

Reducing Sensor Failure and Ensuring Scheduling Fairness for Online Charging in Heterogeneous Rechargeable Sensor Networks

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Reducing Sensor Failure and Ensuring Scheduling Fairness for Online Charging in Heterogeneous Rechargeable Sensor Networks

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Abstract—The breakthrough of wireless power transfer technology provides an effective solution to the problem of energy depletion in Wireless Rechargeable Sensor Networks (WRSNs). Most existing work focuses on charging between a mobile charger and a requested sensor, such as NJNP and SAMER, under the assumption that sensors have the same battery capacity and energy consumption rate. In reality, it is more general that a WRSN consists of different types of sensors where they have different battery capacity and energy consumption rate, which is referred as Heterogeneous Wireless Rechargeable Sensor Network (HWRSN). We propose a novel online charging algorithm called VTMT to solve the charging problem in HWRSN. First, we propose the concept of Virtual Time, which is positively correlated with the waiting time of the requested sensor. Then selects the next charging sensor primarily based on the Virtual Time (VT) of the sensor and the Moving Time (MT) of the mobile charger to the node. Simulation results show that VTMT outperforms other charging schemes, which effectively reduce the failure rate of nodes and ensure the scheduling fairness.

Index Terms—Heterogeneous Wireless Rechargeable Sensor Networks, Energy Replenishment, Online Charging Scheme.

I. INTRODUCTION

As one of the most essential technology in Internet of Things, Wireless Sensor Networks (WSNs) are extensively used in precision farming [1], intelligent transportation [2], temperature regulation [3] and forest fire detection [4], etc. Nevertheless, due to the limited battery capacity of sensor nodes in the WSNs, the performance and lifetime of sensor nodes are severely constrained. How to prolong the lifetime of sensors is an important problem. Existing solutions can be roughly divided into three categories: energy conservation [5], energy harvesting [6] and wireless charging [7]. The wireless charging scheme uses a mobile charger to wirelessly charge the sensor node to extend its lifetime. There are three kinds of wireless power transfer technologies used for wireless charging: inductive coupling, electromagnetic radiation and magnetic resonance coupling [7]. Magnetic resonance coupling is widely used in wireless charging because of its high efficiency, long transmission distance, omni direction and insensitive to weather conditions. Adopting this scheme requires the deployment of mobile charging nodes and service station nodes in the network, which is referred as wireless

rechargeable sensor networks (WRSNs). Such network with multiple types of sensors is called as heterogeneous wireless rechargeable sensor networks (HWRSNs). The mobile charging node is referred as Mobile Charger (MC) and the service station node is referred as Base Station (BS). Different from other schemes, wireless charging scheme can provide continuous and stable energy for nodes in WRSNs.

The current charging schemes can be roughly divided into two categories: offline [8]–[11] and online [12]–[16]. The offline charging scheme is that the MC periodically charges the sensor nodes in accordance with a predefined route. For the existing offline schemes, it is usually assumed that the energy consumption rate of the nodes is constant, which is inconsistent with the dynamic energy consumption rate in the practical applications. For online charging schemes, nodes can periodically send the residual energy message to the BS, so that the node consumption rate of sensors, the online charging scheme cannot plan the charging paths of MC in advance and should schedule the charging orders of sensors in real time, which is more according with the practical applications.

There are some challenges in designing the online charging scheme: First, whether the charging scheme can reduce the node failure rate in the network, which is defined as the percentage of the sensors with energy depletion. It is a key factor in evaluating a online charging scheme. Second, whether the charging scheme can reduce the moving cost of the MC, which is defined as the total moving distance of the MC. Third, whether the charging scheme can guarantee scheduling fairness, which means that the requested sensors cannot wait for charging for a long time. The classic NJNP scheduling strategy [13] always chooses the nearest node to the MC as the next charging node, and new requests can be preempted during the MC's movement. Therefore, this scheme leads to a high node failure rate. Meanwhile, this scheme has a bad performance in HWRSNs.

