Optimizing Exploration - Exploitation Trad-offs for Efficient energy consumption , Accurate data recovery, and computation cost reduction using Q - learning in WSNs

I. Abstract

To enhance data transmission efficiency, reduce energy consumption, and improve data recovery accuracy in Wireless Sensor Networks (WSNs), the application of Compressive Data Gathering (CDG) is proposed. The integration of sleep scheduling with CDG further promotes energy efficiency by aggregating only essential information instead of transmitting raw or redundant data. Existing sleep scheduling methods for CDG have predominantly centered around centralized minimization problems, resulting in a proliferation of control message transmissions. Conversely, some distributed mechanisms have relied on speculative decisions and failed to adapt to variations in node power levels, leading to premature power depletion in certain nodes. To address these challenges, this research introduces the Reinforcement Learning Sleep Scheduling Algorithm for CDG (RLSSA-CDG), which focuses on identifying active nodes through a Finite Markov Decision Process. The Mode-Free Q-Learning algorithm is employed to determine optimal decision strategies (optimal Exploration - exploitation ratio), incorporating node power levels and sampling uniformity into the reward function. RLSSA-CDG significantly reduces control message transmissions, ensures computational efficiency by involving every node in a single decision step, and facilitates load balancing of energy expenditure for accurate data recovery in WSN.

***Index Terms*—Transmission efficiency, Wireless sensor networks, MDP, Load balancing .**

II. Introduction

Wireless Sensor Networks(WSNs)[1]–[3] include wide amount of small sensor nodes. These sensor nodes used to gather surrounding data from real world for Internet of Things(IOT) to create quick- witted resolution. In WSNs , faces several challenges in gather the information from the environment .In the environment , Sensor nodes in WSNs aggregate information and transfer it to the nucleus node (Sink) through wireless connections.In WSNs achieving low cost and high accuracy gathering includes optimizing sensor node abilities and communication protocol. WSN's application encompass environmental monitoring as well as industrial automation for enabling efficient , automated processes, predictive maintenance, increased resource utilization, Healthcare, Smart Cities , Agriculture, Home automation , Military and Defense, Wildlife tracking, Monitoring under the water and on the volcano. for effective data gathering , the main aim is to reduce energy consumption, reduce computation cost and increase accuracy. It is crucial for environmental monitoring, and industry automation due to various reasons. These reasons are cost efficiency ,large scale deployment, precision in analyzing, real time response, resource conservation, information quality for exploration, adaptability to varied surroundings.Nodes are gather the information and transfer it to the sink through wireless links. Sink refers to a designated node or hardware that acts as a central point for gathering information from the network. Is also known as the base station or data aggregator. which is responsible for collecting data from the allocated sensors located in the network. The sink is typically has more computational power and storage ability compared to individual sensor nodes, creating it suitable for handling and maintaining the collected data efficiently and accurately .The communication between sensor nodes and the sink is a necessary aspects of WSNs , and several routing protocols and approaches are employed to optimize information transmission, reduce energy consumption. They generally have bounded energy and computation. to solve these problems several techniques used, Matrix completion is used. this technique used in various fields, such as recommended systems and data imputation, to recover missing or incomplete entries in a matrix based on observed values. this approach sensitive to Matrix rank, outliers and limited interpretability .this method often assume that the underlying matrix has low rank. However, real-world data may not always conform to this assumption, and the performance of matrix completion algorithms can degrade when dealing with matrices of higher rank. Anomalies or noise in the input matrix may negatively impact the accuracy of completion, as these methods do not always account for robustness against outliers.this models may lack interpretability, making it challenging to understand the rationale behind predictions. which is not effective in gathering and transmitting the information.The effective approach to overcome these problems, Compressive data gathering (CDG)[4]. CDG applies compressive sensing (CS) to data aggregating in Wireless Sensor Networks(WSNs).Compressive Sensing , it is a signal processing technique that permits the regeneration of a sparse signal from a tiny number of non- adaptive linear measurements. It is different from traditional compression techniques, CDG compresses sensing information while sampling and largely cuts down information transmissions. It is extremely suitable for resource-restricted Wireless Sensor Networks(WSNs).The are several algorithms in CDG, but Sparse-CDG [5], [6] is one of the effective approaches. It refers to the procedure of efficiently aggregating and regenerating sparse information using compressive sensing techniques. In this approach ,few nodes are chosen to sense information and inaugurate CS measurements for data reconstruction. from the feature of energy efficiency , these nodes are not selected to engage in sparse CS Sampling can move to sleep mode to energy consumption.So, representing sleep scheduling into CDG scheme can encourage energy efficiency. Which is profit increase the lifetime of Wireless Sensor Networks. In CDG , RL agent plays a crucial role, which is the part of Reinforcement learning (RL)[2], [7]–[9]. It is a machine learning paradigm where an agent learns to create decisions by interacting with a surroundings. The agent takes actions within the surroundings and receive feedback in the form of reward and penalties. The aim of the agent is to learn policy, a mapping from states to actions, that increase the cumulative reward over time.it has been successfully applied in several fields, including game playing, robotics, autonomous systems, resource optimization. Therefore , the learning agent modify to dissimilarities in environment .Complexity of Reinforcement learning approach can be tailored to a concrete complication. so, it is an effective quick approach for resource- restricted WSNs. In order to gain load balance of energy consumption among nodes and increase the lifetime of Wireless Sensor Networks. A RL based sleep scheduling algorithm for compressive data gathering (CDG).it is known as RLSSA-CDG. The process of selection active nodes is modeled as a finite Markov decision process(MDP). It is a mathematical model used in the domain of reinforcement learning and decision making under uncertainty. It is characterized by a finite set of states, a finite set of actions and a set of transition probabilities that define the likelihood of moving from one state to another state after taking a particular action. This Markov Decision Process problem resolved by by the mode free Q learning algorithm The RLSSA-CDG is a distributed sleep scheduling method. Q learning consist three phases which are initialization phase , sampling phase, forwarding phase. All the nodes cooperatively manage a common Q table. It is a data structure utilized in reinforcement learning algorithms. The Q table contains values , often denoted as Q- values , that represent the expected cumulative rewards for each possible action in each possible state of finite Markov decision process. Each node holds one row of this Q table . this Q learning algorithm responsible for accurate data reconstruction. by this approach evaluate the Q values, total reward per episode, Maximum Q values change per episode , Exploration -exploitation ratio per episode. Balancing Exploration and exploitation is one of important factor for reducing energy consumption.for optimizing energy consumption, Balancing exploration and exploitation helps ensure that the system focuses on energy-efficient actions while still allowing for exploration to discover potentially more efficient approaches. increase accurate data recovery ,exploration is used to discover new information and potential improvements in the system's understanding of the environment. in this optimal ratio,Exploitation utilizes the current knowledge to make decisions that are likely to yield high rewards.it is Maintaining an appropriate balance ensures that the system continues to explore to refine its understanding, improving data recovery accuracy over time. , for decrease computation cost ,helps in focusing computational efforts on the most promising actions, reducing overall computation costs while still allowing for exploration to adapt to changing conditions and Environments may change over time,An adaptive balance between exploration and exploitation allows the system to adjust to changes in the environment. which used to required the efficient energy consumption , prolong the lifetime of network , accurate data recovery, and reasonable computation cost.in this arbitrary summary, the rest of the sections of this study are summarized as follows: Section 2 represents the related work, Section 3 represents the proposed model and proposed approach , section 4 implementation and analysis of the surroundings, parameter design etc. In the section 5 outcome analysis are presented and in the Section 6 conclusion are represented.

