Path Optimization with Machine-Learning Based Prediction for Wireless Sensor Networks

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Abstract. The trajectory scheduling of the mobile nodes is a critical research problem in rechargeable wireless sensor networks. In this paper, we propose a machine-learning based energy consumption prediction (ML-ECP) approach, which uses machine-learning to predict the energy consumption rates in wireless sensor networks. Based on the prediction, the sensor nodes are partitioned into multiple clusters and the optimal trajectories are obtained for mobile nodes. We compare the proposed approach with the existing approach, the results show that the ML-ECP improves the energy efficiency for sensor nodes recharging and data collection, and the mobile nodes collect information and recharge sensor nodes periodically in the network.

Keywords: Path optimization · Machine-learning · Wireless sensor networks

1 Introduction

Due to the characteristics of low cost and small size, sensor nodes can monitor and record the physical conditions of the environment and have the ability for data processing and wireless communication [2]. For the most existing sensor networks, they are powered by batteries, and their lifetime is limited by the battery capacity. In recent years, the energy provisioning problem is noticed by many researchers. [5] decouples the energy recharging problem into a node deployment problem and a charging and activation scheduling problem. They propose an algorithm and prove that it achieves the optimal solution under a mild condition. [7] develops the joint downlink energy assignment and uplink power control scheme with the heterogeneous statistical QoS provisioning (HeP) for wireless powered sensor networks (WPSNs). In [8], the authors propose a novel energy synchronized mobile charging (ESync) protocol, which simultaneously reduces the charger travel distance and the charging delay.

For this case, mobile nodes have the delay to visit the sensor nodes and the sensor nodes have the limited battery capacity. The task scheduling for sensor

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nodes in the network plays a critical role in achieving a high charging and information collecting efficiency [12]. If we consider the delay of the mobile node and the diversity of sensor nodes energy consumption, one mobile node is not enough for a large-scale network. The multiple traveling salesman problem (mTSP) is a scheduling problem, which is a generalization of the traveling salesman problem (TSP), and which aims to determine a set of routes for m salesmen who start from and return to a home [1]. It has been widely studied in recent years, and how to schedule the traveling trajectories of mobile nodes and how to reduce the energy-hole are two crucial topics in this field.

However, most of the previous works focus on the location of sensor nodes [3,4] and ignore the different energy consumption for each sensor node. In a traveling tour, some sensor nodes are visited when it do not need to be recharged. This increases the traveling distance of mobile nodes and prolongs the waiting time of the energy-hungry sensor nodes [8]. To address this issue, we propose a machine-learning based energy consumption prediction (ML-ECP) approach that considers both the location of sensor nodes and the energy consumption diversity of sensor nodes. Based on the energy consumption rate prediction, the sensor nodes are partitioned in the first step. Then, the sensor nodes search neighbors within its cluster. In the last step, the traveling trajectories and the meeting point locations of mobile nodes are scheduled.

The remainder of this paper is organized as follows. Section 2 proposes energy consumption prediction approach and presents the traveling tour optimization approach. Section 3 provides a particular case of our approach and compares the results of our approach with the existing approach. Finally, Sect. 4 concludes this paper.

2 Proposed Work

We assume the case that N immobile and rechargeable sensor nodes are randomly deployed in a region $\mathcal{R}$. The locations of them are known *a priori*. Each of them has a fixed communication range which is a circular area with radius of r and a unique identification (ID). The energy consumption of a sensor node mainly comes from the information monitoring and data transmission and is different with each other. Based on this difference, we propose ML-ECP approach which construct a set of nested TSP tours to balance the energy provisioning.

2.1 Machine-Learning Based Energy Consumption Prediction

First of all, all sensor nodes are fully charged. The different kinds of sensor nodes may have the different consumption rates and the energy consumption rates of the same sensor node may vary over time [8]. We assume the mobile nodes have certain knowledge on the energy consumption conditions of all sensor nodes. Based on this assumption, the prediction on their energy consumption rates is feasible [11]. ML-ECP solves the issue by three steps.

In the first step, we use fuzzy machine-leaning clustering algorithm to partition the network based on the different energy consumption rates of sensor nodes. Instead of the hard clustering algorithm, the fuzzy clustering algorithm is less likely to get stuck in the certain energy consumption rate in iteration through the use of membership values, and a sensor nodes can belong to more than one cluster. For high energy consumption sensor nodes, this is a effective method to avoid the sensor nodes death before the mobile nodes recharge them.

