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Efficient Wireless Sensor Network for Radiation Detection in Nuclear Sites

Sherief Hashima, and Imbaby Mahmoud

***Abstract*—Due to the severe damages of nuclear accidents, there is still an urgent need to develop efficient radiation detection wireless sensor networks (RDWSNs) that precisely monitor irregular radioactivity. It should take actions that mitigate the severe costs of accidental radiation leakage, especially around nuclear sites that are the primary sources of electric power and many health and industrial applications. Recently, leveraging machine learning (ML) algorithms to RDWSNs is a promising solution due to its several pros, such as online learning and self-decision making. This paper addresses novel and efficient ML-based RDWSNs that utilize millimeter waves (mmWaves) to meet future network requirements. Specifically, we leverage an online learning multi-armed bandit (MAB) algorithm called Thomson sampling (TS) to a 5G enabled RDWSN to efficiently forward the measured radiation levels of the distributed radiation sensors within the monitoring area. The utilized sensor nodes are lightweight smart radiation sensors that are mounted on mobile devices and measure radiation levels using software applications installed in these mobiles. Moreover, a battery aware TS (BA-TS) algorithm is proposed to efficiently forward the sensed radiation levels to the fusion decision center. BA-TS reflects the remaining battery of each mobile device to prolong the network lifetime. Simulation results ensure the proposed BA-TS algorithm's efficiency regards throughput and network lifetime over TS and exhaustive search method.**

***Keywords*—Wireless Sensor Networks (WSNs), Radiation detection, Multi-armed bandit (MAB), Thomson sampling, and Network lifetime**

I. Introduction

RECENT improvements in wireless communications and electronics have facilitated employing wireless sensor networks (WSNs) in essential applications of real life [1]. Figure 1 illustrates the main components of any WSN, where any sensor nodes compose of four fundamental units, namely, sensing, processing, transmission, and power units. The sensing unit investigates the surrounding environment (radiation in our case). Then it informs the central processing unit (CPU) to compute/process/store the sensed data. The transmission unit receives the information from the CPU and transfers it to the cluster head (CH) or base station (BS). Finally, the power unit manages battery power to the sensor node [2]. WSNs have been widely applied in vital applications like precision agriculture, smart cities, industrial, climate, forest, and animal tracking. Developing a radiation detection wireless sensor network (RDWSN) gained a great focus due to the increased objection against nuclear power plants (NPPs) after large nuclear accidents such as Chernobyl and Fukushima Daiichi [3]. The usage of such networks helps the authorities keep watching and continuously identifying the radiation levels of the infected areas without threatening workers' lives. The main objective of any RDWSN is to measure and monitor the radiation levels inside the monitored area then provide an early alarm if these levels exceed the threshold values [4]. A common challenge for a RDWSN is how to efficiently integrate the available information from individual sensors to make a global decision about the presence of a contaminated materials or radiation leakage.

Ionized radiation can harm the human body in several manners, where the disadvantageous health impacts produced from the exposure can remain for several months without clear appearance. Such harmful impacts vary from light diseases like skin reddening to severe consequences like cancer or even death death, according to the amount of radiation stored inside the body, the radiation form, exposure time interval, and the exposure way. In most of the world, a radiation emergency status arises when nuclear material is leaked or blasted during a disaster or crime. In such major event, radioactive materials are released in either high doses that may extremely threaten biological life and cause sudden death within a week or low doses that might result in cancer and later disadvantageous health outcomes. The radiation hazard of nuclear power utilization issues from all classes of the nuclear power applications like nuclear power plants (NPPs) is very dangerous and should be kept under continuous observations from the responsible authorities. Hence, there is an urgent need to have a continued radiation monitoring network that operates within and around the NPP to provide continuous real time radiation levels measurments as an early precaution stage.

The main fear from any accident inside or around NPP is exposure to radiation with large doses. In such accidents, the exposure sources certainly are the leaking radioactive material to the surrounding environment, such as radioactive gases and liquids. Moreover, toxic clouds and atoms, breath, and ingestion of radioactive materials are other forms of dangerous radiation exposure methods to the livings inside and around the NPP. According to the nuclear safety report issued by the international atomic energy authority (IAEA), there is still more work that can be done to strengthen nuclear management systems by making use of new technology. Case studies that

S. Hashima is with Engineering Dept., Nuclear Research center, Egyptian Atomic Energy Authority, Cairo 13759 Egypt (e-mail: eng_shrif@yahoo.com).

