problem space and the Particles are randomly initialized. Each particle in the population has a fitness value, which is evaluated by a fitness function to be optimized in each generation. The particles movements are influenced by two factors using the information as iteration-to iteration and as particle-to-particle .Each particle know its best position visited so far and store in as pbest and the best position so far visited by any particles gbest. In each generation the velocity and the position of particles will be updated. This process continues, iteratively, until an expected optimized solution is obtained.

Algorithm 1 Scheduling heuristic.

1: Calculate average recharging cost of all WCV in all clusters

2: Calculate average cost of travelling of WCV between sensor nodes

3: Set Total Energy of all nodes Etot as average Energy level

4: Set Initial Energy es1,s2 as energy of individual sensors nodes

5: Compute PSO({ti})

6: **repeat**

7: **for** all "ready" WCV{ti} ∈ T **do**

8: Assign WCV {ti} to Sensor nodes {pj} according to the solution provided by PSO

9: **end for**

10: Dispatch all the assigned nodes

11: Wait for polling time

12: Update the ready charging list

13: Update the average cost of travel between WCV to sensor nodes to the current position

14: Compute PSO({ti})

15: **until** there are unscheduled tasks

Algorithm 2

PSO algorithm

1: Set particle dimension as equal to the size of ready WCV in $\{t_i\} \in T$

2: Initialize particles position randomly from sn = 1, ..., j and velocity vi randomly.

3: For each particle, calculate its fitness value as in Equation 4.

4: If the fitness value is better than the previous best pbest, set the current fitness value as the new pbest.

5: After Steps 3 and 4 for all particles, select the best particle as gbest.

6: For all particles, calculate velocity using Equation 6 and update their positions using Equation 7.

7: If the stopping criteria or maximum iteration is not satisfied, repeat from Step 3.

The PSO algorithm steps are given in Algorithm 2. The algorithm starts with random initialization of particle's position and velocity. In this problem, the particles are the sensor node for the WCV to be assigned and the dimensions of the particles are the number of Sensors nodes for a WCV.

The values assigned to each dimension of particles are the WCV. Thus the particle represents scheduling of WCV to the sensor nodes. The evaluation of each particle is performed by the fitness function given in Eq. 5. The particles calculate their velocity using Eq. 6 and update their position according to Eq. 7. The evaluation is carried out until the specified number of iterations.

5. SIMULATION RESULTS

The proposed algorithm has been simulated in NS2 environment .Simulation is done using NS2 by making simulation environment with 100 nodes with 2 WCV in the area of 100*100. The initial energy level of sensor node is given as 0.5J.The results are shown in Fig 1 and Fig 2.

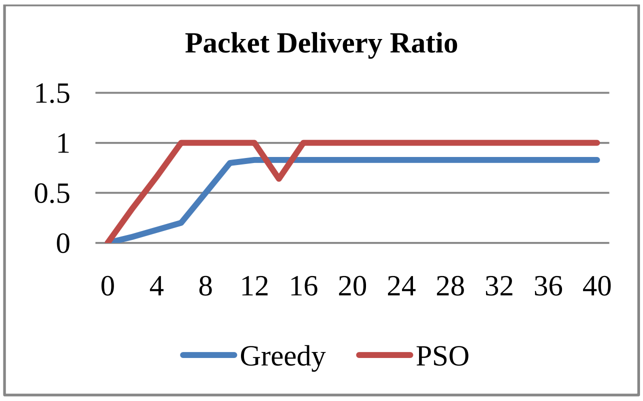

Fig 1. PDR Graph

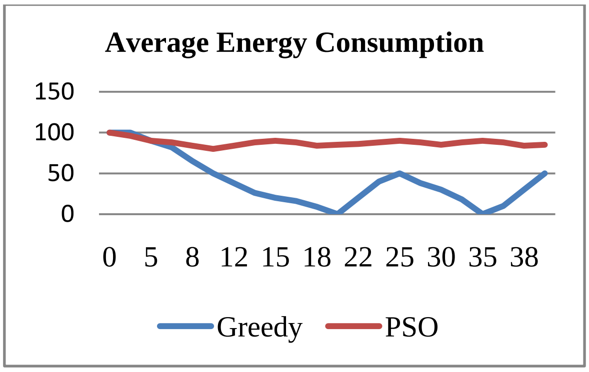

Fig 2. Average energy consumption Graph

6. CONCLUSIONS AND FUTURE WORK

In this paper, a scheduling heuristic based on Particle Swarm Optimization (PSO) is presented. The heuristic is used to minimize the total cost of recharging using wireless charging vehicle in wireless sensor network. The Results obtained by PSO based heuristic is compared against existing heuristic. PSO based WCV-SN mapping can achieve at least three times cost savings as compared to existing one. As a part of our future work, Integrate PSO based heuristic into our real time applications to schedule charging vehicles of real applications such as mobile robots, battery cars in amusement parks and others.

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