Research Article

Novel wireless charging algorithms to charge mobile wireless sensor network by using reinforcement learning

Santosh Soni[1] · **Manish Shrivastava**[2]

Abstract

Generally, mobile wireless sensor network (MWSN) senses the sensitive and typical kind of events in various application areas along with the frequent mobility of sensor nodes as compared to traditional wireless sensor network. Due to mobility feature, MWSN extended the working of WSN. To design MWSN, certain key factors like energy efficiency, mobility, data routing, localization and charging strategy are involved. Mobile sensor nodes consume extra amount of energy due to mobility along with sensing and data routing task which exhaust network lifetime rapidly. In this research study, authors have proposed two wireless chargers (fixed and mobile) for sensor nodes. The main difference between fixed and mobile wireless charger is: fixed wireless charger invites mobile sensor nodes for wireless charging at base station whereas mobile wireless charger travels to the position of mobile sensor nodes for wireless charging. Both chargers fulfilled the charging request of sensor nodes efficiently. This is the first research study to propose such type of charging strategy for mobile wireless sensor network (MWSN) as per the available literature. The RL (reinforcement learning) technique is used here for optimization purpose of charging cost. These wireless chargers simulated in MATLAB enviorment and results showed that there is a significant improvement in network lifetime due to these charging strategies when compared to the existing algorithms.

Keywords Mobile wireless sensor network · Wireless charging · Energy efficiency and reinforcement learning

Abbreviations

WSN	Wireless sensor network
RMWSN	Rechargeable mobile wireless sensor network
PMSAFC	Proposed Manish Shrivastava algorithm for the fixed charger
PMSAMBC	Proposed Manish Shrivastava algorithm for mobile charger
SN	Sensor node
RL	Reinforcement learning
MDP	Markov decision process
FCFS	First come first serve
RMobileSensorNode	Rechargeable mobile sensor node

1 Introduction

Due to the most research expectations already achieved in a wireless sensor network, the scientist, researchers and industry are looking for the mobile wireless sensor network. The mobile sensor nodes are capable of sensing the various types of events even in hassle environments. The applications of MWSN are already placed in the field of patient monitoring, goods movement, animal monitoring, military surveillance and drone enabled services.

Independent of how MWSN achieved, it contains a number of challenges which impacts the overall performance of sensor networks. These challenges are contact detection, reliable data transfer, managed node mobility, loss of network connectivity, reduced lifetime, mobility

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aware power management and battery power. The energy efficiency is the most challenging task in MWSN. Unlike static sensor nodes in WSN, MWSN contains mobile sensor nodes that require extra energy for mobility along with basic sensing task, which leads to lower network lifetime and early replenishment of battery power, hence author(s) motivated towards energy requirements of mobile sensor nodes with following research questions:

1. How to fulfil the energy requirements of MWSN?
2. How to optimise the charging cost of MWSN?

To best address above research questions, author(s) thought for mobile wireless energy transfer in MWSN along with following proposed approaches:

1. Installation of the fixed charger at base station in the centre of MWSN where mobile sensor nodes get wireless charging.
2. Installation of mobile charger at base station near to fixed charger in the centre of MWSN where mobile charger provides on-demand charging to critical rechargeable mobile sensor nodes at their position only.

As per the available literature review, this is the first ever research study to present such types of approaches in MWSN to enhance the network lifetime and lower node failure rate. Many research studies have designed optimization methods for developing the charging path to minimize the charging cost however the charging path planning has not been considered. The reinforcement learning technique is used here for the optimization of the charging path. Finally, the main contribution of this research study is as follows:

1. Proposed algorithm to charge rechargeable mobile sensor nodes in MWSN by using the Fixed charger.
2. Proposed algorithm to charge critical rechargeable mobile sensor nodes in MWSN by using Mobile charger.
3. Optimization of charging path to lower charging cost by using reinforcement learning technique.
4. Performed extensive simulations for a better outcome of this research study.
5. Comparison of the proposed algorithms with the existing state of the art algorithms Greedy [1], Heuristic [1], IPCTS [3] and CSRL [4] to better prove this research study.

2 Related works

2.1 Charging strategies

The charging in WSN is the latest research issue due to the higher energy requirements of sensor nodes. Various researchers have proposed on-demand charging of sensor nodes by introducing mobile chargers for small-scale as well as a large-scale sensor network. Up to certain extent, some of the researches of charging path planning have been succeed due to optimization methods. Sangare et al. [1] has proposed a hardware platform to transfer RF energy towards sensor nodes in a pre-planned path and the numerical results have proved the research outcome adequately. Based on the on-demand charging concept, He et al. [2] proposed efficient nearest-Job-next with pre-emption (NJNP) discipline for the mobile charger, and provide analytical results, throughput and charging latency from the perspectives of the mobile charger and individual sensor nodes, respectively. Tu et al. [3] proposed the charging car which moves on the path based upon TSP method. Here the mobile charging time of every sensor nodes are calculated depending upon the linear programming. Wang et al. [4] presented a model in which a mobile charging vehicle carries various chargers along with the portable high-volume battery which reduced the problem of scheduling. Khelladi et al. [5] proposed multi-node charging where the numbers of sensors charged at every stop for energy transfer. Aoudia et al. [6] proposed a novel RL man algorithm based upon reinforcement learning for the energy conservation of the sensor nodes. This method gained almost 70% of the average packet rate. The lightweight heuristic approach set the tour path planning [7, 8]. Nikoletseas et al. [9], Zhang and Ma [10] proposed two protocols to control the working of the charger. The first protocol performs good charging efficiency throughout the experiments and second protocol performed uniform distribution of energy. Zou et al. [11] focused on the charging path for the mobile charge in MWSNs by using reinforcement learning (RL) and prolonged the lifetime of the network and efficiency of the mobile charger. Zhu et al. [12] addressed the node failure of mobile charging for WRSNs which targets to lower the number of invalid nodes. Here the charging nodes are selected as the next charging node for online charging. Wu et al. [13] presented multiple drone wireless charging scheme in large scale WSN by using optimal surrogate solution. Huang et al. [14], Xu et al. [15] introduced the idea of equipping charging vehicle with different charging array to charge multiple sensor nodes [16, 17]. Khelladi et al. [5], Anand et al. [18] presented the coverage problem in WSN in the context of wireless charging where the charger is capable of taking self-decision for path planning. Li [19] presented Joint Routing and Charging Scheme to prolong Sensor network lifetime and joint charging and rate allocation for utility maximization in sustainable sensor networks. This research study has combined RL with charging path strategies in MWSN [20, 21]. Xie et al. [22] presented the Reformulation–Linearization Technique (RLT) for accuracy while performing multi-node wireless energy transfer technology. Wu et al. [13], Journal and Basic [23] proposed algorithm to control the velocity of charging a vehicle in the sensing area. The framework of RL is MDP which contains states, actions, reward function and policy which helped us to calculate routing data path to perform mobile wireless charging in WRSNs [24, 25].

2.2 Reinforcement learning based charging path

Yahyaouy et al. [26] presented multi-agent systems useful in decision making systems. Learning algorithms mainly derived from reinforcement learning with various sets of interaction and trial with the unknown environment, the learning agent uses the reward to develop the policy which later on optimizes the policy plan along with path planning of sensor nodes and mobile charger [27–29]. The sensor nodes and mobile chargers can become learning agents to plan for charging path in an unknown environment [30–32]. This optimal charging path leads to a collision-less network along with good signals strength [33–36, 40, 41].