III. Related Work

The main aim of low cost and high accuracy data gathering in Wireless sensor networks is to reduce energy consumption and increase accuracy. It is important in various applications and industries. Various challenges to achieve low cost and high accuracy in wireless sensor networks (WSNs).it plays a key role and necessary of attaining this balance. which are environmental monitoring, Precision Agriculture, Industrial IoT, Smart cities, Healthcare, Wildlife Monitoring, Disaster Management, Home Automation, Retail and Inventory Management, Scientific Research. The role of low cost and high accuracy data gathering in WSNs is to give reliable and timely data for accurate outcome , resource optimization, cost deduction and enhancing overall efficiency. now is the existing work which to solve these problems with several methods.which following:

Kun Xie et al.[10] recommended a work on data aggregation, he worked on Matrix completion has emerged very recently and gives a latest locale for low cost data gathering in Wireless sensor networks (WSNs).Environmental information vary in profane and geographical areas. By observing a huge amount of atmospheric condition information gathered from 196 sensors in ZhuZhou, China, he disclose that atmospheric condition information have the several characteristics these are low-rank, temporal stability, and relative rank stability. He taken the benefits of these attributes . he suggested an real time data gathering stratagem based on matrix completion theory, which is known as MC-Weather.Basically he highlighted on uninterrupted and real time data gathering in WSNs. He demonstrated that the analyzed that relative rank stability is a habitual attribute in uninterrupted data gathering methodologies . depend on this essential attribute and his pronouncement, he discussed three sample learning principles, which were appealed to conduct his adaptive sampling algorithm . it is used to rapidly establish the effective sampling set. To full advantage of our sample learning principles, he also discussed a Uniform Time-slot and Cross Sample model (UTSCS). In this it was contrasted with the Bernoulli model, he demonstrated that his b UTSCS model authorized for superior data matrix regeneration. Trace-driven simulations, depend upon real atmospheric condition information discovers and different sensory data discovers (PM 2.5 and PM 10) it is display that MC-Weather can attain a high accuracy in data recuperation with low sensing, computational cost and communication costs in a vigorous nature world. Yi Xu et al.[11] discussed a approach to achieve energy consumption and high accuracy .In this project , he recommend a novel data-collection technique based on MC for large-scale Wireless Sensor Networks. He create a RRSS method, in this approach sensor nodes are picked randomly and systematically and those nodes are in the sleep mode continually to a considerable amount decrease the energy consumption. From the samples achieved by the recommended sampling method, a correlating with FSVT algorithm is provided to reconstruct the data , efficiently ,accurately and rapidly. The observations are escorted with two real-world data sets and the its simulation outcomes display that the discussed sampling approach can improve the corresponding algorithm. Furthermore , the discussed data-collection approach overcomes other techniques in expressions of the reorganization correctness and rate. Praveen Kumar Kodoth et al.[12] proposed a method to attain reduction in energy consumption .The paramount c provocation in Wireless Sensor Networks (WSNs) is to experiment the techniques for energy-efficient data gathering. Within the operating assortment of Wireless Sensor Network (WSN), the sensor nodes are diversed to deliver the sensed data to the base station. In the course of the transmission of data, few aggregate of energy is emaciated. Therefore , in this work, author is centre of attention on giving an energy-efficient data gathering approach by Circular Clustering and Hybrid Crow Search Algorithm(HCRA) . these are utilized in improve the duration of life of network. Learning to intensify the duration of life of network and to achieve efficient energy efficiency. In this recommended approach, this approach is beneficial for vigorous information collector node nomination ; firstly , the circular cell clusters are realizing by segregating the whole domain of the sensor network. From now on , to nominate precise data collecting node in the circular cell cluster domain, a multi objective based weighted sum technology is employed for juxtaposition, transmission cost, unconsumed energy and coverage. after that, a routing and dynamic mobile sink relocation approach are implemented to collect information form cluster head utilizing hybrid crow search algorithm (HCSA). According to the attributes such as whole energy consumption, various alive nodes, and network duration of life, the ability of the suggested mechanism has been experimented . The suggested scheme has superior execution observation when compared to the existing mechanisms. Hongjuan Li et al.[13] recommended a technique of secure data aggregation in wireless sensor networks. Due to the immanent attributes of resource-constrained sensors, communication overhead is always a crucial treat in wireless sensor networks (WSNs). Data aggregation is an necessary mechanism to decrease the communication budget and extend the duration of network lifetime. Since data aggregation outcomes are habitually utilized to create complicate decisions, the accuracy, precision of overall aggregation outcomes is paramount. Furthermore, as wireless sensor networks are enhancing being locate in privacy –complication applications, he should take privacy into deliberation as well. So , for such applications, experiments , data aggregation protocols must be greatly energy efficient and greatly accurate outcome while being capable of allow an opponent from purloining secrete information taken by each sensor node. In his work, he recommend an energy-efficient and high-accuracy (EEHA) mechanism for secure data aggregation. The principal proposal of his mechanism is that accurate and correct data aggregation is attained without providing secrete sensor information and without initiating remarkable overhead on the battery-restricted sensors. He oversee substantial replication to execute the performance of energy-efficient and high-accuracy (EEHA). His observation and reconstructions display that EEHA is additional efficient and accurate than the existing approaches the aggregation accuracy is paramount for responsive applications such as battlefield military.Donghao Wang et al.[6] proposed a method for efficient data gathering .In this work, the data gathering complication depend upon Matrix Completion theory is experimented. Excluding for the low-rank property, the sensed information are analyzed to be scattered under the graph based transform .Two novel replication algorithms (named GBTR-ADMM and GBTR-A2DM2) are recommended in his work . to take the whole profit of these attributes. In this method ,the time complexity is also observed, which displays their complexity is moderate. Various investigations on both natural and artificial raw data are carried out. It display that his suggested mechanisms conquer the latest algorithm for data gathering complication in Wireless Sensor Networks after that, it is analyzed that GBTR-A2DM2 intersect more quicker than GBTR-ADMM .Shu-Chuan-Chu et al.