I. Mahmoud is with Radiation Engineering Dept., National Center of Radiation Research and Technology (NCRRT) Egyptian Atomic Energy Authority, Cairo, Egypt (e-mail: imbabyisma@yahoo.com).

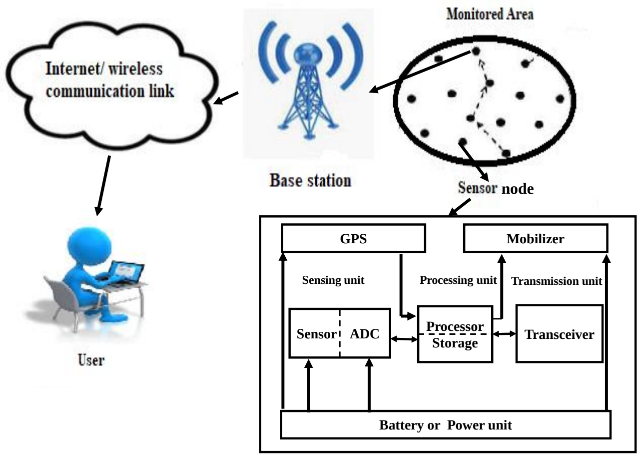

Fig. 1. WSN main elements

ensure the detection of radioactive materials and accidental radiation leakage is a life-threatening issue for environmental facilities, public health, and safety are as follow:

- **Case 1** (Fukushima disaster) the Fukushima Daiichi nuclear disaster resulted from the earthquake in Japan on March 11, 2011, has produced severe atomic pollution in Japan and around the world. The quake caused a 14-meter-high tsunami that crossed the plant's seawall (12 m height) and flooded the plant's lower grounds around the units 1–4 reactor constructions with seawater, filling the bunkers and hitting the emergency generators. Large amounts of water polluted with radioactive isotopes were released into the Pacific Ocean during and after the disaster. Still, there are severe outcomes of the nuclear crisis due to the long half life time of the leaked materials. Although the main cause was from nature, this accident showed a considerable safety plus security shortage existence in most of the NPPs around the world. In NPPs, large amounts of nuclear fuel and waste that include large quantities of uranium or other radioactive materials are stored. To enhance the safety and security level of any NPP, it is vital to advance a fast and precise detection system for any radiation leakage.
- **Case 2** (Radon detection) Radon cannot be seen by the human eye, unperfumed, and tasteless radioactive gas produced through the normal decay of radium, uranium, and thoron in dust, crag, and water, respectively. Its relationships with various diseases, particularly lung cancer, are well known. Radon can penetrate homes through cracks and holes. Although ease of detection of radon level nowadays in residence, ways to determine the source of decay have not been well-studied. Detection and further removal of the decay source can lower the radiation pollution generated by Radon and accordingly improve the environments of nearby residents [5].
- **Case 3** (Nuclear waste leak detection) the industry of nuclear power and also industrial petroleum digging companies create thousands of tons of deadly nuclear wastes every year all over the world [6]. Such wastes are requested to be transported into specialized treatment centers to reduce its severe damage to the health of the nearby residents.

Additionally, nuclear fuel and waste that contain uranium or other radioactive materials are also utilized in all NPPs. They are sealed in fuel rods that are bundled together into nuclear fuel authorities. If these materials are wrongly leaked, thousands of people will be under danger over a lot of years. This is due to the long half lifetime of the leaked materials that can move past homes, workplaces, stadiums, stations, schools, and hospitals. A human that stands just one yard from an unshielded, 10-year-old fuel waste might obtain a fatal dose of radiation in a few three minutes. A 30 second exposure time at such places would significantly raise the risk of deadly diseases like cancer and genetic damage. Hence, it is life-threatening to rapidly and precisely locate any radiation leakage.

A radiation detector, also recognized as a particle detector, is an equipment used to detect, track, identify high-energy particles released from radioactive materials. These particles include neutrons, alpha particles, beta particles, and gamma rays. Generally, the detected radiation counts of the detectors can be demonstrated as a combination of the radioactive source signal and the regular background radiation [7]. There are various types of radiation detectors, such as scintillator detectors, ionizing gas detectors, and Geiger counters. According to the proposed scenario, our primary focus in this paper is on smart Giger types that are mounted on mobile devices, as will be shown later.