We propose a novel online charging algorithm in HWRSNs, called a charging algorithm based on virtual time and moving time (VTMT). First, we define three concepts, virtual time,

moving time and starvation node rate. Virtual time (VT) is positively related to the waiting time and the energy consumption rate of the requested node. Moving time (MT) is defined as the time of the MC moved to the node. We also define the concept of starvation node rate, which used to judge the scheduling fairness. Second, we investigate a simple and effective method of calculating the energy consumption rate of node based on historical information. The main idea of VTMT algorithm is to divide the VT by the MT as the Service Value (SV), and then select the node with the highest Service Value (SV), which is the ratio of VT to the MT, as the next charging node. The requested sensor with a longer virtual time are more likely to be charged preferentially. The nearer candidate node are chosen to reduce the moving cost of the MC. Experiments demonstrate that our algorithm results in the low node failure rate, short moving cost of MC and good scheduling fairness in HWRSNs.

The rest of the paper is arranged as follows: We introduce related works in Section II. The system model and notions will be given in Section III. In Section VI, we present the the VTMT algorithm. Simulation experiments are performed in Section V. Section VI concludes this paper.

II. RELATED WORK

With the development of wireless rechargeable sensor networks, two types of charging schemes are proposed, offline charging schemes and online charging schemes.

For offline schemes, Fu et al. [8] transformed the charging delay minimization problem into a solvable linear programming problem, and proposed a heuristic algorithm to further reduce the computational complexity. Li et al. [9] put forward a joint routing and charging scheme to maximize the lifetime of HWRSNs. Xie et al. [10] used the piecewise linear approximation technique to find an approximation algorithm to maximize the proportion of the MC's vacation time over the cycle time. Peng et al. [11] transformed the energy replenishment problem into a classic traveling salesman problem and proposed two greedy algorithms to extend the lifetime of the sensor network. However, these offline schemes did not consider the real-time dynamic energy consumption rate of sensors, which are not applicable to many real-time applications.

The online schemes can handle the dynamic energy consumption rate of sensors. For the existing online charging schemes, He et al. proposed a first-come-first-serve (FCFS) scheduling strategy [12], which is simple but performs poor performance. It only considered the arrival time of requests, but did not consider the distance between the node and the MC, which led to the high moving cost of the MC and high node failure rate. In order to reduce the moving cost of the MC, He et al. proposed an efficient scheduling strategy called NJNP [13], which is based on the principle of nearest job next with preemption. This scheduling strategy can reduce the node failure rate and MC moving costs, but lack the scheduling fairness. In the work [14], Tomar et al. proposed an algorithm that multiplies the tolerable time of node by the distance of MC to node as the cost, and then selects the node with the lowest cost as the next node. The complexity of the algorithm was improved by the heap structure. Compared with NJNP, this algorithm can reduce the node failure rate and the average charging latency. In order to ensure the fairness of the scheduling and reduce the node failure rate, Feng et al. proposed a Starvation Avoidance Mobile Energy Replenishment scheme (SAMER) [15], which can avoid energy starvation through calculating and considering the maximum tolerable latency of each charging requirement. This scheme abandons the failed nodes. On the basis of SAMER, Zhu et al. proposed an Invalid Node Minimized Algorithm (INMA) [16]. INMA preferentially selects the node that causes the least number of other nodes to fail after charging it. Experiments show that compared with SAMER, the algorithm can reduce the failure rate of nodes under certain conditions.

III. SYSTEM MODEL AND NOTIONS

A. System Model

We define heterogeneous wireless rechargeable sensor networks as a triple (N, BS, MC), as shown in Fig. 1. N is the set of sensor nodes in HWRSNs, where $N=\{N_1, N_2, ..., N_n\}$. The battery capacity of N_i is E_i , and the energy consumption rate of N_i is P_i . Sensors are randomly distributed in a square with side length M, and the Euclidean distance between N_i and N_i is denoted by D_{ij} . Sensor nodes can communicate with BS, where the time of communication and the energy consumed by communication can be ignored. BS is the only base station which has enough energy and the ability to calculate and store, and can communicate with MC. It can recharge the MC or replace its battery in negligible time. MC is the only wireless mobile charger in HWRSNs, whose battery capacity is E_{MC} and moving speed is v. Let P_{MC} denote the energy consumed by the MC per unit distance of movement, and η is the charging rate between MC and the node. The threshold of MC is denoted as χ . If its residual energy is lower than χ , MC will return to the BS to supplement the energy. Except for the energy consumed by charging and moving, other energy consumption of MC is negligible. It can communicate with the BS, and the time and energy consumed by the communication can be ignored.