[7] discussed a technique for recognizing accurateness data scheme for aggregating data in cluster heads of wireless sensor network, a new strategy of gathering data categorization for aggregating data in cluster heads (CHs) in hierarchical WSN based on the naive Bayes approach was proposed . caused by the requisite of the accurate data in various victorious WSN applications, a decision function of classification should be located in Clustering Heads for malfunctioning observation to collection the habitual data for the succeeding procedure. The gathering environmental details like temperature, humidity, and contamination levels is categorized as gathering “fault” or “normal” data to gather and transmit them to the base station (BS). The system prototype of the suggested scheme comprises of majority factors such as the gathering and pre-processing information, recognizing and standardizing elements of information , and training and testing data-sets. The noise is detached from the information that can be important to acquire more precise. The components of selected elements in data-sets can authorize observation precision. In the investigational part, the system was tested with the gathering information by naive Bayes classification. Differentiated with the various approaches in this work like the support vector machine (SVM), decision tree (DT), hidden Markov model (HMM), and cloud computing scheme (CLOUD), it represents that the suggested approach provides an efficacious procedure of progressing the accurate information for WSN applications. The prototype offers an precision of more than 97 percent all over the data learning procedure . In data testing, the efficiency of the enhanced information error observation provides more accurate than another merciless systems. Shilpa S G et al.[8]expressed her work ,in her work Wireless Sensor Network is an energy inhibited network. Since most of the energy has enfeebled for transmitting and accepting information , therefore the information collection becomes important in the network. Information collection or information aggregating support to remove replica information transmission in Wireless Sensor Network (WSN). It has fascinated a lot of awareness in the current time. In her work, she has recapitulated few experimentation outcomes on data aggregating and data routing in WSN. pliability to construct overhead, routine link breaks, Setup, Scalability, mobility of nodes, energy conservation approach, and Timing master plan , data collection protocols with cluster technique accomplish well differentiated with different protocols and can made energy efficient WSN with these protocols. She and her team contemplated current suggested clustering protocols for WSNs and categorized these into four categorizations depending on the network topology and additionally the hop communication these are homogeneous, heterogeneous, single and multi-hop.U.Nilabar NIsha et al.[9]recommended techniques , Wireless Sensor Network consists millions of little sensor nodes in a physical environment for observing and announcing the circumstances. Wireless sensor networks (WSNs) are prognosticated for aggregating the information like substantial or the nature worlds qualities from topographical region. Data aggregating is depend on the connection-less transmissions between the sensor node and the sink node. quarry pursuing and various information aggregation are momentous application in wireless sensor network. A differentiation of various existing target tracking and information collection approaches in wireless sensor networks are investigated . From the investigation, the existing approaches resulted in higher target tracking time and drained abundant of energy. this review displays that the dependableness in expressions of time was not increased utilizing encumbered assignation outlining . In the existing approaches, the latency endured unconsidered. In addition, the routing overhead was not decreasing utilizing Contact-Aware ETX. The wide range of investigations on existing approaches calculates the relative performance of the various information aggregating and target tracking approaches with its restrictions. From this study wireless sensor network(WSN) for target tracking and information aggregating using machine learning approaches and ensemble classifier. Keyan Cao et al.[1]discussed efficient information aggregation techniques, Wireless sensor networks are extensively utilized in various fields, such as medical and health care, military observing , target tracking, and human's life, because of their benefits of convenient arrangement, low cost, and good obliteration. although, caused by the low battery volume of sensor nodes and universal changes, the energy exhaustion of nodes is deliberate and the precision of information aggregation is low. the qualities of compressed sensing in wireless sensor networks are estimated, and the arbitrary walk path collection stratagem is experimented in extent. This work suggested an efficient data aggregation algorithm in a fixed habitat for the ambiguous climate of the wireless sensor network(WSN) and the complications that happened in the middle of the information aggregation procedure of a complicated blueprint. Then, it is prolonged to suggest an efficient data collection algorithm based on ELM location forecasting in mobile network climate and creates various simulation investigations to authenticate the preciseness of the algorithm. In the last, the archetype system is planned to certify the preciseness and persuasive-ness of the algorithm.Shima Pakdaman Tirani et al.[2] suggested approaches, in her work , observe the complications of energy consumption, load-balancing, and Compressive Sensing (CS) recuperation performance in hybrid proactive-reactive wireless sensor network, in this approach , sensors are divided into two representative and relay nodes. She and their team mutually contemplate the charismatic compressive information collecting, angle-based random walk, and spatial correlation to suggest an efficient technique named "Dynamic Compressive Data Gathering using Angle-based Random Walk (DCDG-ARW)". The suggested technique utilizes the CS theory made up of the angle-based random walks to transmit CS measurements from sensors to the sink node. They dispensed with the enhancement of the energy consumption, load-balancing, and aspect of CS recovery performance in a hybrid proactive-reactive WSN. To achieve this aim , they suggested an efficient algorithm named DCDG-ARW to mutually identify the complications of dynamic compressive data gathering, angle-based random walk, and spatial correlation. A DCNS procedure was granted to dexterously chose a starting node for each RWP that is adequately distant from one and all.Koppala Guravaiah et al.[3] proposed a method , categorization of data aggregation routing protocols in WSN has been comprehensively suggested. Several approaches such as clustering, duty cycling, aggregation, network coding, sink mobility, and cross-layered solutions, and directional antennas have been used by data aggregation routing protocols for achieving long duration of life , energy efficiency, fault tolerance, and low latency. In this work these are surveyed shortly . Finally, this work authenticates a paramount differentiation among the existing techniques. which are applicable on information aggregation procedure in Wireless Sensor Network.