The most classic fuzzy clustering algorithm is the fuzzy c-means algorithm that is proposed by [6,10]. The algorithm provides a degree of membership for each data point to a given cluster. The values of the degrees of membership are between 0 and 1. When it close to 0, the data point has the low probability to be assigned to the corresponding cluster. Conversely, the data point has the high probability to be assigned to the cluster when the value close to 1. In this paper, based on the differences of the energy consumption rates, the clustering issue is based on minimization of the following objective function:

$$\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}|e_i - e_{c_j}|^2 \qquad 1 < m < \infty \tag{1}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of the sensor node i in the cluster j, e_i is the energy consumption rate of the sensor node i, e_{c_j} is the mean value of the energy consumption rate of the cluster j, and $|\cdot|$ is the difference between any sensor node energy consumption rate and the mean value of the energy consumption rate.

Initially, the mean values of the energy consumption rate are randomly selected. Every sensor nodes will be assigned to the similar mean value cluster. Fuzzy clustering is carried out through an iterative optimization of the objective function, with the update of membership u_{ij} and the mean value of the energy consumption rate e_{cj} by:

$$u_{ij} = [\sum_{k=1}^{C}(\frac{|e_i - e_{c_j}|}{|e_i - e_{c_k}|})^{\frac{2}{m-1}}]^{-1} \tag{2}$$

$$e_{c_j} = \frac{\sum_{i=1}^{N} u_{ij}^{m} e_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{3}$$

This process will stop when it satisfies the Eq. (4), where ε is a termination criterion, U_l is the matrix of the degree of membership in the lth iteration.

$$|U_{l+1} - U_l| \leq \varepsilon \tag{4}$$

Therefore, we have the clusters $G_1, G_2, ..., G_j, ..., G_C$.

2.2 Path Optimization for Mobile Nodes

In the second step, each sensor node finds the neighbors of itself within its cluster. The mobile nodes know the serial numbers and the location information of sensor

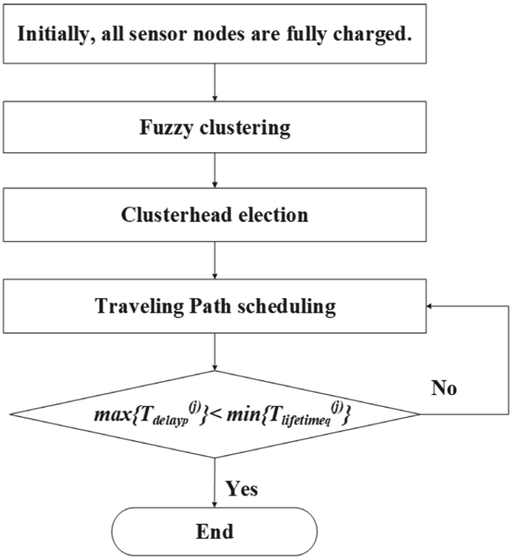

Fig. 1. The flow of the ML-ECP approach.

nodes. Only the sensor nodes that belong to the same cluster and is within its 1/2 communication radius can become the neighbors. Through several iterations, based on the location information, the neighbors become the child nodes and belong to only one clusterhead. The sensor node that has more neighbors is more likely to become a clusterhead, and the sensor node that has no neighbors becomes the clusterhead of itself.

After we obtain a series of clusterheads, in the third step, the traveling paths are scheduled for each cluster based on these clusterheads, and the mobile node will stop at the meeting point that is at the circle of clusterheads' 1/2 communication radius. This can be formulated as a traveling salesman problem, which is NP-hard. We adopt the two-step solver [9] to solve it. After running the solver, each cluster will obtain an optimized path and the meeting points information.

Then, the mobile nodes need to estimate whether the number of sensor nodes within its cluster are more than the threshold. That can be judged by the following function:

$$max\{T_{delay_p{}^{(j)}}\} < min\{T_{lifetime_q{}^{(j)}}\} \tag{5}$$

where $max\{T_{delay_p{}^{(j)}}\}$ is the maximum delay in the cluster j, and min $\{T_{lifetime_q{}^{(j)}}\}$ is the minimum lifetime in the cluster j.