3 Preliminaries

3.1 Energy model

Assume that the transmit antenna has an antenna gain in the direction of the receive antenna (Fig. 1) given by G_T, the power density equation becomes:

$$p = \frac{P_T}{4\pi R^2} \tag{1}$$

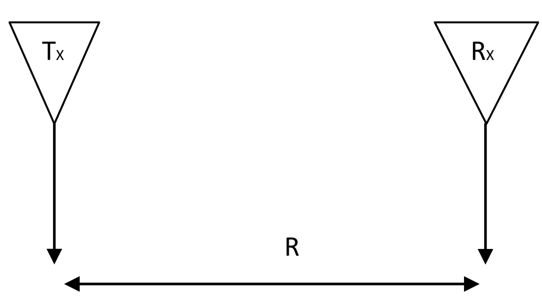


Fig. 1 Transmit (TX) and receive (TX) antennas separated by R

where P_T is the watts of total power is delivered to the transmit antenna and R represent distance. If the transmit antenna has an antenna gain in the direction of the receive antenna given by G_T then the power density equation will be:

$$p = \frac{P_T}{4\pi R^2} G_T \tag{2}$$

The gain term factors in the directionality and losses of a real antenna. Assume now, that the receiver antenna has an effective aperture given by A_{ER}. Then the power received by this antenna will be (P_R):

$$P_R = \frac{P_T}{4\pi R^2} G_T A_{ER} \tag{3}$$

Since the effective aperture for any antenna expressed as:

$$A_e = \frac{y^2}{4\pi} G \tag{4}$$

The resulting received power will be:

$$P_R = \frac{P_T G_T G_R y^2}{(4\pi R)^2} \tag{5}$$

$$P_R = \frac{P_T G_T G_R c^2}{(4\pi R f)^2} \tag{6}$$

3.2 Mobility model

The node mobility model represents the movement of nodes from one position to another position. In the random waypoint mobility model, mobile nodes stays in one position for some time, then move towards random destination. The value of pause and speed is relevant here.

The Fig. 2 represents random waypoint model in following manner:

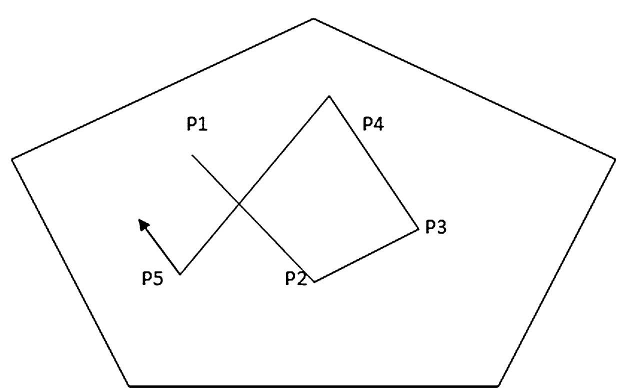


Fig. 2 Random waypoint model

- Here each node moves from one waypoint P_i to the next P_{i+1}.
- The waypoints are distributed uniformly over the convex area.
- The nodes are called intelligent when they reach each waypoint before going for next vertex.

The mobility based cost performance of used model is shown in Table 1.

3.3 Wireless energy transfer

Due to the mobility of sensor nodes along with sensing task in MWSN, the consumption of energy is higher than the static sensor node in WSN which leads to increase node failure rate and lower network lifetime. In this regard, authors have proposed two solutions to fulfil the energy requirements of mobile sensor nodes: in first solution, mobile sensor nodes send out their charging request to the fixed charger at base station whenever their energy level reaches to a certain threshold value. The fixed charger maintains a queue table to store the received charging requests which served according to the first proposed algorithm. The second solution works only for critical mobile sensor nodes whose energy level reaches below to threshold value, these critical mobile sensor nodes send out their charging request to the mobile charger at the base station. Further, the mobile charger stores charging request into queue table which served according to the second proposed algorithm. The primary goals of these proposed algorithms are to fulfil the energy requirements of normal and critical rechargeable mobile sensor nodes by using wireless energy transfer (Fig. 3).

3.4 Basic assumptions and charging model

This research study has made the following assumptions:

- The mobile wireless sensor network is rechargeable.
- The chargers (fixed and mobile) are capable of transferring wireless energy to rechargeable mobile sensor nodes.
- The wireless charging radius is approximate 01 m.

Here, author(s) proposed wireless energy transfer chargers (fixed and mobile charger), base station (centrally located) and rechargeable mobile sensor nodes. The base station is able to compute the information of remaining residual energy and energy consumption rate from rechargeable mobile sensor nodes. The base station also performs the following task:

- Formation of charging strategy for fixed and mobile chargers.
- Charging path for mobile charger.
- Charging of fixed and mobile chargers.

The full amount of energy stored by fixed and mobile chargers are presented by E_{FC} and E_{MC}. It is assumed that the wireless energy transfer of fixed and mobile charger is ET_{OUT}. ER_{IN} is the energy received by rechargeable mobile sensor nodes. The below equation represents the relation between transferring energy power and receiving energy power:

$$ER_{IN} = ET_{OUT} \times \epsilon(d_t) \tag{7}$$

where (d_t) presents distance between the chargers and rechargeable mobile sensor nodes in the range of (0, 1). If rechargeable mobile sensor nodes are close to chargers then $(d_t) = 1$, then

$$ER_{IN} = ET_{OUT} \tag{8}$$

3.5 Contribution

The main contribution of this research study is as follows:

1. Proposed algorithm to charge rechargeable mobile sensor nodes in MWSN by using Fixed charger (PMSAFC).
2. Proposed algorithm to charge critical rechargeable mobile sensor nodes in MWSN by using Mobile charger (PMSAMBC).
3. Optimization of charging path to lower charging cost through reinforcement learning technique.

3.6 Proposed wireless charging plan for MWSN

The proposed wireless charging plan for MWSN shown in Fig. 4 based upon Tables 2, 3, 4, 5 and Eq. 9 (Euclidean distance calculation):

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{9}$$

Table 1 Mobility based cost performance of random waypoint model

Performance parameter	Iteration 1	Iteration 2	Iteration 3	Iteration 4
Average end to end delay (s)	0.0035945	0.0035900	0.0035989	0.0035129
Throughput (bits/s)	38012	38,012	38,001	38,019
Average jitter (s)	0.000165589	0.000165588	0.000175624	0.001802

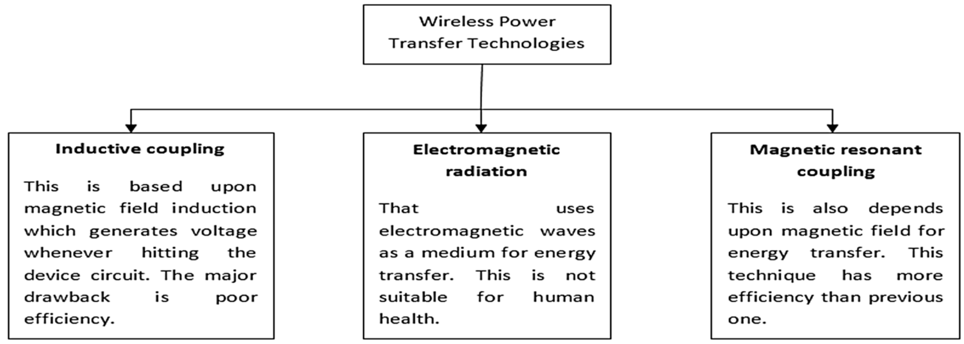


Fig. 3 Wireless power transfer technologies

Table 2 Proposed phases of wireless charging plan for MWSN by fixed charger

Current position advertisement of fixed charger from base station	Request from rechargeable mobile sensor nodes for charging
Confirmation message sent to requesting nodes for charging	If multiple requests sent from rechargeable Mobile Sensor nodes for charging then wireless charging plan executed as per the FCFS (Table 4)
Wireless charging starts by fixed charger	Rechargeable mobile sensor nodes return to their position