Ghaida Muttashar Abdulshahir et al.[14]recommended a work upon accurate and efficient data collection, WSN data collection for the observation of data to decrease energy consumption and throughput in Wireless Sensor Networks, with the aims of reducing power consumption. The extreme objective is to save power in an exertion to enhance the duration of life of the network. Even so, the advantageous information aggregation in the WSN is omitted by several algorithms. As for upcoming experiments, it is equitable to penetrate superior the connotation of the system method and power consumption and experiment other linked complications like broadcasting with a analogous technique. Additionally , in correlative investigation to the wireless-based data collection and the routing path selection, the proposed procedure has verified high outcomes with reference to information aggregation and network performance. He and his team have drained from a network architecture all though our experiments therefore that the information can be gathered as expeditious as achievable. information is of great connotation in several sensor network applications and should achieve the base station as instantly as possible. The suggested Wireless Sensor Network (WSN) architecture can approximately power decrease the information aggregation time while managing adequate values of entire communication area and network growth.Ranjan Bala et al.[15]proposed a method , decreasing the amount of wireless communication in sensory information aggregating for activated information field investigation in wireless sensor networks (WSN), which is a considerable cause of energy consumption. (CS) is a new in-node compression approach that is economically utilized for information collecting in an power-constrained Wireless Sensor Network. Among existing CS -based routing, cluster-based approaches provide the most transmission-efficient structure. Most CS-based clustering techniques in whatever way select nodes to form clusters, overlooking the geopolitics architecture . A novel base station (BS)-assisted cluster, spatially correlated cluster using CS (SCC-CS), is suggested to decrease number of communications in and form the cluster by nefarious spatial correlation based on topological immediacy. The suggested BS-assisted clustering technique follows hexagonal deployment technique. In SCC-CS, cluster heads are wholly convoluted in information aggregating and communicating CS experiments to BS, saving intra-cluster transmission cost, and therefore , network growth enhanced as verified by simulation. Soroush Abbasian Dehkordi et al.[16]suggested a approach, in this method ,The goal of this experiment is to offer a essential platform to establish new advanced prototypes in the domain of internet of things . The highlight is depend upon on the enhancement of information collection approaches in wireless sensor network (WSN) with view to four task domains (i.e., earthbound , sunken, subaqueous , and anatomy). apropos that last, subsequently proposing the complications with the Internet of Things and in view of WSN as kind of it and deciding information collection as one of the suggested problems, endeavors were created to collect the existing data aggregation approaches with a more full scene to promote the procedure of approach collection by reader through collecting several information collection approaches and announcing their profits and drawbacks . caused by the expansion of the argument and the absence of a broad and comprehensible method for information collection, a broad and appreciable techniques is enforced. Various decagon after the insertion of WSN, still no broad and comprehensible method has been displayed in the domain of information collection which is applicable of connecting security, transmission aerial, power consumption, and data confining ratio. T. Sujithra et al.[17] proposed a work in, this work experiments several information aggregating methodologies in wireless sensor networks in several forms. Transmission distance, the power level of the sensor node, information collecting speed, memory size of the sensor node, the abnegation instruction of the mobile attribute actuate the performance of the wireless sensor network viz. packet delivery ratio, duration of life of the sensor network, routing overhead, etc. It has been attended that several experiments boulevards are expedite for energy efficient data aggregating in wireless sensor network.Samir ifzarne et al.[18]discussed a method , in this work suggested a lightweight, secure routing protocol named PC2SR. It distinguishes several Wireless Sensor Network privacy intrusion and decreases the transmission cost without inconvenient the information precision level. For that, the suggested PC2SR accommodates a semi-homomorphic cryptosystem named as paillier cryptography with compressive sensing. Provision of strong paillier keys with key refreshing mechanism, the PC2SR substantially increases the privacy level of nodes over Wireless Sensor Network. The compressive sensing depend on information aggregation within intra-cluster decreases the transmission cost and also perpetuates duration of life without delicate the precision of information . Also , the nil explosion aspects with bequeathed information enhance the attack revelation precision level at BS and also improves the information precision level.Bernhard Buchli et al. [19] recommended a technique for high accuracy, This study displays the prototype, execution , and end-to-end system perception and assimilation of a wireless data acquisition scheme for high-accuracy sighting applications. A wireless network of GPS-equipped sensor nodes, assembled from low-cost off-the-shelf entrails , individually achieves L1 GPS data for contrasting GPS (DGPS) clarification of raw satellite data . The contrasting clarification on the backend architecture attains analogous location and fluctuation of individual nodes within the network with sub-centimeter precision . advantaging on global GPS time integration , network-wide integrates measurement scheduling, and duty-cycling coupled with energy minimized exploitation and heftiness against rigid topological conditions create the explained sensor node well suitable for observing or discriminating applications in inaccessible domains. Abandoned exploitation, high spatial and earthly description and low cost categorize this method from classical , very expensive and time taking technologies . The architecture data acquisition scheme depend upon a low-energy speck assembled with a economically convenient GPS module has been profitably executed and substantiated in a testbed setting

. Xun Wang propsed et al.[4] a method for Compressive data gathering (CDG) is an accurate approach to decrease the extent of information communication , thereby reducing power consumption for wireless sensor networks (WSNs). Sleep scheduling unified with CDG can more advance energy efficiency. Several of existing sleep scheduling approaches for CDG were methodized as constitutional minimization complications which explained various more control message interchanges . Meanwhile, some categorized approaches habitually embraced stochastic decision which could not acclimate to deviation in enduring power of nodes In this work , a reinforcement learning-based sleep scheduling algorithm for CDG (RLSSA-CDG) is suggested . Active nodes selection is prototyped as a countable Markov decision procedure . The mode-free Q learning algorithm is utilized to find optimal decision techniques . enduring power of nodes and sampling uniformity are categorized into the reward function of the Q learning algorithm for load maintain of power consumption and precise information regeneration . The simulation outcomes displays that the suggested RLSSA-CDG exceed the two divergence approaches in expressions of power consumption, duration of life of network , and data recovery precision . The suggested RLSSA-CDG decreases power consumption by 4.64 percent and 42.42 percent , respectively, contrasted to the DSSA-CDG and the original sparse-CDG, extends life time by 57.3 percent , and encourages data recovery precision by 84.7 percent contrasted to the DSSA-CDG.

The comparison among algorithm which is used for load balancing of power consumption, accurate data recovery and low computation based upon their metrics and Drawbacks . which is shown in below table I.

IV. System Model and Problem Formulation

In this section, the wireless sensor network model is explained in the section and then Problem formation is explained:

A. *System model:*

A two-dimensional wireless sensor network (WSN) is taken as the network model in this research. It is displayed in 1 . sensor nodes are heterogeneously and homogeneously distributed in a two-dimensional observing domain.In this nodes are powered by batteries which are not rechargeable. These nodes relentlessly recognize physical phenomena (like temperature, humidity, and Air quality) in the domain and frequently describe their sensing information to the sink through shortest routing paths. The sink is located at the nucleus of the domain and is equipped with unbounded storage and arithmetic costs.The of this approach describes in below figure 1. and its parameters represents in figure 2 in this set all sensor nodes are denoted by

$$S = \{\text{SensorNode}_i \mid i = 1, 2, \ldots, n\}$$

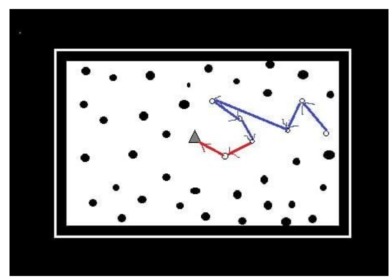

Fig. 1. System model:

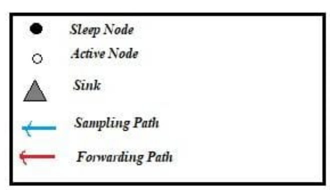

Fig. 2. parameters of above model

A RL-based sleep-based sleep scheduling is deployed in wireless sensor networks. A section of nodes are active which are responsible for aggregating sensing information and the rest of the active nodes are not in the process which are asleep. The procedure of data aggregating id categorized into two steps, first is the sampling phase (the blue path in Fig.1) and the forwarding phase (the green path in Fig.1). The entire Wireless Sensor Network is a Reinforcement

