Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 4, July 2021: 1548-1573

SYNTHESIZED ENERGY EFFICIENT APPROACH FOR LIFETIME MAXIMIZATION IN WIRELESS RECHARGEABLE SENSOR NETWORKS

Mona Quaisar[1], Naved Ahmed[1], Dr. Shraddha Prasad[2]

[1]Reasearch Scholar, Jharkhand Rai University, Ranchi
[2]Associate Professor, Jharkhand Rai University, Ranchi

ABSTRACT
Wireless Rechargeable Sensor Networks (WRSN) tackles the energy replenishment problem of sensor nodes. This kind of network uses mobile wireless charger (MWC) to charge sensor nodes periodically by its demand. The main issue in WRSN is to reducing the charging time and cost in improving energy efficiency of sensor nodes. In this case, it is required to analyze MWC charging factors as Traveling Speed, Number of Sensors to Charge, Charging Power, Traveling Path, and Charging Time. Hence, in this paper we propose synthesized energy efficient approach (SynE2A) for promising network lifetime and minimum energy consumption in WRSNs. To predict the optimum traveling path and reduce the issues of MWC, we presented Chessboard based sensor network with the following operations: (1). Unequal Cluster Formation, (2). Adaptive Duty Cycling, (3). Inter-Cluster Routing and (4). Charging Path Schedule. Firstly, unequal clusters are formed in terms of 1-hop, 2-hop, 3-hop and 4-hop clusters. Compound Entropy Determination (ComED) method is presented to elect optimum cluster head (CH). Secondly, adaptive duty cycling is implemented using Neural Neutrosophic Flexible Duty Cycling (N2-FlexDC) scheme. This is a generative adversarial network (GAN) to assign optimum timeslots for sensors. Thirdly, tri-cohesive multi-path backup routing (Tr-CoMBR) protocol is used for multi-path routing. Adhoc Ondemand Multipath Routing with Dijsktra Algorithm is presented to determine multiple paths from source to the destination and then the Hybrid Markov Model evaluates the paths and finds the best path from set of possible paths. Finally, intelligent move is determined for MWC by Intelligent Q-learning algorithm. It is performed like a Queen in chessboard (move anywhere in a straight line, horizontally, vertically, or diagonally). Next to the move prediction, the charging path is predicted by Weighted Planar Graph in which charging threshold for clusters are defined to replenish energy to sensors. Simulations conducted using NS3.26 network simulator and the performance is analyzed for energy consumption, arriving time of MWC, throughput, delay, network lifetime and PDR. The performance proved that it is outperforms than the well-known methods of WRSN.

Keywords—Wireless Rechargeable Sensor Networks, Chessboard Network, Mobile Wireless Charger, Travel Path Planning, Adaptive Duty Cycling and Generative Adversarial Network

I. INTRODUCTION

The sensor nodes are resource constrained and it requires to perform its sensing, data collection, processing, aggregation and transmission. Thus, saving of energy and extends the network lifetime in sensor network is one of the main issue [1], [2], [3]. The most significant factors that affects the energy consumption are idle listening, node isolation, data transmission, overhearing, redundant data, collisions and frequent transmissions. These factors can be handled by several methods as clustering, cluster bead routing, multi-path routing, sink mobility, duty cycling, energy harvesting and wireless charging. Wireless rechargeable sensor network (WRSN) has gained much attention in recent years due to its extensive growth. WRSN is an evolving paradigm that comprises sensor nodes with recharging capabilities [4].

A mobile wireless charger (MWC) can recharge the sensor node deployed in the network. Define the number of MWC is an important issue, but random deployment of multiple MWCs requires high cost and setting charging paths for sensor nodes become critical issue. However, optimizing charging path of the mobile charger is an important issue in WRSN to improve the network lifetime. Thus an uneven clustering approach has been proposed in WRSN to improve energy efficiency [5]. While the single MWC may induces huge latency for charging all resource constrained sensors. Previous works only solves the partial issues of WRSN to replenishment problem and however, it is not capable to meet the urgent changing demand of sensor nodes which shorten the network lifetime of sensor nodes.In WRSN, energy consumption of each sensor node varies due to the variation in an environment include network density and location of each sensor node.

For solving traditional issues of WSN, cluster formation, energy efficient routing, and adaptive duty cycling. These processes reduce energy consumption and increases network lifetime. The major objective of cluster formation is to improve data aggregation as well as charging quality. Besides, energy balanced routing is also performed to optimize the data transmission path [6]. Here link weight value and energy harvesting capabilities are major constraints for forwarder selection. The charging path scheduling can be performed based on buffer and battery constraints [7]. Charging path scheduling, energy harvesting based routing [8], optimal CH selection [9], and medium access control (MAC) design [10] are significant solutions in rechargeable WSNs to improve the network lifetime and charging quality. The major objectives of thus research work are,

- To extend the network lifetime
- To improve the charging quality and to minimize the average energy consumption
- To improve the data transmission rate