Table 3 Proposed phases of wireless charging plan for MWSN by mobile charger

Current position advertisement of mobile charger from base station	Request from critical rechargeable mobile sensor nodes for charging
Confirmation message sent to requesting nodes for charging	If multiple requests sent from critical rechargeable mobile sensor nodes for charging then wireless charging plan executed as per the Table 5
Wireless charging starts by mobile charger	Mobile charger returns to base station

Table 4 Request from rechargeable mobile sensor nodes for charging to fixed charger

RMobileSensorNode ID	Position co-ordinates	Distance (m)
Node 6	(3.1)	10
Node 8	(3.5)	5
Node 1	(1.1)	12
Node 5	(2.3)	3
Node 6	(3.1)	6
Node 4	(2.1)	3.5

Table 5 Request from rechargeable mobile sensor nodes (Critical) for charging to mobile charger

RMobileSensorNode ID (Critical)	Position co-ordinates	Distance (m)
Node 9	(4.3)	13
Node 1	(1.1)	10
Node 3	(1.3)	9

Table 6 Q-table after learning from a specific environment

Episode	Q-value	Q-value	Q-value	Q-value
1	0	16.67718	0	13.50852
2	0	18.5302	15.00946	18.5302
3	0	38.74205	16.67718	20.58911
4	0	28.24295	22.87679	0
5	13.50852	22.87679	0	65.61
6	10.9419	*47.82969*	*38.74205*	72.9
7	*34.86784*	81	22.87679	*43.04672*
8	20.58911	72.9	31.38106	0
9	59.049	31.38106	0	90
10	34.86784	100	81	65.61
11	16.67718	90	90	72.9
12	65.61	81	81	0
13	28.24295	0	0	34.86784
14	0	0	0	0
15	53.1441	0	100	15.00946
16	72.9	0	90	0

where x and y represents Euclidian vectors (Table 6).

Proposed phases of fixed charger are based upon Table 2. Figure 4(a–h) represents the traversal of sensor nodes towards fixed charger. Similarly proposed phases of mobile charger are based upon Table 3. Figure 4(i–n) represents the traversal of mobile charger as per the charging

Fig. 4 Proposed wireless charging plan for rechargeable mobile sensor nodes

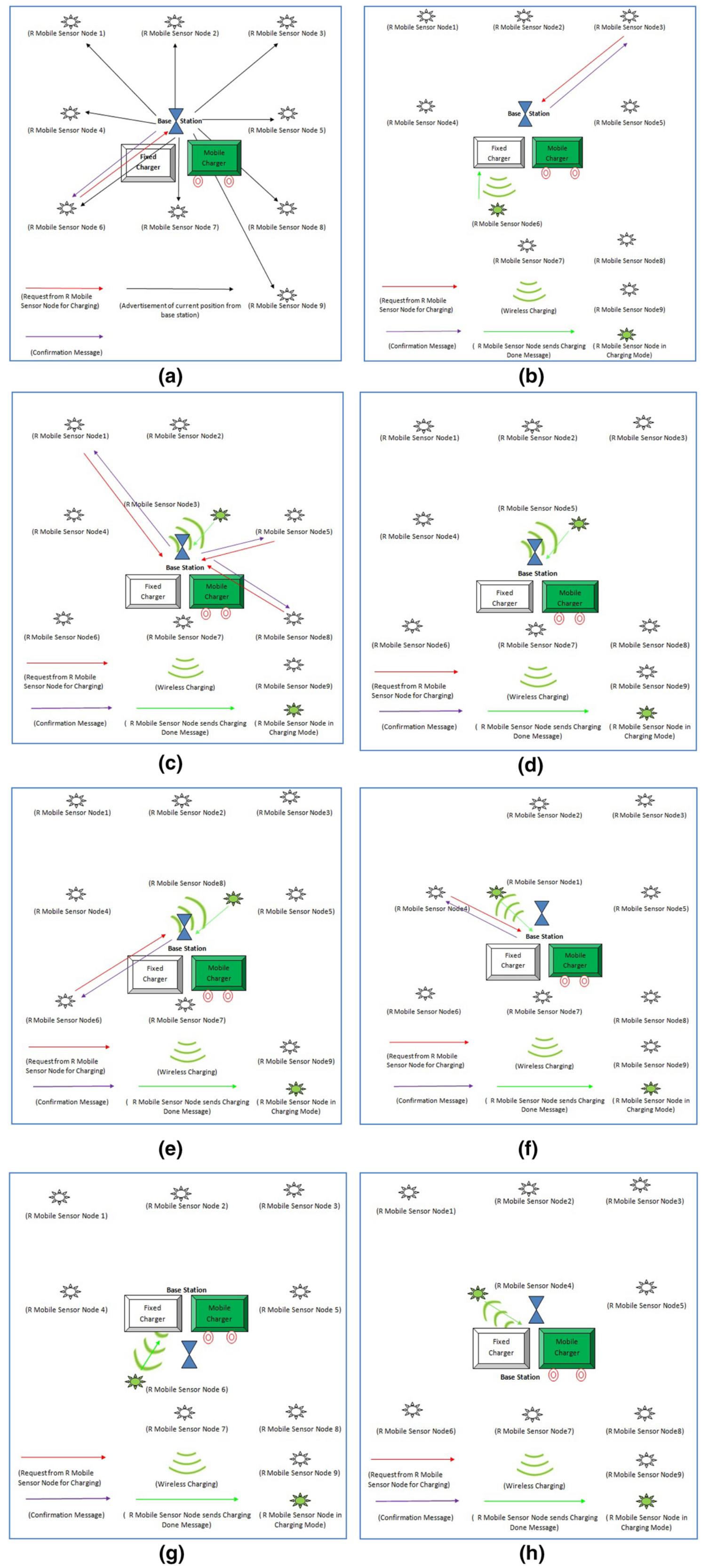
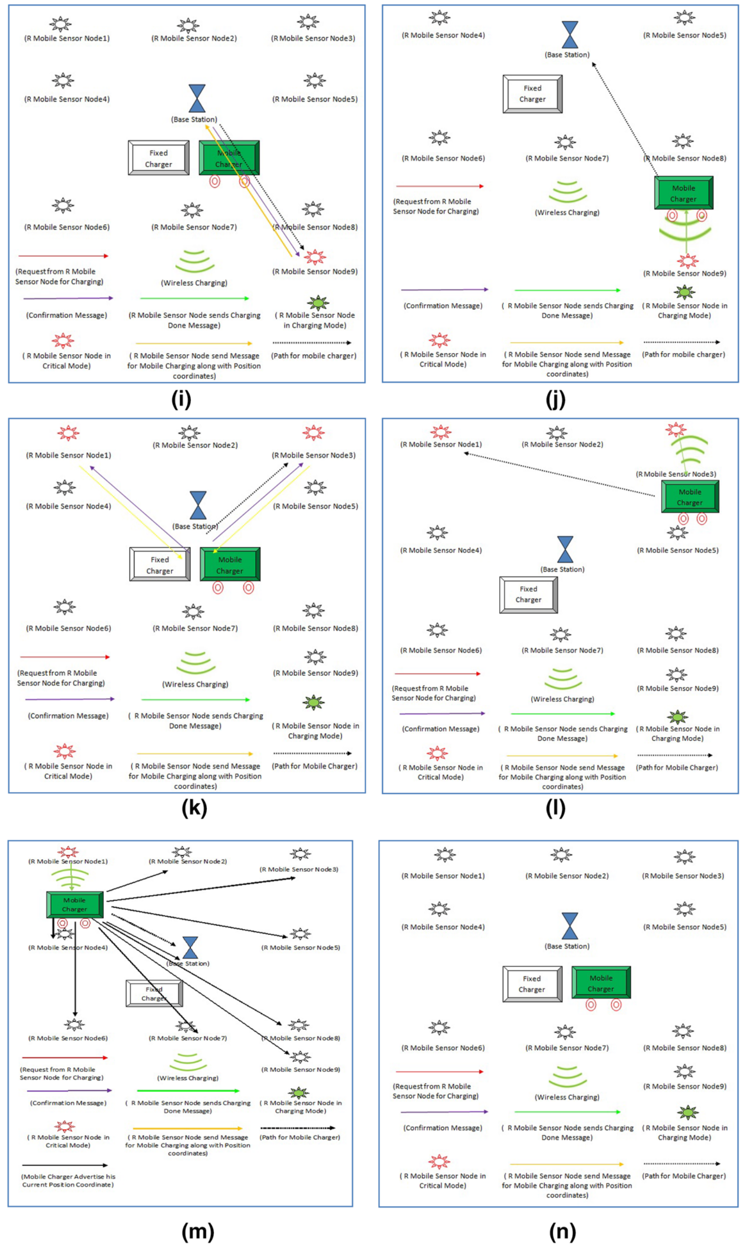