If the number of sensor nodes in this cluster cannot satisfy the above function, this means there are some sensor nodes will stop work before the mobile node recharge them. To avoid this situation, for this cluster, there are more than one mobile nodes will be assigned to visit it, and the extra mobile nodes will be selected from the waiting mobile nodes. Figure 1 shows the procedure of the proposed approach.

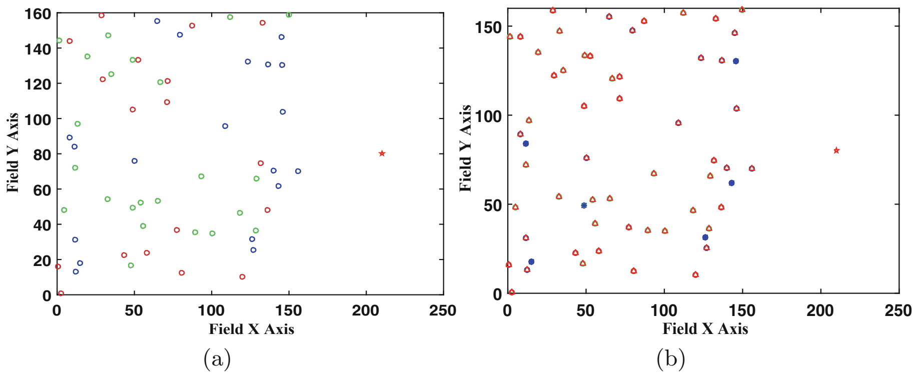

Fig. 2. The simulation results of the first two steps in a synthetic example of ML-ECP. (Color figure online)

3 Performance Evaluation

In this section, we present the procedure by applying ML-ECP to a synthetic example. In order to show the outstanding performance of our approach, we compare the performance of our approach with the existing approach.

3.1 An Example of ML-ECP

To illustrate our approach, we first randomly generate 60 sensor nodes in the size of $160 \times 160\,\mathrm{m}^2$. Then we use fuzzy algorithm to partition these sensor nodes into 3 clusters based on the different energy consumption rates. The result is shown in Fig. 2a where different clusters are labeled with different colors and the red five-pointed star represents the sink point. Figure 2b shows the simulation result when the clusterheads have been elected in the second step. The red plus sign icons represent the sensor nodes have been elected to the clusterheads and the blue asterisks show the sensor nodes have become the child nodes.

3.2 Investigating the Traveling Distance

We invistigate the traveling distance with different network scales in this section. Based on the same sensor nodes' location, we utilize TSP and our ML-ECP approach to calculate the traveling trajectories when the number of sensor nodes varies from 20 to 140 and the size of network is $160 \times 160\,\mathrm{m}^2$. The results is shown in Fig. 3. We can see the traveling distances of ML-ECP for each mobile node are obviously shorter than the results of TSP.

3.3 Investigating the Traveling Delay

We analyze the effects of the number of the sensor nodes on the traveling delay of mobile nodes. From 20 to 140 sensor nodes are randomly deployed in the size

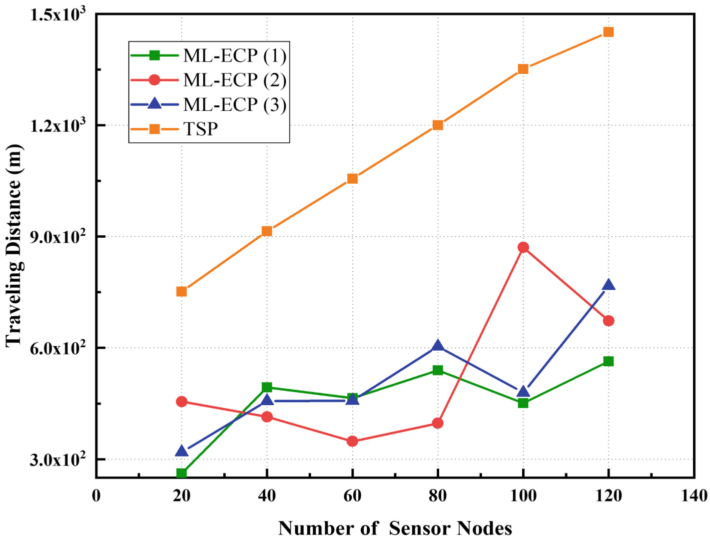

Fig. 3. Effects of the network scale on the traveling distance.