Recently, Artificial intelligence (AI) techniques, particularly machine learning (ML), is a talented solution for radiation detection tasks because of its online-learning and self-decision-making characteristics. This will overcome the difficulties of dealing with a large number of sensors and the continuous upgrade of radiation levels around the NPP. Reinforcement learning (RL) is one of the main branches of ML, where the player associates with the environment and attempts to maximize the long-term rewards by online learning. It is worth noting that RL techniques are promising online solutions and instant radiation level notifications through informing the decision-maker if the radiation level in a specific area is increased. If a sensor device measures a high radiation level, it must automatically forward its data to the decision-maker for this critical notification. However, due to the nature of utilized wireless communication channels that may be blocked due to radiation and blockage effects, we leverage a multi-armed bandit (MAB) algorithm to forward the data to the manager through other mobile devices.

The state-of-the-art communication network, such as recent ones that are based on millimeter waves (mmWave) like our case, permits the construction of RDWSN, where the measured radiation levels/data can be forwarded in real-time to the data fusion center for analysis and interpretation. However, once a nuclear radiation disaster happens, the ordinary networks and electric power sources will be stopped. Hence, in this paper, we propose a scenario where the workers inside and around NPP measures radiation levels from their own mobile devices through mounting smart Giger, which is cheap, light, and practical. Moreover, there are mobile devices mounted in a fixed, known place around NPP. These mobile devices construct an RDWSN and forward its data to the fusion data center. These devices utilize mmWave channels that have a large bandwidth and cope with 5G/B5G requirements. Even though mmWaves have short wavelengths, highly absorbed by oxygen, blocked by thin papers. Hence beamforming between transmitter and receiver is required every time. By leveraging ML to efficiently forward the measured data, we propose an energy-efficient MAB algorithm based on Thompson sampling (TS) strategy while considering the remaining batteries of the mobile sensors. This scheme speeds up the searching process and makes beamforming one time only to the targeted device, not like exhaustive search that performs beamforming to all surrounding devices/detectors, resulting in large overhead and large processing time.

Paper organization as follows. Section 2 reviews the related work of RDWSNs. Section 3 discusses the utilized network scenario using mobile devices as smart radiation sensors. The proposed battery aware TS (BA-TS) algorithm is described in section 4, after providing short notes about the TS algorithm. Section 5 previews simulation results that confirm the superior performance of BA-TS. Finally, section 6 concludes the work.

II. RDWSNs Related Work

WSNs have fascinated many researchers, resulting in rapid development in essential applications such as environmental monitoring and military surveillance. A general overview of different programming methodologies and other model-based methods for developing WSNs is given in [8]. A safe monitoring WSN system that detects x-ray levels in hospitals and industrial places using both X-ray radiation sensor and body infrared sensor on the sensor network nodes is proposed in [9]. Another WSN design from a group of radiation detection stations with variant types of sensors is discussed in [10]. Their design located the stations in different areas and assumed that the sensors would utilize the GSM network to send its data to a central control station. The location of each sensor is determined using GPS module. A combined simulation of WSN and radiation detection with directional gamma-ray detectors is conducted in [11]. They assumed that the radiation source (60Co and 137Cs) is transported through crossroads, and they proposed two algorithms to localize and quantify the radiation sources with different speeds and communication protocols. An overview of detecting radiation using mobile sensor networks is discussed in [12]. An active radiation monitoring system for mobile radiated environments is proposed in [13]. The monitoring technique defines if the radiation source is inbound or outbound.

The authors of [14] proposed a radiation detection system for a nuclear facility that consists of Geiger miller tube (GMT) detectors controlled from a single receiver end. The proposed design permits faraway operators to manage/store the radiation levels data issued from radioactive source at different times, which plots the radiation curve of a whole year. A self-regulating micro controller-based system that includes the standard internet protocols and designated for detecting