TABLE I

COMPARISON TABLE OF ALGORITHMS WITH EMPHASIS ON TECHNIQUES AND DRAWBACKS

Author	,Methods	Technique Used	Drawbacks
Kun Xie et al. [10]	Adaptive Sampling Algorithm	Dynamic Allocation, Variance Reduction, Stratification	Risk of over-fitting
Kun Xie et al. [10]	Sampling Learning Principles	Cross-Validation, Ensemble Methods	Potential for under representation
Shankar Madkar et al. [20]	PEGASIS ,LEACH	Chain Construction, Clustering	Energy consumption disparities, limited network adaptability
Yi Xu et al. [11]	Rotation Random Sparse Sampling	Data Rotation/Transformation	Potential data loss
Yi Xu et al.[11]	Fast Singular Value Thresholding	Singular Value Thresholding ,Proximal gradient descent	Application constraints, convergence issues
Yi Xu et al. [11]	Nesterov Accelerated Gradient	Gradient Optimization	Challenges in parallelization
Praveen Kumar Kodoth et al. [12]	Hybrid Crow Search Algorithm	Advanced Clustering Techniques	Higher computational costs, limited generalizability
Hongjuan Li et al. [13]	EEHA	Data Aggregation	Complexity in implementation, cost considerations.
Donghao Wang et al [6]	Signal Processing	Transform and Encoding Compression	Communication overhead
Donghao Wang et al[6]	Compressive Sensing	Compression and Sampling	Optimization challenges in data handling
Donghao Wang et al[6]	Information Theoretic Approaches	Distributed Source Coding (DSC)	Security vulnerabilities, implementation complexity
Anum Masood et al.[21]	GBTR-ADMM	Matrix Completion Methods	Complex hyper-parameter tuning, sensitivity to noise and outliers
U.Nilabar NIsha et al.[9]	TEEN, DECSA ,	Threshold-based Clustering	Reduced network throughput
Shilpa S G et al.[8]	ECHSSD	Clustering	Reduced network throughput, Domain dependence
Ranjan Bala et al. [15]	Load Balancing Algorithm	Dynamic Clustering	Overhead concerns, scalability challenges
Soroush Abbasian Dehkordi et al.[16]	Linked Cluster Algorithm	Clustering Strategies	Context-specific applicability, prototype limitations
T. Sujithra et al. [17]	Distributed Cluster Algorithm	Energy-Efficient Clustering	Increased communication overhead, security challenges
Xiaoxia Song et al.[22]	Naive Bayes Classification	Probabilistic Clustering	Sensitivity to outliers
Jiajia huang et al.[23]	CLUDDA	Advanced Clustering	Load balancing challenges
Samir ifzarne et al.[18]	RRCH	Clustering	Implementation complexity
Samir ifzarne et al. [18]	EBC	Clustering	Overhead in Cluster- Head information
Bernhard Buchli et al. [19]	Angle-based Random Walk	Data Aggregation Strategies	Risks of stagnation
Soroush Abbasian Dehkordi et al.[16]	Regular Low-Density Parity Check Matrix	Matrix Completion Techniques	Performance variability, encoding challenges
T. Sujithra et al.[17]	Cost-aware Stochastic Compressive Data Gathering	Cost-efficient Data Aggregation	Implementation complexity
Bernhard Buchli et al. [19]	Paillier Cryptosystem and Compressive Sensing based Routing	Secure Data Transmission	Complexity in implementation

Learning agent .in this is the Q learning algorithm is utilized to choose active nodes in data aggregating from aspects of remaining energy and number of active times with the aim of evenly energy expenditure and precise information recovery.

B. Energy Expenditure Model:

Energy consumption is the amount of electrical energy or power required to capture, process, and transmit sensory information from sensors to other components or systems. Sensory data typically comes from sensors that collect information about the environment, such as temperature, humidity, pressure, Air Quality. A sensor node is typically composed of sensing energy, data processing energy, and wireless communication energy, idle or sleep mode energy, overall system energy. Wireless communication components explore most of energy and data processing components takes second place. In a sleep scheduling algorithm, active nodes handle transmitting and receiving information and make its neighbour active node . after converting neighbour into active node, it become sleep . .Sleep nodes consume very little power which is usually negligible.

The energy consumption (E) in the RLSSA-CDG algorithm with Q-learning can be modeled using the following formula:

$$E = E_{\text{base}} + E_{\text{active}} \cdot t_{\text{active}} + E_{\text{sleep}} \cdot t_{\text{sleep}} + E_{\text{communication}} \cdot \text{Communication Energ}$$

Where:

$$\begin{aligned} E_{\text{base}} &: \text{Standby power mode)} \\ E_{\text{active}} &: \text{10-100 milliwatts} \\ t_{\text{active}} &: \text{10 milliseconds} \\ E_{\text{sleep}} &: \text{0-0.1 milliwatts} \\ t_{\text{sleep}} &: \text{0.1-0.5 millisecond} \\ E_{\text{communication}} &: \text{10-50 communications} \\ \text{Communication Energy} &: \text{10-15 millijoule} \end{aligned}$$

Total active time is determined by below formula:

$$t_{\text{active}} = \sum_{t=1}^{T} \text{Active Time at time step } t$$

Here, T represents the total number of time.

t_{sleep} be the total sleep time.

The formula for calculating total sleep time can be represented as:

$$t_{\text{sleep}} = \sum_{i=1}^{N} \text{Sleep Interval}_i$$

Here, N is the total number of sleep intervals, and Sleep Interval_i represents the duration of the i-th sleep interval.

V. Problem Formulation:

1) Elucidation of FND:: the lifetime of wireless sensor networks means a perennial working period. It happens when a node releases its energy. is known as the node dies. for data integrity, take the first node dies (FND)as the feature of prolonging of lifetime of WSNs. FND is elucidated as the number of working travel rounds accomplished by a WSN previous to the first node dies .

FND = Time when the first node in a network fails

2) Elucidation of Mean square error(Mean Square Error):: Information reconstruction error is estimated by Mean square error (Mean Square Error).It computes the average squared difference between estimated value and actual values.A smaller Mean Square Error represents a better fit to the model to the information.

The Mean Squared Error (MSE) is given by:

$$\text{Mean Square Error} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where:

- n is the number of observations.
- y_i represents the actual values.
- $\hat{y}_i$ represents the predicted values.