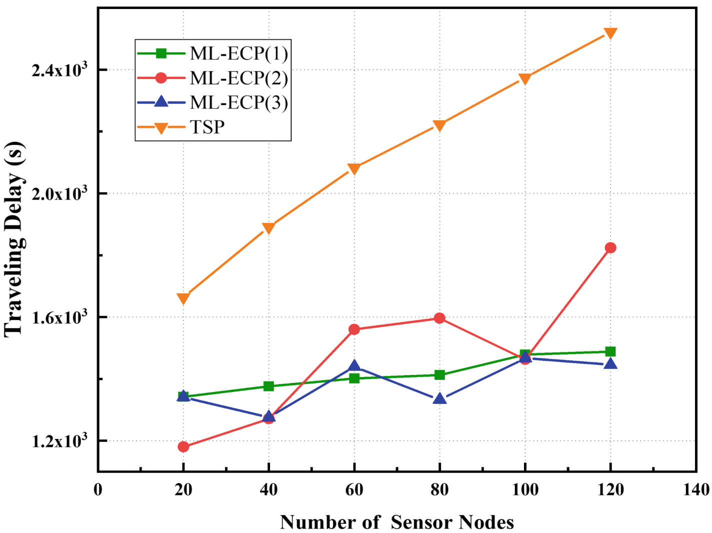

Fig. 4. Effects of the network scale on the traveling delay.

of $160 \times 160\,\text{m}^2$. We assume $t_0 = 900\,\text{s}$ and each sensor node generates a data packet at every 1 s. The movement speed of mobile nodes is 1 m/s. In Fig. 4, the yellow line shows the delay results of TSP and the others represent the delay results of ML-ECP for each mobile node. The results represent ML-ECP has obvious advantage over TSP.

4 Conclusion

This paper mainly focused on the optimization of the traveling tour for multiple mobile nodes in rechargeable wireless sensor networks. To improve the efficiency of recharging, we use machine-learning to predict the energy consumption rates of sensor nodes in the network. Then, the mobile nodes can visit these sensor nodes based on the prediction periodically. We evaluate and compare the proposed approach by extensive simulations. The results show that the performance of the energy efficiency and the traveling delay have been improved significantly.

References

1. Bektas, T.: The multiple traveling salesman problem: an overview of formulations and solution procedures. Omega **34**(3), 209–219 (2006)
2. Boyinbode, O., Le, H., Takizawa, M.: A survey on clustering algorithms for wireless sensor networks. Int. J. Space-Based Situated Comput. **1**(2–3), 130–136 (2011)
3. Ding, K., Yousefi'zadeh, H.: A systematic node placement strategy for multi-tier heterogeneous network graphs. In: 2016 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6. IEEE (2016)
4. Ding, K., Yousefi'zadeh, H., Jabbari, F.: A robust advantaged node placement strategy for sparse network graphs. IEEE Trans. Netw. Sci. Eng. **5**(2), 113–126 (2018)
5. Du, R., Xiao, M., Fischione, C.: Optimal node deployment and energy provision for wirelessly powered sensor networks. IEEE J. Sel. Areas Commun. **37**, 407–423 (2018)
6. Dunn, J.C.: A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters (1973)
7. Gao, Y., Cheng, W., Zhang, H., Li, Z.: Heterogeneous statistical qos provisioning over wireless powered sensor networks. IEEE Access **5**, 7910–7921 (2017)
8. He, L., et al.: ESync: an energy synchronized charging protocol for rechargeable wireless sensor networks. In: Proceedings of the 15th ACM International Symposium on Mobile Ad Hoc Networking and Computing, pp. 247–256. ACM (2014)
9. Jianxin Ma, S.S., Gu, X.: An optimization-based MTSP-CR mobile data gathering algorithm for large-scale wireless sensor networks. In: Vehicular Technology Conference, VTC Fall 2018. IEEE (2018)
10. Peizhuang, W.: Pattern recognition with fuzzy objective function algorithms (James C. Bezdek). SIAM Rev. **25**(3), 442 (1983)
11. Wang, Y., Vuran, M.C., Goddard, S.: Stochastic analysis of energy consumption in wireless sensor networks (2010)
12. Zhou, Z., Du, C., Shu, L., Hancke, G., Niu, J., Ning, H.: An energy-balanced heuristic for mobile sink scheduling in hybrid WSNs. IEEE Trans. Ind. Inform. **12**(1), 28–40 (2016)