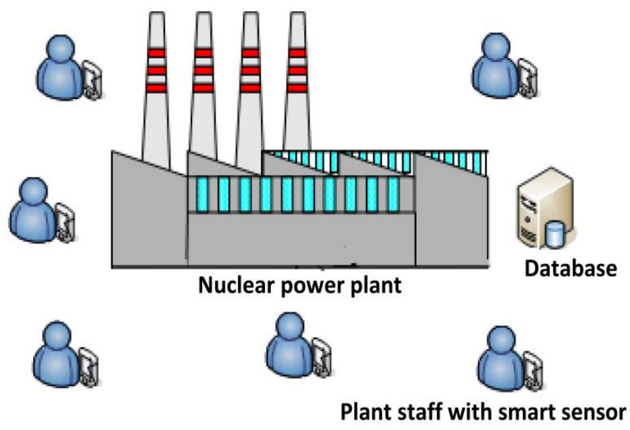

Fig. 2. RDWSN with smart sensors inside/around NPP

radiation in gamma ray area is proposed in [15]. The measured data are sent to the decision-making factors via wireless networks. Furthermore, the authors of [16] presented a mobile ad-hoc wireless network (MANET), to monitor environmental settings inside and around an NPP, particularly radiation levels. Sensors were deployed in a fixed position around the plant. Also, the staff were equipped with mobile sensing devices like PDAs that detect radiation levels. An extreme learning machine (ELM) algorithm is proposed in [17] to protect WSN from several attacks hence extending its life time.

However, existing related work doesn't consider new mobile network scenarios, i.e., 5G nor recent detectors like smart Gigers that can be easily mounted on mobile devices of the NPP staff to measure radiation levels everywhere. Furthermore, to the best of our knowledge, the paper firstly leverages recent ML techniques to implement in radiation monitoring utilizing mmWave communications. The network is vital for continuous inspection during stoppage periods and during accidents to avoid hazardous situations.

III. System Model

Figure 2 shows the suggested RDWSN network architecture, where multiple mobile devices mounting smart Gigers are distributed in the NPP area, which is called the sensor nodes. These sensor nodes are handheld by the workers inside the NPP. Each sensor collects its own radiation readings through its mounted smart Giger dongle. Then, it should relay this reading to the nearest radiation fusion center for analysis and making decisions. In the considered RDWSN, each radiation sensor should proactively discover its nearby sensors and then select one of them to relay its own readings, and so on till reaching the fusion center. The selected nearby mobile sensor should maximize the achievable data rate of the sensor-to-sensor link while considering the limited remaining energy of the sensors. Moreover, we follow the mmWave link model that models the blockage as Poisson distribution.

Our problem formulation is defined as follow the smart sensors need to forward their measured data to the fusion center. Hence it searches for the best nearby device to establish device to device link so as to forward the measured data to the fusion center. Hence, the selected nearby device should be selected in a way to maximize the throughpt and also considering the blockage around. The problem is formulated as MAB where the player chooses an arm of the bandit to choose the optimal route with the highest probability of reward maximization i.e., signal to noise ratio (SNR) or throughput. Achieving such target is a challenging issue due to the unknown probability distribution of highly dynamic wireless communication channels. Hence, we propose levering TS to solve the problem as will be shown next section. Moreover, TS are modified to consider the remaining battery of each sensor/device. In our MAB model, there is a set of K devices (arms). In each round t, the player (a smart sensor that needs to transmit data) selects an arm a_t and detects the reward r_t for the selected arm. There is an important compromise between receiving new info about rewards, i.e., exploration, and optimal selections by means of the existing info, i.e., exploitation.

IV. PROPOSED MAB ALGORITHM

In this section, we will first discuss the proposed TS algorithm to forward the sensed data. Moreover, the TS is modified to consider the remaining batteries of the mobile devices to simulate real scenario and make sure the data are forwarded. Hence BA-TS algorithm is presented.

A. *Thompson Sampling (TS) Algorithm*

TS also was first introduced in 1933 [18] for modeling experimental effort in two-armed bandit problems issued from clinical trials. It is an online decision MAB algorithm where sequential actions are taken to weigh between exploiting and exploring new arms. The algorithm marks a wide range of difficulties in a computationally efficient, hence, enjoying wide usage and applications. TS central strategy is to assume prior distribution for the rewards and updates the posterior distributions within the learning process. Throughout the learning process, each arm is sampled according to the recommended posterior distribution and choosing the device that gives the maximum reward.