Fig. 4 (continued)



requirements of sensor nodes. Finally as per Fig. 4, the first round of wireless charging plan worked as follows:

(a) For Fixed Charger: RMobileSenorNode6 → RMobileSenorNode8 → RMobileSenorNode1 → RMobileSenorNode5 → RMobileSenorNode6 → RMobileSenorNode4
(b) For Mobile Charger: RMobileSenorNode9(Critical) → RMobileSenorNode1(Critical) → RMobileSenorNode 3(Critical)

4 Reinforcement learning

The RL algorithm permits an agent to learn an unknown environment. The primary objective of agent is to outperform actions which increase the reward in future. This algorithm works as follows:

Algorithm 01 [Reinforcement Learning algorithm]

Step 01: Environment initialization
Step 02: Generate random start state (S)
Step 03: Select randomly any one action (A)
Step 04: Check if present state equals to the previous state, if yes go to step 02 else next Step.
Step 05: Check for goal state, if yes then next step else copy (State, Action) in table
Step 06: Update reward
Step 07: Copy (State, Action, Reward)
Step 08: Update table (Q)

$$Q\,(S_t, q_t) = r_{t+1} + \gamma\, Max(S_{t+1}, q_{t+1}) \text{ ---- } (10)$$

(Where S, q, r and γ are state, function, reward and learning rate)
Step 09: Generation of next state using table (S, A)
Step 10: Starting of next episode
Step 11: End

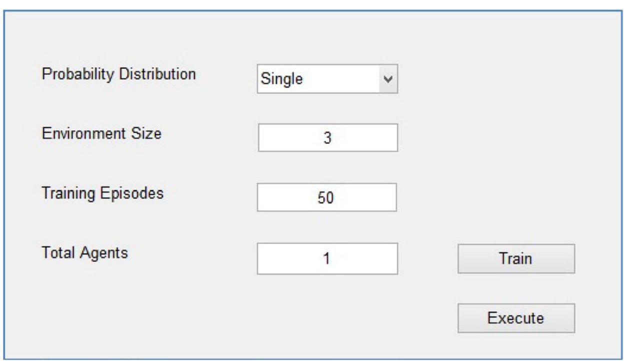


Fig. 5 Agent training using RL

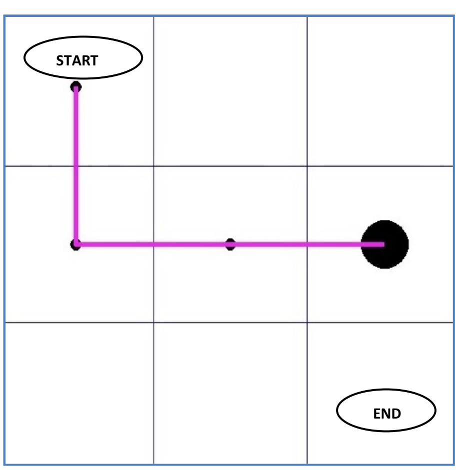


Fig. 6 Decision path one

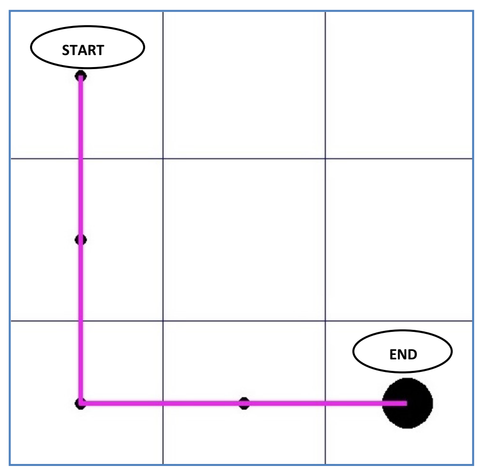


Fig. 7 Decision path two

The above algorithm is simulated in MATLAB for agent learning purpose.

Agents are trained in the form of a state-action pair. Figure 5 represents agent training with four input parameters probability distribution, size of the environment, number of training episodes and total learning agents. The Q-table [18] (Table 6) and decision paths (Figs. 6, 7, 8, 9) generated after agent training. The agent training is based upon the Q-learning to find the optimal policy. The capability of learning in agent increases optimally in Marcov domains through experience usually stored in look table (Q-table) (Table 6). Before agent training, initially state-action values are filled with random values. In this process, the state is input, and target output is a goal state. Reward values

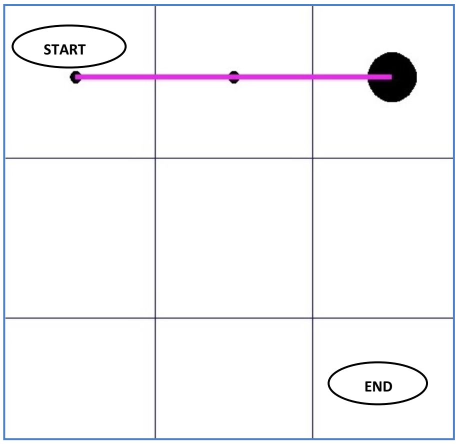


Fig. 8 Decision path three

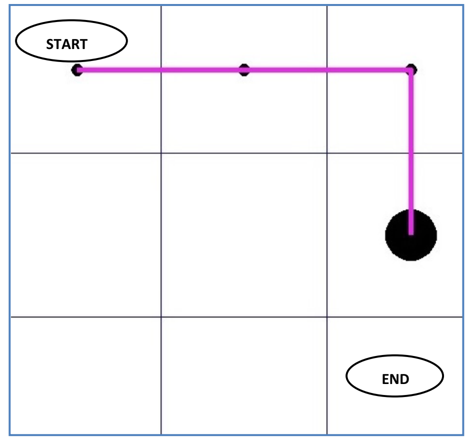


Fig. 9 Decision path four

performs the evaluation of state-action values. Generally, Q-learning algorithms uses reward function to finalize the state-action pairs through discount factor (ү) [33, 34]. The values (Table 6) marked in italic are the best action for the given state. The decision paths generated to understand the unknown environment (Figs. 6, 7, 8, 9).