The system works as follows: In HWRSNs, the node N_i , $i \in \{1, 2, ..., n\}$, sends a residual energy message (ID, RE, T, NC) to the BS every Δ time, and the BS will calculate the node's dynamic energy consumption rate PD_i and determine whether the node needs to be charged based on this message. Among them, ID is the serial number of the node, RE is the residual energy of the node, where RE \geq 0, T is the timestamp of the node sending message, NC indicates whether the node needs to be charged, and NC \in {TRUE, FALSE}. The BS maintains a Dynamic Energy Consumption Rate Pool (DECRP), which records the latest dynamic energy consumption rate PD_i of the node. The BS maintains a Residual Energy Message Pool (REMP), which records the lastest residual energy message of each node. The BS will maintain a Charging Request Pool (CRP) which records the

first charge request of each node, that is, the first NC is TRUE in the residual energy message. When the node sends the residual energy message, it will detect its own residual energy. If the residual energy is lower than the threshold ϕ_i , the node will set NC to TRUE, indicating that the node needs to be charged, otherwise the NC is set to FALSE by default.



Fig. 1. Network Model

During MC charging, the charged node will suspend sending the residual energy message. When the MC completes the charging, MC will send a completed service message (ID) to the BS to inform that the charging service is completed, and the ID is the serial number of the completed charging node. At this time, the BS will remove the records about the node in DECRP, REMP and CRP to avoid the interference of outdated messages on subsequent scheduling. After the MC completes charging of the node, it will send a request (RE_{MC} , L) to the BS to query the next service location. RE_{MC} denotes the residual energy of the MC. L denotes the location of the MC, and $L \in \{L_0, L_1, ..., L_n\}$. L_0 is the location of BS and the location of N_i is L_i. After BS calculates MC's next service location L using our online charging algorithm, it will send a response (L) to the MC. L denotes the next service location of the MC. And then the MC will go to the next location for service.

The MC does not allow other sensor nodes to preempt during the charging process to avoid interruption of the charging process. Table I shows the symbols used in this paper:

B. Notions

Before showing the online charging scheme, we first give some definitions.

Definition 1. (Node Starvation) If the failure time of a sensor is greater than τ time, this sensor is said to be in the node starvation state.

If a sensor node is unable to be selected as the next charging node for a long time, resulting in the node being in a node starvation state. Node starvation rate is an important measure indicating whether the charging scheme is fair. The lower the starvation rate of the nodes, the fairer the charging scheme is. The formula for judging whether the node is in the node starvation state is as follows:

$$TC - TF \ge \tau \tag{1}$$

TABLE I LIST OF NOTATIONS.

Symbol	Description
М	Side length of network
P_{MC}	Energy consumed by travelling one unit distance of MC
v	Moving velocity of MC
η	Charging rate between MC and the node
RE_{MC}	Residual energy of MC
E_{MC}	Battery capacity of MC
χ	Threshold of MC return BS supplementary energy
RE_i	Residual energy of N _i
E_i	Battery capacity of N _i
\mathbf{P}_i	Energy consumption rate of N_i
PD_i	Dynamic energy consumption rate of N_i
ϕ_i	Threshold of N_i send charging request
α	Update rate of dynamic energy consumption rate
Δ	Sensor node sends the residual energy message interval
L_i	The location of the BS or sensor node in the network
D_{ij}	Euclidean distance between L_i and L_j
TC	Current timestamp

Where TF denotes the timestamp of node running out of energy, and τ is a given constant. When $\tau=0$, this formula can be used to judge whether the node fails.

Definition 2. (Virtual Time) The virtual Time of sensor N_i , denoted as VT_i , is defined to be a measurement used to select the next charging node, which is calculated as follows:

$$VT_i = \frac{(TC - T_i)PD_i}{\overline{PD}} \tag{2}$$

Where T_i denotes the timestamp of the node's first charging request, and \overline{PD} is the average dynamic energy consumption rate of all nodes that need to be charged.

When calculating the virtual time, we consider the waiting time of the nodes to ensure fairness. The node with the longer waiting time will be more likely to be selected as the next charging node. Besides, we also consider the energy consumption rates of nodes, since the energy consumption rates of different nodes differ greatly, as shown in Eq. 2. The higher the energy consumption rate, the longer the virtual time.

It can be considered that the higher the energy consumption rate, the faster the virtual time increases with the waiting time.

Definition 3. (Moving Time) The moving time of sensor N_i , denoted as MT_i , is the time cost by MC moving to this sensor, which is calculated as follows:

$$MT_i = \frac{D_{ji}}{v} \tag{3}$$

Where D_{ji} denotes the distance of the MC from the current location L_j to the next node N_i 's location L_i .