Although TS was proposed using Bernoulli distribution as a prior assumption, we implement Gaussian distribution to our reward. This is due to most of the wireless communication channels distributions are gaussian ones generated from the white Gaussian noise distribution. Hence modified TS with normal distribution is implemented here a as in [19]. Regards Gaussian bandits, picking up a device m generates a reward of 1 and 0 with probability Φ_m and $1 - \ \Phi_m$, respectively. In the first-round $t = 1$, action a_1 is taken and reward $r_1 \sum (0, 1)$ is collected with success probability $p(r_1 = 1|$ a$_1$,$\Phi_)$. r_1 is recorded, then another action a_2 is operated then the process is repeated. In TS adopted in this paper, a random sample Φ_k for each arm m based on its normal distribution. Hence the policy of TS is as follow

Algorithm 1: BA-TS for forwarding radiation levels in WSN.

1: Input: $\Xi_{\text{th}}, \Xi_m (t = 1), 1 \leq m \leq M$

2: Initialization: pull each smart detector m once for $t = m$ first rounds and modify the remaining levels of the batteries $\Xi_m (t)$ every round t for all M detectors

3: If $\Xi_m (t) > \Xi_{\text{th}}$ for any $m \in M$ do

- Round update $t = t + 1$
- Select the maximum rewarded smart detector $k^*_{BA-TS}(t)$ using (2).
- modify the remaining battery of the selected detector in last step

else

game end (all detectors are out of battery)

End IF

Fig. 3. Proposed BA-TS algorithm

$$k_{TS}(t) = arg \max_{1 \leq m \leq T} [\Phi_m(t)], \Phi_m(t) \sim N(\bar{\Upsilon}_m (t), \frac{1}{T_{m,t} + 1}) \quad (1)$$

where $\bar{\Upsilon}_m (t)$ is D2D link throughput in bps between the TX mobile device and nearby device m at time t. $T_{m,t}$ reflects how many times device/smart detector m has been nominated till time t. Hence, a random sample is taken from each smart detector m based on the PDF of the normal distribution and selecting the arm that has the maximum reward.

B. *BA-TS algorithm*

An important issue that simulates the real-life scenario is the remaining batteries of mobile devices. This motivated us to modify the TS algorithm to be battery aware. Hence, a budget constraint MAB algorithm is implemented where the remaining battery of each device is considered. A threshold limit is defined as any device remaining battery is below this threshold is quitted from the game. The BA-TS algorithm main equation is as follow

$$k_{BA-TS} (t) = arg \max_{1 \leq m \leq T} [\Phi_m (t) - \frac{d_m}{E_m (t)}], \quad (2)$$

The newly added term $\frac{d_m}{\Xi_m (t)}$ is appended to the typical TS equation (2) to reflect the remaining battery levels of the devices that utilize smart radiation sensors related to its remoteness from the sensor device that needs to forward its data. Figure 3 describes the BA-TS algorithm steps in more detail. The proposed algorithm simulates real-life scenarios where the detectors/mobile devices that have low battery are quitted from the game to save the small remaining battery percentage for main communications. Moreover, the TS algorithm provides a strong guarantee to select the most appropriate arm (link route).

V. NUMERICAL RESULTS

Numerical simulations are implemented to approve the superior performance of the proposed BA-TS over both conventional TS without adding the residual energy term, i.e.,