3) Problem Formulation:: in this paper, we architect the wireless sensors network as a RL agent . it is utilized to consecutively arouses asleep nodes to fulfill compressive data aggregating . the main aim is extending FND of the Wireless Networks with avowal of authorized Mean Square Error through achieving load balance of energy consumption and sampling uniformity among nodes in the proposed sleep scheduling technique.In RL technique, the is achieved by reward functions. The aim of RL agent is to increase its achieved rewards.therefore the goal parameter of this work is defined as follows:

The Mean Squared Error (MSE) between $Q_{\text{new}}(s, a)$ and $Q_{\text{old}}(s, a)$ is given by:

$$\text{MSE}(Q_{\text{new}}(s, a), Q_{\text{old}}(s, a))$$

And $\text{MSE}(Q_{\text{new}}(s, a), Q_{\text{old}}(s, a)) \leq \text{Threshold}$.

A. Algorithm Description:

Peculiar illustrations of the proposed RLSSA-CDG approach are explained in this Section, it is depend upon on the Reinforcement Learning frame and conscious of residual energy of nodes which goal at accomplishing load balance of energy expenditure.which is consecrated to increase the lifetime of network of wireless sensors networks.RLSSA-CDG executes in the demeanour of rounds. Each round is categorized in into three phases.which are following:

Initialization Phase

Sampling Phase

Forwarding Phase

in the initialized phase heterogeneously generates earliest active nodes to begin CS measurements.in the sampling phase , these earliest nodes successively awake their neighbour in the domain . it is depend upon local Q table then transfer sensing data to newly active node.and in the last phase forwarding phase terminates transferring aggregating CS parameters to the centre node through the shortest routing path.

B. Q learning based active nodes preference approach:

1) Reinforcement Learning:: Reinforcement learning is one the method of machine learning techniques. This technique emulates human behavior and acquires a knowledge from communication with atmosphere. mainly it is the procedure of interaction between agent and environment .it can be adapted as finite MDP.Interaction between agent and environment represent in below figure 3In MDP, we use state–action value function Q(s,a) to examine actions. Q(s,a) represents the value of action a in state s. Thus, an optimal policy π can be defined as the policy resulted in maximum value.

$$\pi^*(s) = \arg\max_a Q^*(s, a)$$

where:

$$\begin{aligned} \pi^*(s) &: \text{Optimal action to take in state } s \\ Q^*(s, a) &: \text{Optimal Q-value for state-action pair } (s, a) \end{aligned}$$

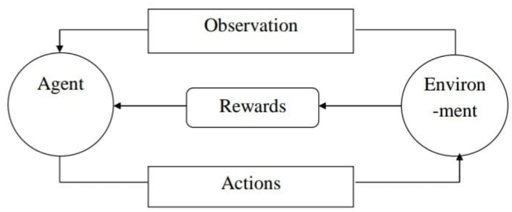

Fig. 3. Interaction between agent and environment

At the time step agent observe the environment achieve a current states then takes action , which is depend upon its observation. these action changes into new state the agent receives reward from the atmosphere.The agents aim is to increase total rewards over long time. therefore discovering the optimal mechanism that attain several of reward over the long time is the specific task of RL algorithm.

2) Parameter prototype:: The parameter design in Reinforcement Learning-based Sleep Scheduling Algorithm for Compressive Data Gathering (RLSSA-CDG) can involve several parameters that impact the algorithm's performance and behavior. the objective is to achieving prototyping affordable parameters of the Q learning algorithm.it consists several parameters to achieve the load balance of power consumption and information regeneration by selecting proper active nodes.

- **Learning Rate :** It Controls the rate at which the Q-values are updated. It determines how much the new information overrides the existing Q-values. A suitable learning rate balances between quickly adapting to new information and maintaining stability in learning. It is denoted by α
- **Discount Factor:** it is used to Influences the balance between immediate and future rewards. It determines the importance of future rewards in the agent's decision-making process. This is Choosing an appropriate discount factor balances short-term gains against long-term benefits. It is denoted by δ
- **Exploration and Exploitation :** Exploration and Exploitation used Governs the trade-off between exploring new actions and exploiting known actions. and balancing exploration and exploitation is essential for the agent to discover optimal techniques while ensuring it doesn't get stuck in sub optimal solutions.
- **Threshold or Convergence Criteria:** Threshold value is utilized to checking when the learning process should stop. Defining a suitable convergence criterion ensures that the algorithm converges to an acceptable solution without unnecessary iterations.
- **Reward Function Design:** The design of the reward function significantly influences the agent's behavior. it is main task for RL agent for equally consume power for load balance and accurate data regeneration done precisely.It is denoted by r .
- **State Representation:** The current active node is defined as the recent state. In the recent state , the initial active nodes takes an action of waking up the one nearest neighbour of the node. Then this recently active node becomes next state and the previous node goes into sleep node.

$$s_t = f(\text{environment features or state variables})$$

- **Initial Q-values:** initial Q-values can influence the agent's initial behavior. it is Sensible initialization can consume learning by selecting a proper active node.
- **Number of Episodes:** It is used to determine Determines the number of episodes . Sufficient episodes are required for the agent to expand several functions and converge towards an optimal policy.
- **The Action selection approach:** in this work, for active selection approach used which is the ϵ-greedy rule .

3) The procedure of RLSSA-CDG:: in this section , summarized a whole procedure of RLSSA-CDG. THE entire Wireless Sensor Networks act as a Reinforcement Learning agent , and nodes in this procedure successively accomplish learning tasks in distributed sequence. The achievement of aggregating a CS measurement . these are known as episode.The agent have need of to terminate a sequences of episodic tasks concentrates experiences of right actions in the forms of update Q table. this is provide the explanations of the algorithmic representation. for the recommended algorithm.Every node makes an foremost row of the Q table and correlating action set . The starting of a round activated by the start message of the nucleus node(sink). in the round, there are three phases . first is initialization phase , second is sampling phase. third is forwarding phase.active nodes are heterogeneously constructed to CS measurements in the initialization phase . The remaining nodes switch to sleep mode.In sampling phase , these foremost nodes start to terminate the learning approach. in the initial round Reinforcement Learning agent has no experience. in initial part Q table is corresponding to zero. therefore agent can heterogeneously choose an action from but in the rest round the agent selects the actions with the maximal Q value with corresponding probability 1- epsilon and keeps a unsequential action with probability epsilon . The M starting nodes can execute learning episodes in either parallel or serial form. A learning episode is determined as come after. An foremost node awake their chosen neighbour node and transfers its sensing information to this recently active node . selected neighbour receives sensing information and sums it to its own information . The Reward is computed by selected neighbour in the state . after that sent back to foremost active node. foremost active node update Q table after that it becomes a sleep node . Q values are determined by the formula given in The line 10. for update the Q tables for achieving the reward function. Recently active node recapitulates the above procedure . the episodes terminate until t nodes have been switched on The

IDs of the consecutive active node in a learning episode are recorded in homogeneous path which is utilized to construct the CS measurement matrix for information recovery. in the last and final phase (forwarding phase), the rearmost active node in the episodes transfer aggregated information(i.e., CS measurements) to the nucleus node by optimized routing path procedure. after achieving all measurements, the nucleus node constructs the measurement matrix depend upon the vector path.