The moving distance of the MC is an important factor in scheduling, because reducing the moving distance of the MC not only helps to reduce the energy consumption of the MC, but also indirectly reduces the node failure rate and the starvation rate. Therefore, in our algorithm, the node closer to MC will be more likely to be selected as the next charging node. In addition, as shown in Eq. 3, we convert the distance of MC to node into the moving time of MC.

IV. SYSTEM WORKING PROCESS AND VTMT ALGORITHM

A. System Working Process

In this subsection, BS will use the following method to calculate the dynamic energy consumption rate, denoted as PD, of the node once it receives the residual energy message not for the first time. The dynamic energy consumption rate PD of the node is calculated based on the historical information.

Before calculating PD, we first define the current energy consumption rate, denoted as PR_i of the N_i as follows:

$$PR_i = \frac{RE_{io} - RE_{in}}{\Delta} \tag{4}$$

Where RE_{io} denotes the residual energy in the last residual energy message of the node (o represents old), RE_{in} denotes the residual energy of the current residual energy message (n represents new). We do not calculate PR, when the BS receives the first residual energy message.

We define the dynamic energy consumption rate PD_i as follows:

$$PD_{i} = \begin{cases} (1-\alpha)PD_{i} + \alpha PR_{i}, & \text{PD}_{i} \text{ exists} \\ PR_{i}, & \text{PD}_{i} \text{ not exists} \end{cases}$$
(5)

Where α is parameter. The larger the α is, the faster the dynamic energy consumption rate is more updated. When α =1, PD_i=PR_i, that is, the real-time energy consumption rate to the node is taken as the dynamic energy consumption rate.

When the BS receives the MC's request (RE_{MC} , L) for the next destination, the BS will calculate the next destination L_{next} of the MC according to the VTMT algorithm. If L_{next} is the location of the BS, then the MC will return to the BS. If it is the location of the node, then the MC will go to the next node to charge it.

B. VTMT Algorithm

In this subsection, we propose the VTMT algorithm, which is used by BS to select the next charging node of the MC. The VTMT algorithm works as follows:

1) step 1: First, determine whether the CRP is empty. If it is empty, return L_0 . Otherwise, go to step 2.

2) step 2: For all nodes in the CRP, calculate the moving time of MC to node MT and virtual time VT, and normalize the MT and VT respectively to be MT^{*} and VT^{*}. Then divide VT^{*} by MT^{*} as the service value (SV) of the node and find out the node N_i with the largest service value among all requested nodes as the next charging node. Go to step 3.

 SV_i is calculated as follows:

$$SV_i = \frac{VT_i^*}{MT_i^*} \tag{6}$$

3) step 3: Determine whether the MC has enough energy to return to the BS after charging the node N_i , that is, whether it meets Eq. 7. If it is satisfied, then return L_i . Otherwise, return L_0 .

The formula for judging whether the MC can serve this node is as follows:

$$RE_{MC} - D_{ji} \times P_{MC} - TC_i \times \eta \ge \chi \tag{7}$$

Where D_{ji} denotes the distance between current location L_j to L_i , TC_i is charging time for MC to charge node N_i.

 TC_i is defined as follows:

$$TC_{i} = \begin{cases} \frac{E_{i} - ERE_{i}}{\eta - PD_{i}}, \text{ERE}_{i} > 0\\ \frac{E_{i}}{\eta - PD_{i}}, \text{ERE}_{i} \le 0 \end{cases}$$
(8)

Where $\text{ERE}_i=\text{RE}_i-(\text{TC-T}_i)\times\text{PD}_i-\text{MT}_i\times\text{PD}_i$, which denotes the estimated residual energy. RE_i denotes the residual energy in the last residual energy message of N_i , T_i denotes the timestamp of the last residual energy message of N_i , and MT_i denotes the moving time of MC from current location L_j to L_i . Since the nodes also need to consume energy during charging, the actual charging rate is η -PD_i. If the energy of the node is exhausted when the MC reaches the node, that is, $\text{ERE}_i \leq 0$, then $\frac{E_i}{\eta - PD_i}$ is used to calculate the charging time of the node.

The pseudo code of the VTMT algorithm is given in Algorithm 1.