A. Motivation

In clustered network, optimal CH selection and routing is necessary to improve the network performance. However, both CH and route selection must consider the energy harvesting constraints in WRSN [11], [12]. In general, optimal route selection must consider significant characteristics of the route to mitigate the problem of data loss. Charging cycle increases the waiting time of nodes to be charged and CH selection is insufficient to handle the effectual data aggregation [13], [14]. Charging schedule has been proposed with routing algorithm for achieving better performance. Charging schedule based on predefined points is not efficient [15], [16]. Thus the research issues in rechargeable WSN are,

- Designing a charging path schedule that improves the charging quality and energy efficiency rate.
- Non-optimal path selection cause high packet loss and also retransmission rate.
- Improper network management leads to higher energy consumption

According to the limitations of MWC in WRSN, such as battery capacity and high energy consumption of sensors [17], [18], the following research questions must be focused to design the recharging plan for sensors.

- How to choose sensors that required for recharging in order to minimize the moving distance of the MWC and also maximize the recharging efficiency in the condition of guaranteeing that node dies?
- How to allocate recharging tasks to MWC to balance network load and avoid any delay in recharging? [19], [20].

B. Contributions

In this paper we proposed an optimum solution that utilizes single MWC is equipped with multiple battery cells which are called as separable charging array.In this paper, we mainly focuses on the MWC travel path planning for energy efficiency improvement which does not affects the battery capacity of MWC, which is known as Synthesized Energy Efficient Approach (SynE2A) model. The major contributions of this paper is summarized as follows,

- Network is designed as chess-board and each cell is further divided into multiple clusters with unequal size based on the cell level. In this step, hop aware cluster formation algorithm is proposed which form clusters by its hop count (1-hop, 2-hop, 3-hop and 4-hop, etc.). In each cluster, optimal CH is selected by compound entropy determination algorithm (ComED). For cluster formation, entropy value is computed using Residual Energy, Average Distance, Charged Time Variance and Mobility. In this step end, optimum set of clusters are generated.
- Adaptive Duty Cycling is implemented Neural Neutrosophic based Flexible Duty Cycling (N2-FlexDC) scheme. Here, neutrosophic algorithm is integrated with Generative Adversarial Network (GAN) to assign optimum timeslots for sensor nodes. The N2-FlexDC is performed in which residual energy level, expected energy level, and current buffer level is computed. Sleep scheduling is performed by CH in an adaptive manner which improves the network lifetime without affecting data transmission.

- Inter-cluster routing is implemented by Route selection by Tri-CoMBR protocol improves the data transmission by considering multiple significant metrics as energy level, congestion metric, link stability, and hop count. In this Tri-CoMBR protocol, Ad hoc on demand Multipath route (AOMR) with Dijsktra algorithm is presented for multiple paths selection. Then optimum path is selected by Hybrid Markov Model.
- Charging path is selected by Intelligent Q-Learning with Energy Awareness (IQL-EA) and weighted planar graph methods which can handle large scale network. IQL-EA algorithm first learns the optimal cell which needs to be charged immediately and then finds optimal path by weighted planar graph with multiple criteria. It is based on the average energy consumption of the clusters in cell, no of clusters in cell, expected energy consumption.
- The performance of SynE2A model is proved that it is outperformed than the previous works in terms of arriving time of MWC, energy consumption, network lifetime, packet delivery ratio (PDR), throughput and delay.

The rest of this paper is organized as follows. Section II describes the related work that reviews some researches that are related to WRSN. Section III discusses the major problems that are addressed in this paper and the objective functions are mentioned. Section IV shows the detailed description of the proposed new WRSN model with unequal cluster formation, adaptive duty cycling, routing and wireless charging. In Section V, experimental results together with corresponding analysis and comparison of our proposed SynE2A model and algorithms are shown. In the final analysis, some summary of the proposed work is presented in conclusion and future directions are given.

II. RELATED WORK

A mobile wireless charging device (MWCD) is utilized [21] and the charging path is scheduled to improve the charging quality. Although, wireless charging scheme improves the energy efficiency it is also necessary to optimize the charging path and data transmission path to achieve enhanced network performance. In [22] author presents the uneven cluster-based mobile charging scheme (UCMC) for wireless rechargeable senor networks. In addition, this paper also presents a charging path planning scheme for improving the charging quality. The uneven cluster formation is performed by computing the wireless charging radius. In each cluster, CH is selected for data aggregation. Authors have highlighted that uneven cluster formation improves the network lifetime and charging quality.

In [23] author deals joint routing and energy harvesting strategy for network lifetime improvement in WSN. In this work, the network is considered as a grid and split into multiple equal cells with the BS located in center of the network. For optimal routing, a shortest path tree with energy balance routing strategy (SPT-EBR) is proposed. Here optimal forwarder node is selected based on the link weight value and energy harvesting capability is incorporated.

In [24] author designs an energy harvesting WSN with mobile sink node. For data transmission, a far-relay approach is presented. In far-relay approach, the node which is presented nearer to the sink node is selected as a relay for the nodes that are presented far away from the sink node. In addition, a buffer-battery-aware adaptive scheduling (NO-BBA) scheme is presented based on Lyapunov drift theory to schedule the energy harvesting.