Algorithm 1 Q-learning-based Sleep Scheduling for Compressive Data Gathering

Initialize Q-table $Q(s, a)$ with random values for each sensor node
Initialize parameters: learning rate α, discount factor γ, exploration rate ϵ
for each time step **do**
  for each sensor node i **do**
    Observe state s_i, including available data, energy level, and neighboring node status
    Choose action a_i for node i based on ϵ-greedy rule Q
    Perform action a_i: decide to sleep, gather data, or transmit
    Update energy levels, data recovery, and computation cost based on the action taken
    Obtain reward r_i considering energy saved, data recovered, and computation cost
    Update Q-value: $Q(s_i, a_i) \leftarrow (1-\alpha) \cdot Q(s_i, a_i) + \alpha \cdot (r_i + \gamma \cdot \max_{a'} Q(s'_i, a'))$
  end for
end for

VI. Performance evaluation:

In this section, simulation observations are executed to examine the performance of the proposed approach. in this work we utilize the google colab as the simulation platform.the simulation features are temperature, humidity and air quality.A amount of 1000 sensor nodes are heterogeneously and homogeneously deployed in the monitoring area of kannauj. the center node (sink) is located at the nucleus of this domain. in order to prevent random errors, every simulation execute ten times and for better accuracy calculate the average result.

The Q learning algorithm consist three phase. first start the process then section the active nodes which the main task of this algorithm which is modeled as Finite Markov Process(MDP). after that agent takes action for achieving experience . by this initial active node update the reward in the Q table. and the sampling phase , the foremost active node wake up its neighbour in the domain which is based on local Q table .then transfer the sensing information to the recently active node after that foremost active node goes in sleep node . recently active node repeat this procedure until required number of sample aggregated and . in the last phase rearmost node transfer the aggregated CS measurements to the nucleus node through optimized routing path then nucleus node regenerate the information of the entire WSN based achieved CS measurement . this procedure shown in form of The flow graph of this Q-learning algorithm shown in below figure.4

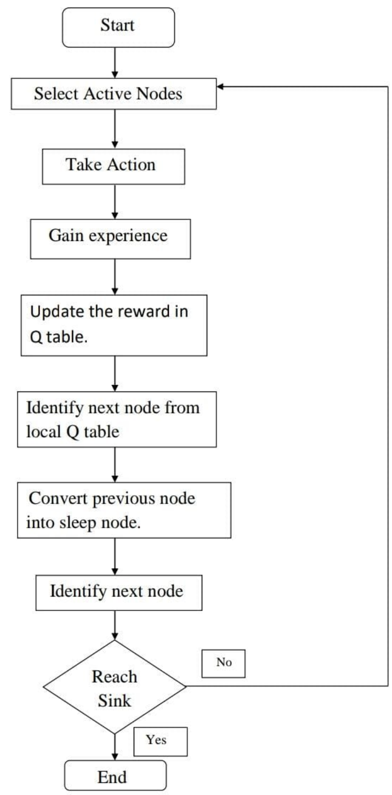

Fig. 4. Flow chart of Q - learning Algorithm

VII. Implementation

In this section , a brief description produces a liberal understanding of the simulation , circumscribing the software utilized, network architecture, functions, parts and the main focus of the simulation in the regarding of sensor networks. MATLAB retained as the main instrument for implementing the simulation. MATLAB is a versatile tool that is valued for its ease of use, extensive mathematical capabilities, and widespread adoption across academia and industry. It simplifies complex mathematical tasks and allows users to focus on simulating complex systems , consisting environment sensor networks. it authorizes detailed analysis , examination of network exploits under assorted conditions. The simulated surroundings includes 200 tactically positioned sensor nodes equipped with sensors for information aggregation . further the network consists of two surface nucleus node. it is used to gathering the information from the active nodes.it works with in confined space of 200 meters in the all sides of the surroundings, in which sensor nodes transmission within a large communication range of 100 meters. the transmission range promotes information exchange and network coordination .every sensor node is actuated with the energy level is 10-15 joule at the particular set implementation. The initial energy of a sensor node is the energy it has when it is first deployed or activated. it helps to node usefulness like information transmission and computation within the network . the main goal of this implementation is to explore the behaviour and analysis of the sensor network under restrained states. operating several parameters and variables within this implemented surroundings are represented in below Table II

TABLE II
SIMULATION PARAMETERS

Simulation Parameters	
Simulation Tool	MATLAB
Number of sensor nodes	100
Number of surface sink nodes	2
Network Size	$200\,\mathrm{m} \times 200\,\mathrm{m} \times 200\,\mathrm{m}$
Transmission Range	100 meters
Initial energy of sensor nodes	$10 - 15\,\mathrm{J}$

VIII. RESULT ANALYSIS

A. Q - values :

In this, Q(s,a) represents the quality or utility of taking action a in state s. These Q values are stored in a table or a function estimator, commonly referred to as the Q-table or Q-function, respectively. The Q values provide an estimate of the expected cumulative reward the agent will receive starting from state s, taking action a. it is the expected cumulative rewards for each action taken in a particular state. by updating these Q-values recurrently based on a observed rewards and future expected rewards. updating Q values shown in figure VIII-A3

1) Updating Q values:: The Q-values are updated iteratively using the bellman equation , which connects immediate rewards with maximum expected future rewards from the next state. The update rule is given by :

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

where:

- $Q(s,a)$ is the Q-value for state s and action a.
- α is the learning rate.
- r is the reward received after taking action a in state s.
- γ is the discount factor.
- s' is the new state after taking action a in state s.

2) Convergence to Optimal Q- Values:: it is done by repeated iterations with the atmosphere and updates to the Q-values, the algorithm converges to Optimal Q-values , the algorithm converges to the optimal Q- values , representing the maximum expected cumulative rewards for each state- action pair under the optimal policy.