5 Proposed algorithms

This section presents proposed wireless charging algorithms for Rechargeable Mobile Sensor nodes by using fixed and mobile chargers:

Algorithm 02 [Fixed Charger for Rechargeable Mobile Sensor Nodes]

Input: (a) Initial energy information of fixed charger and Rechargeable Mobile Sensor Nodes
(b) Request for charging
(c) Position co-ordinates from Rechargeable Mobile Sensor nodes
(d) Fixed charger
(e) Algorithm 01

Output: Rechargeable Mobile Sensor nodes charged at base station.

Step 01: Obtain learning by executing algorithm 01 (RL algorithm).
Step 02: Fixed charger advertises their current position coordinates from the base station.
Step 03: Rechargeable Mobile Sensor nodes send their request for charging along with their Current position coordinates.
Step 04: Fixed charger from base station sends confirmation message to Rechargeable Mobile sensor nodes.
Step 05: If multiple request messages for charging received then
Step 5.1: Fixed Charger calculates the distance of rechargeable mobile sensor node As per the equation 9 and stores in table 04.
Step 5.2: Fixed charger creates the charging strategy and starts the execution.
Step 06: Rechargeable Mobile Sensor node reaches the fixed charger and starts receiving the Wireless energy.
Step 07: Rechargeable Mobile Sensor node returns to their position.
Step 08: Go to step 02.
Step 09: End

Algorithm 03 [Mobile Charger for Rechargeable Mobile Sensor Nodes (Critical)]

Input: (a) Initial energy information of Mobile charger and Rechargeable Mobile Sensor Nodes (Critical).
(b) Request for charging from Rechargeable Mobile Sensor Nodes (critical).
(c) Position co-ordinates from Rechargeable Mobile Sensor Nodes (critical)
(d) Mobile charger
(e) Algorithm 01

Output: Rechargeable Mobile Sensor Nodes (critical) charged at remote location

Step 01: Mobile charger advertises his current position coordinates from the base station.
Step 02: Rechargeable Mobile Sensor Nodes (critical) sends their request for charging to Mobile Charger along with their current position coordinates.
Step 03: Mobile charger stores this information in table 02 and sends a confirmation Message.
Step 04: If multiple request messages received for mobile charging then
Step 5.1: Mobile charger calculates the distance of Rechargeable Mobile Sensor Nodes (Critical) as per Equation 9 and stores in table 05.
Step 5.2: Mobile charger creates the traversal path for charging and performs the Execution.
Step 05: Mobile charger reaches towards RMobileSensorNodes (Critical) and start charging.
Step 06: Return to the base station for vacation time
Step 07: Go to step 01
Step 08: End

6 Performance evaluations and result analysis

In this section, author(s) have evaluated the overall performance of proposed algorithms 01, 02 and 03 through extensive simulation in MATLAB 2012 (a) with certain simulation parameters specified in Table 7. The proposed PMSAFC and PMSAMBC algorithms are unique charging strategies in RMWSN along with mobility support [37, 38]. PMSAFC evaluated with the two existing benchmark algorithms GREEDY and HEURISTIC whereas PMSAMBC algorithm evaluated with latest algorithms IPCTS and CSRL. The mean, variance, minimum and maximum of RWSN's remaining lifetime of various algorithms are shown in Table 8. The relevant information of every rechargeable sensor node is shown in Table 9.

The performances of proposed algorithms evaluated adequately by node failure rate and network lifetime which are the main performance criteria. Therefore, it is compulsory to ensure less node failure rate and higher increment in network lifetime [39]. The optimization of the charging path adopted by both proposed algorithm is based on reinforcement learning technique which minimized the charging cost [42–44]. The simulation results well compared with existing state of the art algorithms like GREEDY, HEURISTIC, IPCTS and CSRL on the basis of following performance metrics:

- *Node failure rate* Here, author(s) consider the failure rate of mobile sensor node due to battery power. This should be minimum.
- *Network lifetime* That represents the death of the first mobile sensor node during the starting of MWSN operation. If more sensor nodes are alive during the last round, the network lifetime is said to good. This should be higher.
- *Charging efficiency* That represents the mobile sensor node's charging through fixed and Mobile Charger within the Stimulated time. This should be higher for any charger.
- *Charging cost* The charging cost is related to the self-energy consumption of charger while travelling or charging the mobile sensor nodes. This should be minimum.

- *Network size* This is directly related to the scalability of the network in large-scale MWSN. Here, the network size vary from 50 × 50 up to 200 × 200 meter^2 to check the network lifetime of sensor nodes along with the performance of proposed algorithms.

6.1 Performance analysis of first PMSAFC proposed algorithm

Figure 10 shows the node failure rate of various algorithms where the numbers of sensor nodes increase from 20 to 120 in 100 × 100 m area. In contrast to GREEDY and HEURISTIC algorithms, the proposed algorithm PMSAFC has 6.5% less lower node failure rate than the GREEDY and HEURISTIC algorithm due to fast charging of sensor nodes.

Figure 11 shows the network lifetime of various algorithms, where the performance measured in terms of a number of sensor node alive versus the number of rounds. The simulation extends to 1200 rounds with 120 sensor nodes. The result (Table 8) shows that GREEDY and HEURISTIC algorithms worked well but only 4 to 5 sensor nodes were alive up to the last round whereas about 25 sensor nodes were remained alive up to the last round in proposed algorithm PMSAFC which shows about 7% improvement in network lifetime over existing GREEDY and HEURISTIC algorithms.

6.2 Performance of second PMSAMBC proposed algorithm

Figure 12 shows the node failure rate of various algorithms when the numbers of sensor nodes increase from 20 to 120 in the 100 × 100 m area. In contrast to CSRL and IPCTS algorithms, PMSAMBC has shown 30% less node failure rate compared to CSRL and IPCTS algorithms due to the mobile charging strategy.

Figure 13 shows the network lifetime of various algorithms where the performance measured in terms of a number of sensor node alive versus the number of rounds. The simulation works up to 1200 rounds initially with 120 sensor nodes. The result shows that initially IPCTS and CSRL algorithms work very well but only 10 to 11 sensor nodes were alive up to the last round whereas about 35 sensor nodes were remained alive up to the last round in proposed algorithm PMSAFC which shows about 4% improvement in network lifetime over existing IPCTS and CSRL algorithms.