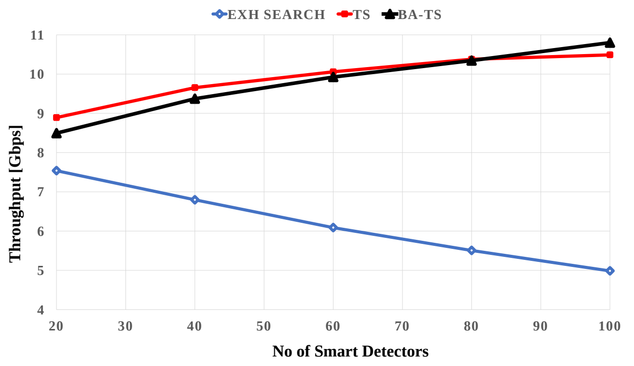

Fig. 4. Throughput Vs no of smart radiation detectors

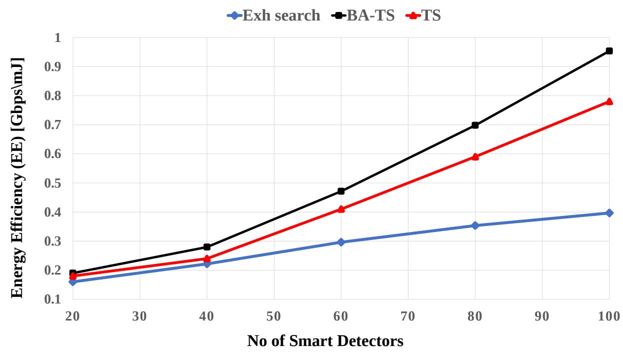

Fig. 5. Energy Efficiency vs no of distributed smart radiation detectors

$\frac{d_m}{E_m(t)}$, in (2), and exhaustive search schemes. In the exhaustive search, the detector which wants to forward its data, searches all neighbor mobile devices/detectors around it and tries to communicate with each one causing large overhead of trying to send data to all devices around. Then, the best suitable device is selected according to the largest SNR produced to have better quality of service for the communication link. The metrics used to evaluate the performance are the throughput in Gbps, energy efficiency in [Gbps/mJ], and network lifetime.

Figure. 4 displays the throughput evaluations against different number of distributed detectors assuming that there is no blockage between them. The proposed BA-TS algorithm have close throughput to the conventional TS and both have superior performances over exhaustive search approach. For the brute force/exhaustive search method, the throughput is greatly diminished against the increment of distributed detectors because of the large overhead. Meanwhile, both the proposed BA-TS and TS will communicate with a single detector every round. Note that the throughput performance of both MAB based algorithms (TS and BA-TS) is improved as the number of distributed detectors is increased due to the long-term average throughput maximization. The extra remaining battery term, i.e., $\frac{d_m}{\Xi_m(t)}$ modifies the BA-TS and improves its performance by ranking nearer devices achieving higher data rates with high remaining batteries. At 20 (100) smart detectors, the proposed BA-TS has 1.11 (6) over the exhaustive search scheme, respectively.

Figure. 5 previews the energy efficiency (EE) of the proposed BA-TS in Gbps/mJ versus various number of smart detectors at zero blockage. The EE is related to the remaining battery of each smart detector at each round. By increasing the number of smart detectors, EE of the compared methods relatively increased because of the increment in the number of smart detectors that are able to establish the required communication link. This diminishes the used-up energy per selected smart sensor. The proposed BA-TS shows the best performance as it tries to maximize the long-term average throughput while preserving the residual energies of the nearby smart detectors when establishing the communication links resulting in better EE performance. At 20 (100) intelligent radiation detectors, the proposed BA-TS has 1.22 (2.43) and 1.94 (3.25) EE increment than TS and exhaustive search methods, respectively.

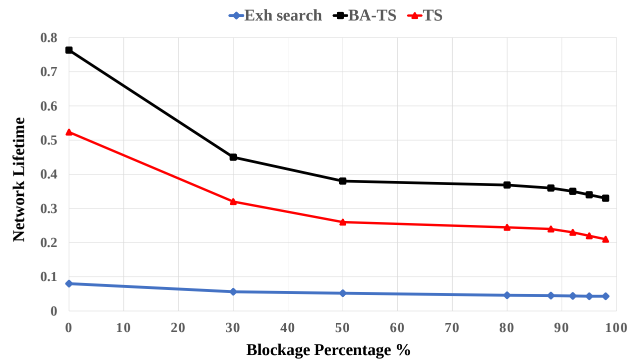

Fig. 6. Network life time

Figure. 6 discusses the performance of network lifetime, known as the time at which the remaining battery of one of the nearby smart radiation detectors falls below the assigned threshold level of the battery,i.e, $\Xi_{th} = 0.11 joule$. In Fig. 6, 50 smart radiation detectors are utilized, and the network lifetime is measured against different blockage percentages. The network lifetime is significantly prolonged due to highly obtained data rates that reduce the data transmission time, followed by low battery consumption. The proposed BA-TS approves superior network lifetime performance over both TS and exhaustive search schemes at all blockage levels. BA-Ts have the best network performance, while Exhaustive search has the worst performance.

VI. CONCLUSION

Radiation detection levels around nuclear sites gained more attention due to its panic importance to society and severe radiation risks to the environment. In this paper, we proposed BA-TS MAB based algorithm that efficiently detects radiation levels around NPP. The network utilizes mmWaves plus a smart radiation detector, which is mounted on the smart mobiles of every worker in the NPP to continuously measure the radiation levels, then forward the measured data to the fusion center by establishing a communication link with the surrounding smart detectors. BA-TS not only hurry the exploration process but also maximize the throughput while counting the remaining batteries percentages of the nearby smart detectors. Also, it approved its superior performance over both regular TS and exhaustive search methods.

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