3) Policy Derivation:: Once the Q - values converge, the optimal policy can be determined by selecting the action with the highest Q - value for each state.

$$\pi_{\text{new}}(s) = \text{argmax}_a \left(Q_{\text{old}}(s,a) + \alpha \cdot A_{\pi_{\text{old}}}(s,a) \right)$$

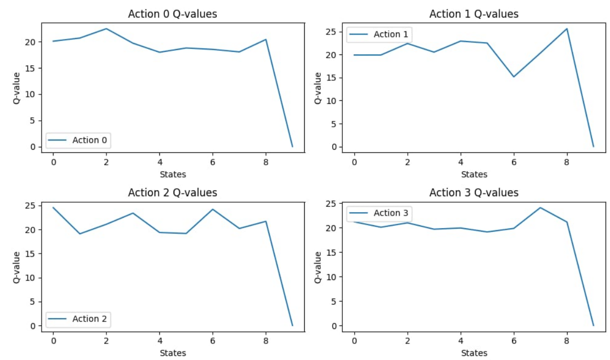

Fig. 5. Q-values

B. Total rewards per Episode:

it is the cumulative reward achieved by an RL agent during the single episode of communication with the atmosphere. The Q learning algorithm is model free reinforcement learning algorithm utilized to discover an optimal action selection policy. it used to energy expenditure and accurate data recovery .it takes actions which used to adjusting device settings, switching between energy sources or minimizing energy usage patterns. reward of these actions penalize high energy consumption or reward efficient energy use. the total rewards per episode shows how better the agent has learned to minimize optimize consumption over the episode duration. it is utilized to optimize energy consumption or consumption or improved accuracy in data reconstruction. observing the total rewards per episode supports to examining the agents learning progress and performance in attaining efficient energy consumption and accurate data recovery.which is shown in figure 6.

$$\text{Total Reward} = R_1 + R_2 + \ldots + R_n = \sum_{i=1}^{n} R_i$$

C. Maximum Q value change per Episode

it is the process where changes in Q-values between consecutive episodes to observe the convergence and stability of the learning process. Q values to stabilize or converge for every state action -pair, showing that the agent has learned the optimal policy. it is used Monitoring the maximum Q value change per episode helps in early termination .this is lead to computational savings by reducing unnecessary iterations or updates. by observing and leveraging the maximum Q-value change per episode effectively . maximum Q values are shown in figure 7

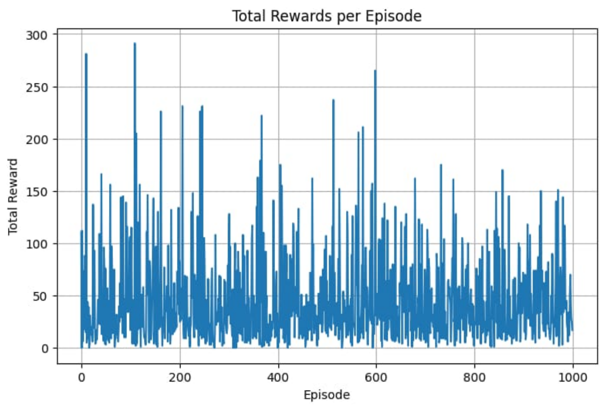

Fig. 6. Total rewards per episode

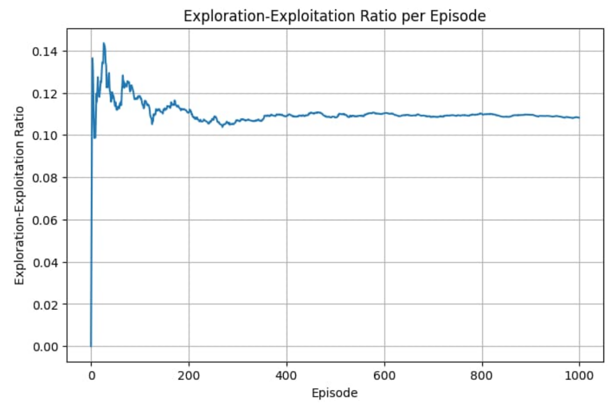

Fig. 8. Exploration and exploitation ratio per episode

$$\text{Max Q-value Change per Episode} = \max_{s,a} |Q_{\text{new}}(s,a) - Q_{\text{old}}(s,a)|$$

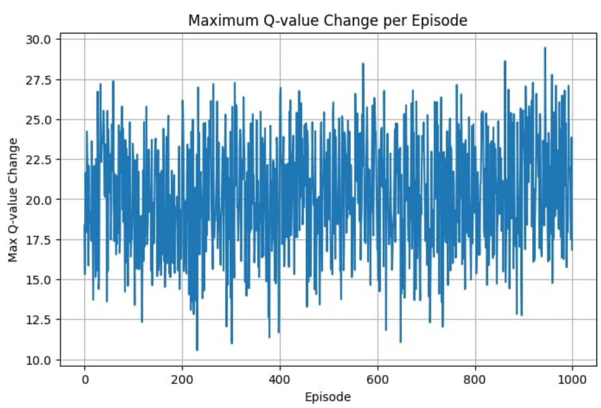

Fig. 7. Maximum Q value change per Episode

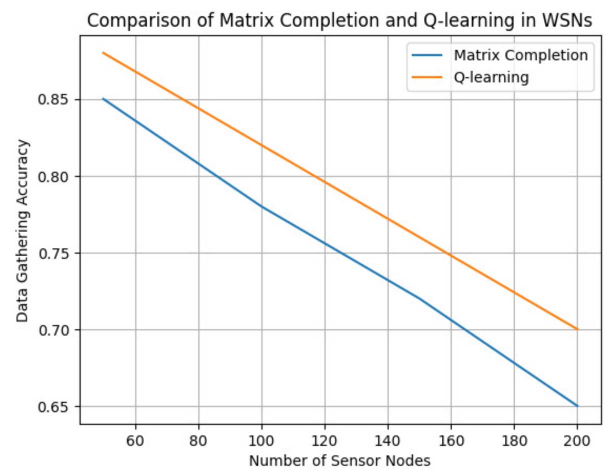

Fig. 9. Comparison graph of existing method with proposed method

D. *Exploration and exploitation ratio per episode:*

it is used in balances the agent's exploration of the environment to discover optimal actions against exploiting known data to maximize rewards the exploration-exploitation ratio per episode shows the proportion of actions taken exploration versus exploitation during each episode.Exploration and exploitation are shown in below figure 8

IX. Comparison graph

In this section , we describe our proposed method to the existing method (Matrix Completion). it presents the better result to existing approach .it shows in figure 9

X. Conclusions

we deployed the sensor in the environment of kannauj for achieving enhancing energy efficiency and prolong the lifetime, precise information reconstruction, reasonable computation cost. for which , a reinforcement sleep scheduling algorithm (RLSSA) for compressive data gathering is proposed in this paper.Sleep scheduling combined with CDG can further enhance energy efficiency and increase the lifetime of network of WSNs. besides nodes sampled homogeneously which provide accurate information recovery. in this, wireless sensor network acts as a RL agents which can recognize unconsumed energy of nodes and active times in a round during the procedure of active node selection.therefore , nodes are correspondingly preoccupy power in order to attain better load balance consumption and increase the lifetime of network.The selection of active node is known as MDP.The Q learning algorithm is used to find minimal decision techniques. Every node involved on in one step of decision process.therefore, computation cost is reasonable for nodes.the Q learning algorithm find Q values for better information reconstruction and exploration-exploitation ratio per episode for better simulation outcome. the simulation evaluations corroborate the productiveness of the proposed algorithm.while RLSSA-CDG is effective in terms of energy efficiency , reducing computation cost and accurate data recovery. but they faces some difficulties which are scalability issues, communication overhead, limited generalization and resource Constraints. in the future work . we will expand the this approach for overcomes these issues.

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