6.3 Charging efficiency of proposed chargers PMSAFC and PMSAMBC

Figure 14 shows the charging efficiency of various charging algorithms where the performance measured in terms of a number of sensor node charged in the stimulated time (in s). The simulation works up to 1800 s and 50

Table 7 Simulation parameters

S.no.	Simulation parameters	Value
1	Initial energy of fixed charger (FC): E_{FC}	10,000 J
2	Initial energy of mobile charger (MC): E_{MC}	10,000 J
3	Energy transfer rate of both chargers (FC and MC): E_{out}	6 J/s
4	Various speed of mobile charger (MC): V_{MC}	1 m, 2 m, 3 m, 4 m and 5 m/s
5	Initial energy of RMobileSensorNode: SN_{in}	20 J
6	Threshold energy of RMobileSensorNode: SN_{th}	8 J
7	Critical level energy of RMobileSensorNode: SN_{crt}	5 J
8	Travel energy of mobile charger: E_{mctrv}	20 J/m
9	Energy consumption rate with a range of node (mj)	(0,6)
10	Area size (m)	50 × 50, 100 × 100, 150 × 150, 200 × 200
11	Number of sensor nodes	10–120
12	Number of episodes	1000–5000
13	Learning rate: γ	0.98
14	Gaussian distribution of mean and variance	S

Table 8 Remaining lifetime of RMobileSensorNode

Algorithms	Mean value(s)	Variance (s2)	Min (s)	Max (s)
PMSAFC	11.5280 × 104	6.5921 × 108	8.3590 × 104	1.9890 × 105
PMSAMBC	10.4500 × 104	6.9720 × 108	7.3741 × 104	1.7895 × 105
CSRL	9.7450 × 104	7.2398 × 108	6.9800 × 104	1.6550 × 105
IPCTS	8.3210 × 104	7.0118 × 108	6.1208 × 104	1.6029 × 105
GREEDY	5.5040 × 104	1.8741 × 109	6.8100 × 103	1.6250 × 105
HEURISTIC	4.5120 × 104	1.2801 × 109	5.9990 × 103	1.3241 × 105

Table 9 Energy consumption rate along with Node position coordinates

Node_Id	Position coordinates	Energy consumption rate (mj)	Node_Id	Position coordinates	Energy consumption rate (mj)
1	31.75, 4.26	1.51	26	25.38, 0.78	2.69
2	46.94, 13.53	2.99	27	22.79, 33.42	3.71
3	7.55, 20.90	3.31	28	37.83, 26.64	2.23
4	33.04, 25.34	2.18	29	26.51, 29.14	4.89
5	4.31, 35.18	2.99	30	25.61, 40.30	3.55
6	12.21, 7.08	2.37	31	5.05, 32.65	2.29
7	30.20, 48.94	3.18	32	10.92, 37.94	4.38
8	13.72, 6.57	2.27	33	29.55, 34.19	4.54
9	25.82, 40.46	3.57	34	46.40, 34.26	2.55
10	42.26, 12.48	2.66	35	34.16, 31.55	2.98
11	17.38, 10.81	3.75	36	8.56, 26.88	2.38
12	1.76, 4.09	2.92	37	31.39, 43.16	3.64
13	15.06, 24.00	2.68	38	9.02, 39.95	2.19
14	8.39, 20.22	3.45	39	31.80, 42.98	4.14
15	12.87, 1.48	2.15	40	24.33, 14.06	1.45
16	29.50, 41.09	1.78	41	35.88, 15.44	2.05
17	5.27, 34.78	2.95	42	26.97, 47.81	1.26
18	20.45, 38.71	3.55	43	25.14, 20.98	1.19
19	33.17, 40.64	4.01	44	43.20, 39.34	4.20
20	48.64, 21.09	3.99	45	9.60, 47.63	2.52
21	45.52, 23.88	2.56	46	1.04, 14.33	2.53
22	11.69, 6.41	3.40	47	0.39, 47.80	3.21
23	26.38, 29.44	3.02	48	10.10, 10.76	1.69
24	23.51, 38.23	2.32	49	49.78, 12.87	1.37
25	46.89, 10.19	2.01	50	35.89, 44.93	3.59

sensor nodes were charged. The observation shows that IPCTS and CSRL algorithms charged 50 sensor nodes in between 1600 and 1800 s whereas proposed algorithms PMSAFC,PMSAMBC has taken 1200, 1600 s to charge 50 sensor nodes which is about 66% charging efficiency improvement over existing algorithms.

6.4 Charging cost of proposed charger PMSAMBC

Figure 15 shows the total energy consumption (Table 9) including charging and travelling energy for the four algorithms. This figure shows that PMSAMBC enhances the mobile charger's performance towards less energy consumption due to reinforcement learning based

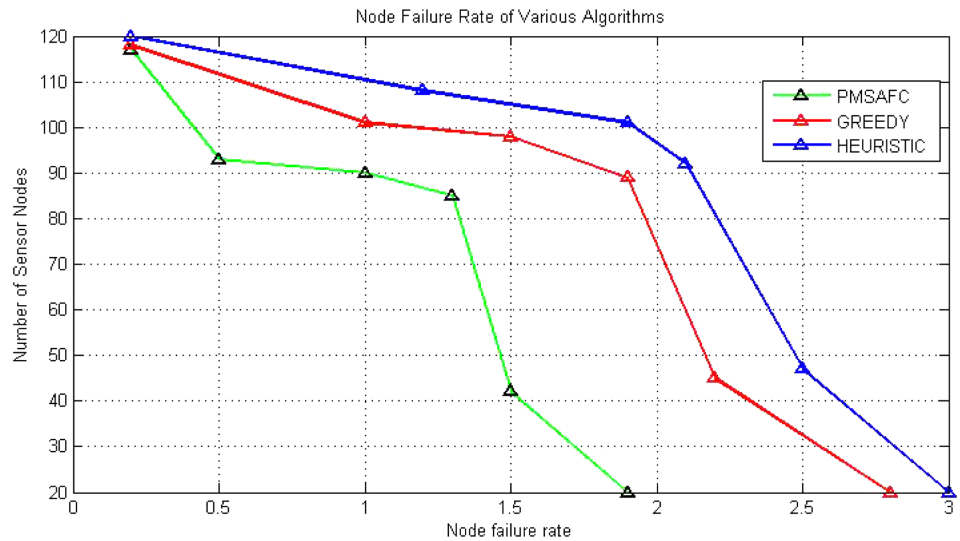


Fig. 10 Comparison of node failure rate of PMSAFC algorithm with GREEDY and HEURISTIC algorithms

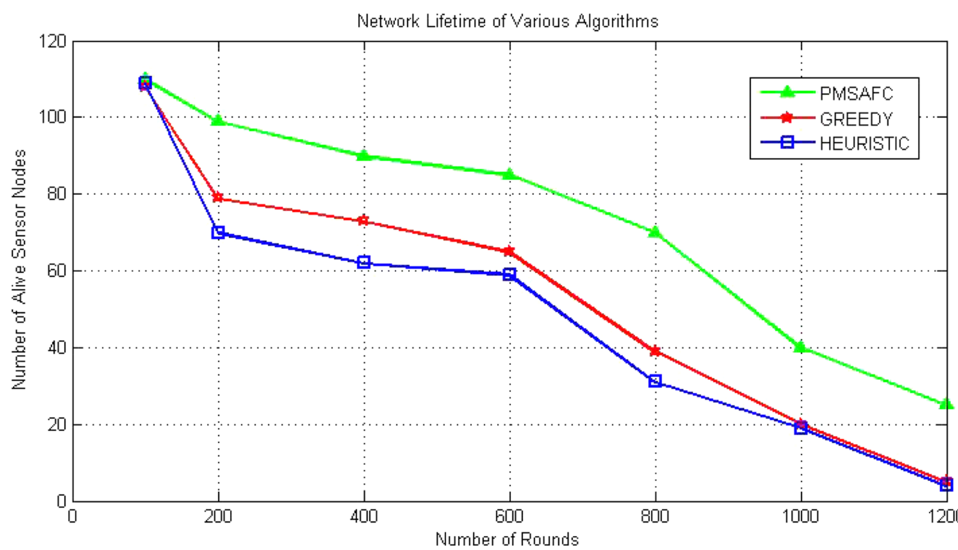


Fig. 11 Comparison of network lifetime of PMSAFC algorithm with GREEDY and HEURISTIC algorithms

optimization while PMSAFC charges every requesting sensor node individually at base station [45–47].