Algorithm 1 VTMT AlgorithmInput: $L_{MC}, DECRP, CRP$ Output: L1: if CRP is empty then2: return L_0 3: end if4: $N = getAllNeedChargingNodes(CRP)$ 5: $\overline{PD} = calculateAveragePD(N, DECRP)$ 6: $VT = \phi, MT = \phi, SV = \phi$ 7: for N_i in N do8: $VT = (TC - T_i) * PD_i/\overline{PD}$ 9: $MT = D_{ij}/v$ 10: end for11: $VT^* = normalize(VT), MT^* = normalize(MT)$ 12: for N_i in N do13: $SV = VT_i^*/MT_i^*$ 14: end for15: $N_{next} = getMaxServiceValueNode(SV)$ 16: if N_{next} satisfies $Eq.$ 7 then17: return $N_{next}.getLocation()$ 18: end if19: return L_0			
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19: return <i>L</i> ₀	18: end if		
	19: return L_0		

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our proposed VTMT algorithm under different network conditions. We analyze the experimental results by comparing with the stateof-the-art charging schemes NJNP and SAMER. The metrics used for comparison are node starvation rate, node failure rate and moving cost.

TABLE II Default parameters.

Parameter	Value
М	100m
Number of Node	150
v	1m/s
P_{MC}	4mJ/m
η	100mJ/s
\dot{E}_{MC}	5,000,000mJ
X	1,000mJ
E_i	Randomly from 1000 to 3,000mJ
ϕ_i	$0.4E_i$
Δ	10s
α	0.25
P_i	Randomly from 0.1 to 1.0mJ/s
au	1,000s
Simulation time	86,400

A. Experimental Environment Settings

The experiment is performed using Java. 150 nodes are randomly deployed in a $100m \times 100m$ area, and the simulation time is 24 hours. The battery capacity of each node is randomly drawn from 1000 to 3,000mJ and energy consumption rate of each node is randomly drawn from 0.1 to 1.0mJ/s. The value in each figure is the mean of 1000 experiments. The experimental parameters are given in Table II.

B. Different Number of Nodes

As shown in Fig. 2, the number of sensors varies from 25 to 300. As shown in Fig. 2(a) and Fig. 2(b), it is found that as the number of nodes increases, the node failure rate and the starvation rate also gradually increase. This is because as the number of nodes increases, the MC cannot serve each node in a timely manner. However, the node failure rate and the starvation rate are obviously lower than NJNP and SAMER, which implies that VTMT is more suitable for HWRSNs. From Fig. 2(b), we can see that VTMT can reduce the starvation rate of nodes, which shows that VTMT is fairer than the other two algorithms. In Fig. 2(c), as the number of nodes increases, the moving cost increases first and then decreases. That is because as the number of nodes increases, the MC needs to serve more nodes and move longer. When the number of nodes grows to a threshold, the MC cannot provide charging services for all nodes in a timely manner. The average distance between nodes decreases, and then some nodes closer to the MC will be selected, resulting in smaller moving cost.

C. Different Charging Rate

As shown in Fig. 3, the charging rate varies from 100 to 300mJ/s. It can be seen from Fig. 3(a) and Fig. 3(b) that as the charging rate increases, the node failure rate and the starvation rate gradually decrease. As the charging rate increases, MC can charge the nodes more quickly, thus reducing the charging time and serving more nodes. And we can see that under different charging rates, both the failure rate and the starvation rate of VTMT are significantly lower than NJNP and SAMER. As shown in Fig. 3(c), as the charging rate increases, the moving cost of all charging schemes also gradually increase.

Since the MC can charge more nodes as the charging rate increases, it needs to move longer.

D. Different Velocity of MC

As shown in Fig. 4, the moving speed of MC varies from 0.6 to 1.5m/s. It can be viewed from Fig. 4(a) and Fig. 4(b) that the node failure rate and the node starvation rate decrease with the increase of MC moving velocity. Since the increasing moving speed can reduce MC's moving time, more time is spent on charging nodes. Compared with the other two charging schemes, VTMT results in the lower node failure rate and the lower starvation rate. As shown in Fig. 4(c), as the moving speed of the MC increases, the moving cost of the MC also increases gradually. This is because as the moving speed of the MC increases, the moving time of the MC decreases, and the MC has more time to charge more nodes. Therefore, it needs to move longer.