Figure 16 shows the overall performance of various chargers in large-scale network. The proposed charger PMSAFC and PMSAMC charged the sensor nodes even in large network size due to its unique method of charging.

Figures 17 and 18 shows the overall strength of proposed chargers on the basis of time, number of sensor nodes charged and remaining residual energy. The fixed charger has catered more number of charging request in less time to increase the lifetime of sensor nodes. The mobile charger has catered little less number of charging request due to its mobility. Further this can be improved in future by installing multiple mobile chargers [48, 49].

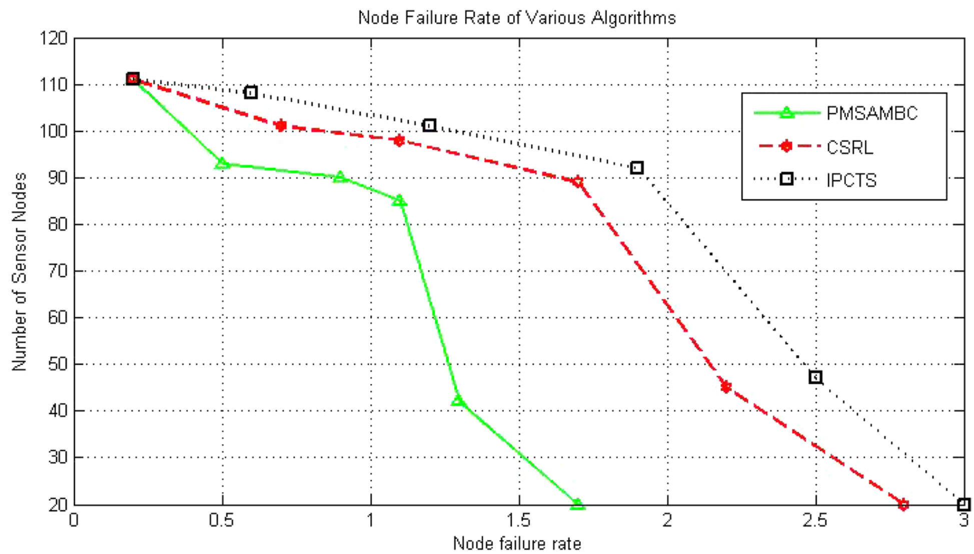


Fig. 12 Comparison of node failure rate of PMSAMBC algorithm with CSRL and IPCTS algorithms

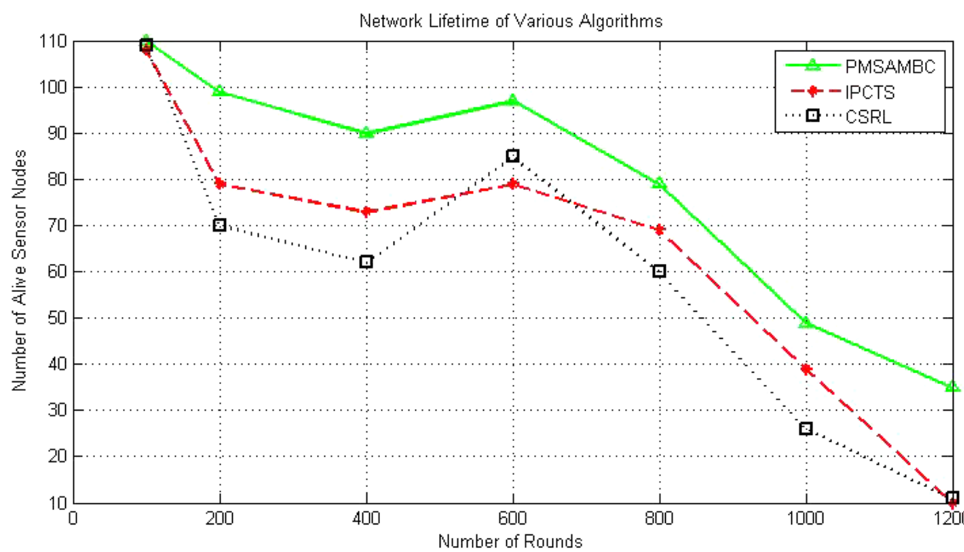


Fig. 13 Comparison of network lifetime of PMSAFC algorithm with IPCTS and CSRL algorithms