VI. CONCLUSION

In this paper, we proposed an online charging algorithm called VTMT, which was suitable for HWRSNs. We also calculated the dynamic energy consumption rate based on historical information, which can give a very good approximation to the energy consumption rate of the nodes. Experiments showed that in HWRSNs, compared with the state-of-the-art NJNP and SAMER, our proposed VTMT algorithm could reduce the failure rate of nodes and ensure the fairness of scheduling. In the future, we will study an one-to-many online charging algorithm for HWRSNs, that is a mobile charger can charge more than one sensor simultaneously.

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REFERENCES

- J. Xia, Z. Tang, X. Shi, L. Fan and H. Li.: An environment monitoring system for precise agriculture based on wireless sensor networks. In: 2011 Seventh International Conference on Mobile Ad-hoc and Sensor Networks, pp. 28–35. IEEE, Beijing (2011)
- [2] Kafi MA, Challal Y, Djenouri D, Doudou M, Bouabdallah A, Badache N.: A study of wireless sensor networks for urban traffic monitoring: Applications and architectures. In: Procedia Computer Science 19, pp. 617–626. Elsevier, Canada (2013)
- [3] Risteska Stojkoska, B., Popovska Avramova, A.: Application of wireless sensor networks for indoor temperature regulation. International Journal of Distributed Sensor Networks, 1–10 (2014)
- [4] Yu L., Wang N., Meng X.: Real-time forest fire detection with wireless sensor networks. In: International Conference on Wireless Communications, Networking and Mobile Computing. 1214–1217. IEEE, New York (2005)
- [5] Bin W., Wenxin L., Liu L.: A survey of energy conservation, Routing and coverage in wireless sensor networks. In: Active Media Technology - 7th International Conference. 59–70. Springer, Berlin (2011)
- [6] Harb A.: Energy harvesting: State-of-the-art. Renewable Energy 36(10), 2641–2654 (2011)
- [7] L. Xie, Y. Shi, Y. T. Hou and A. Lou: Wireless power transfer and applications to sensor networks. IEEE Wireless Communications 20(4), 140–145 (2013)



Fig. 2. Experimental results under different number of nodes.



Fig. 3. Experimental results under different charging rate.



Fig. 4. Experimental results under different velocity of MC.

- [8] L. Fu, P. Cheng, Y. Gu, J. Chen and T. He: Optimal charging in wireless rechargeable sensor networks. IEEE Transactions on Vehicular Technology 65(1), 278–291 (2016)
- [9] Z. Li, Y. Peng, W. Zhang and D. Qiao: J-RoC: A joint routing and charging scheme to prolong sensor network lifetime. In: 2011 19th IEEE International Conference on Network Protocols, pp. 373–382. IEEE, Vancouver (2011)
- [10] L. Xie, Y. Shi, Y. T. Hou and H. D. Sherali: Making sensor networks immortal: An energy-renewal approach with wireless power transfer. IEEE/ACM Transactions on Networking 20(6), 1748–1761 (2012)
- [11] Y. Peng, Z. Li, W. Zhang and D. Qiao: Prolonging sensor network lifetime through wireless charging. In: 31st IEEE Real-Time Systems Symposium, pp. 129–139. IEEE, San Diego (2010)
- [12] L. He, Y. Zhuang, J. Pan and J. Xu: Evaluating on-demand data collection with mobile elements in wireless sensor networks. In: 2010 IEEE 72nd Vehicular Technology Conference - Fall, pp. 36–39. IEEE,

Ottawa (2010)

- [13] L. He, L. Kong, Y. Gu, J. Pan and T. Zhu.: Evaluating the on-demand mobile charging in wireless sensor networks. IEEE Transactions on Mobile Computing 14(9), 1861–1875 (2015)
- [14] A. Tomar, R. Anwit and P. K. Jana: An efficient scheme for on-demand energy replenishment in wireless rechargeable sensor networks. In: 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), pp. 125–130. IEEE, Udupi (2017)
- [15] Y. Feng, N. Liu, F. Wang, Q. Qian and X. Li: Starvation avoidance mobile energy replenishment for wireless rechargeable sensor networks. In: 2016 IEEE International Conference on Communications (ICC), pp. 1–6. IEEE, Kuala Lumpur (2016)
- [16] J. Zhu, Y. Feng, M. Liu, G. Chen, Y. Huang.: Adaptive online mobile charging for node failure avoidance in wireless rechargeable sensor networks. Computer Communications, 28–37 (2018)