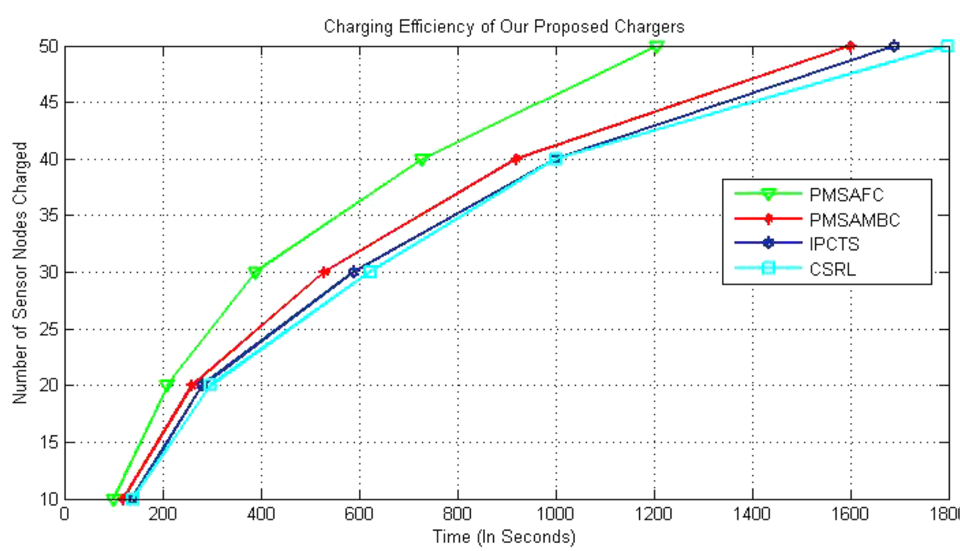


Fig. 14 Charging efficiency of proposed chargers with IPCTS and CSRL algorithms

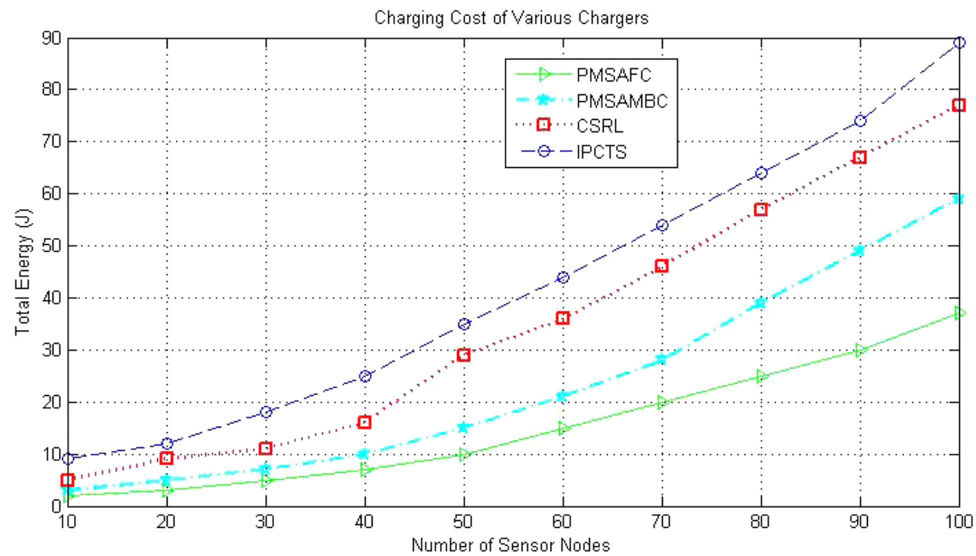


Fig. 15 Charging cost of proposed charger with IPCTS and CSRL algorithms

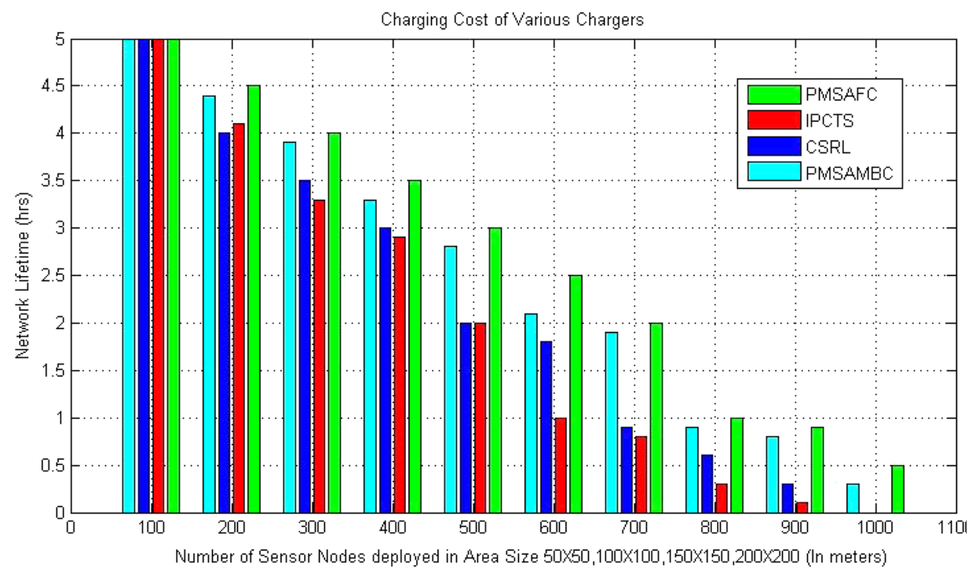


Fig. 16 Performance of proposed chargers in large scale network

7 Conclusion

This is the first research study to propose fixed and mobile charging strategies in rechargeable mobile wireless sensor network (RMWSN) to extend the network lifetime. RL (reinforcement learning) technique used here to lowers charging cost. Simulations results shows that the proposed charging algorithms PMSAFC and PMSAMBC have significantly improved the node failure rate and network lifetime as compare to existing algorithms. In future, author(s) will try to install multiple fixed and mobile chargers at the base station to cater the charging requests of large-scale rechargeable mobile wireless sensor network (RMWSN).

Fig. 17 Performance of fixed chargers in large scale network

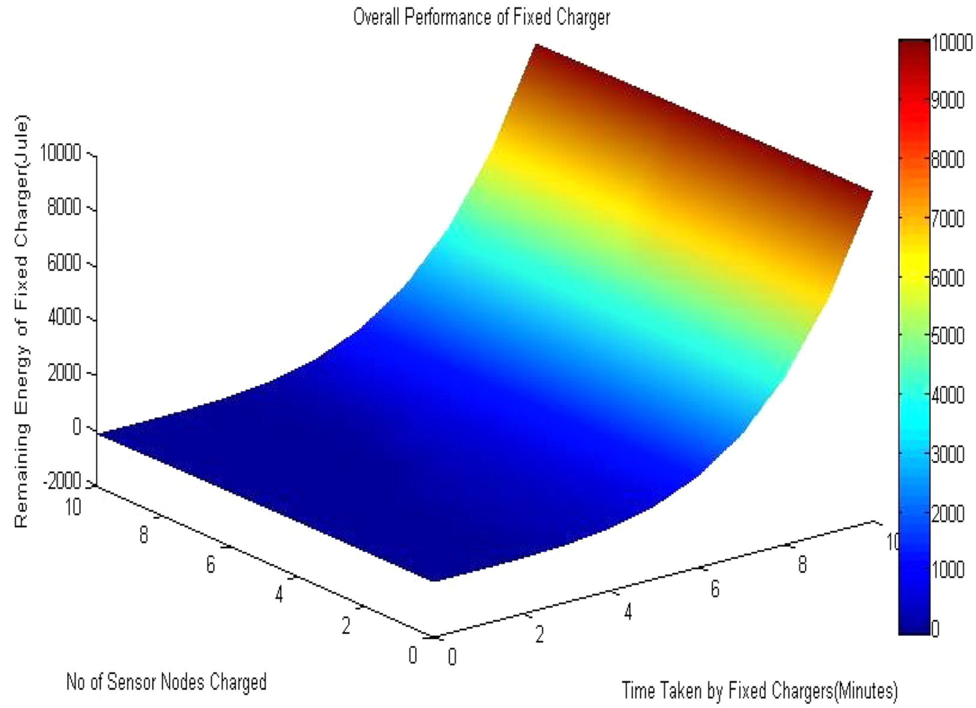
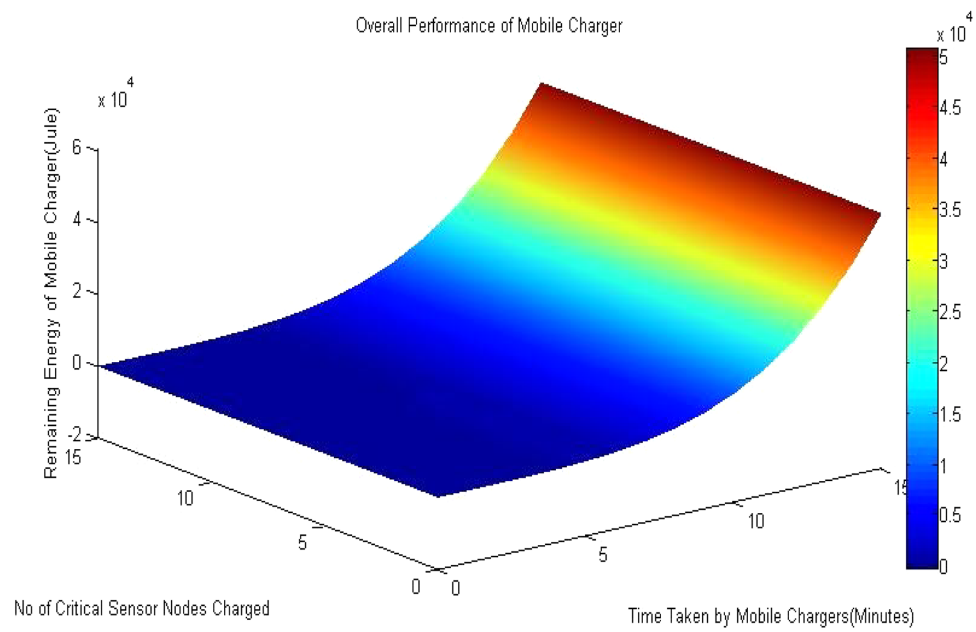


Fig. 18 Performance of mobile chargers in large scale network



Authors' Contribution The first author has performed the literature review, simulation and paper writing. The second author has overall supervised this research study.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Data sharing The author(s) are ready to provide data on request.

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