Data aggregation and routing schemes are presented in [25] for rechargeable WSN. The objective of this work is to maximize the data gathering rate. For that, a data gathering tree is initially established and the data collection strategy is proposed. Herein solar energy is used as energy replenish model. For data collection, a route which maximizes the data collection rate is selected for data transmission. A CH rotation scheme for energy harvesting enabled WSN [26]. Energy conservation is major issue even in energy harvesting WSN. Due to continuous monitoring the energy consumption is high in the WSN. In order to deal with this issue, a double chain Markov model is proposed to monitor the energy harvesting rate. Based on the monitored energy level, the stable election protocol and CH rotation scheme is proposed.Medium access control (MAC) protocol is the major solution for improving energy efficiency in WSN [27]. This paper aims to improve the quality of service (QoS) and energy efficiency in energy harvesting WSN. This paper transmits the data based on priority level to minimize the transmission delay and waiting time. Furthermore, duty cycle adjustment approach is proposed based on current energy level of the nodes to minimize energy consumption.

A loop free routing protocol is presented for energy harvesting enabled WSN [28]. For that this paper presents a loop aware collection tree protocol (La-CTP). In La-CTP, a new metric is proposed to update the parent node. Further, an adaptive beaconing scheme suppresses the occurrence of loops and also unlocks the unavoidable loops. Here parent selection is performed based on loop awareness which doesn't consider other significant metrics. A recharging scheduling is proposed to improve the energy efficiency of wireless rechargeable sensor networks. Initially, a criticality index is computed based on the connectivity of nodes. Then based on the criticality index the charging demand of the node is determined. In order to solve this NP-hard problem, a heuristic algorithm is designed [29].

Criticality index computation is computed in terms of connectivity of the node which is not suitable for charging schedule (current energy level of the node is also important). A research challenge with this scheme is that additional communications exhausted energy and power of the sensors. Further, it is not much easier to estimate a time for charging device in dense environment, which is uncontrollable and the number of dead nodes may increase in this case. The network performance will be improved when the mobile charger traveling time is reduced [30]. In order to achieve this objective, this paper presents a sector based charging schedule (SBCS). Initially, the network is divided into multiple sectors and CH is selected in each cluster. CH selection is performed based on residual energy level and distance with BS. The main drawbacks of this paper are follows.

- Charging schedule is not optimized since the mobile charger travels over the sectors without knowledge on important criteria
- CH selection based on residual energy level and distance is not sufficient to handle effectual data aggregation

An improved grid based joint routing and charging (IGRC) algorithm is presented in [31] to plan the charging path for mobile charger. The network is modeled as $L \times L$ grid and divided into equal cells. Here the network has multiple charging points at the intersections of the cells. The charger visits these charging points at each time to charge the sensor nodes. For that, a shortest path is determined to visit every charging point. Charging scheduling is inefficient since the charging points are predefined.

A two-hop clustering algorithm is designed for energy harvesting wireless mesh network [32]. Here the mesh is formed by tiny sensor nodes which are deployed in a predefined manner. In order to optimize the energy consumption, two-hop optimized clusters are formed in the network. CH is selected based on energy level and energy harvesting level. In this work, hotspot issue is introduced since all nodes are clustered in two-hop clustering manner.

An optimal CH selection is concentrated in energy harvesting WSN [33]. In this paper, the sensor nodes are deployed with solar energy harvesting capabilities. The authors have proposed algorithm for energy harvesting, traffic and energy aware routing, and improved CH selection to increase the stability period of the network lifetime. Herein CH selection is performed based on average distance with sensor nodes and sink node. CH selection without considering energy harvesting capabilities is not efficient and affects the network lifetime. In [34] author deals optimal route selection scheme for energy harvesting in WSN. Initially the network is segregated into multiple clusters by k-means algorithm. In this method, the node with harvesting capability is selected as centroid and the other nodes are joined as cluster members.

Further routing is performed by ant colony optimization and artificial bee colony algorithm. Cluster formation by k-means algorithm requires optimal number of clusters otherwise it will produce non-optimal clusters and ACO and ABC algorithm consume more energy and time for route selection. Authors in [35] present a lifetime maximization technique for rechargeable WSN (RWS). In this work, fireworks optimization with adaptive transfer function (FWA-ATF) algorithm is proposed to improve the energy efficiency. Herein Recharging of sensor nodes is performed in a regular interval (i.e.) mobile wireless charging device moves around the network. FWA-ATF algorithm is utilized for cluster formation by identifying the partition line. CH is selected based on energy level and distance. The main drawbacks of this paper are follows,

- In this work, WCD regularly charges the sensor nodes without knowledge of sensor's current energy level. Thus there is high possibility to charge the nodes which do not require energy at that time.
- CH which is responsible for data aggregation and transmission is selected by using limited metrics. Thus the stability of the CH is decreased.Route selection based on distance metric is not effectual.

Table I summarizes the existing issues in WRSN environment. For each work, we had given the advantages and disadvantages.

TABLE I: SUMMARY OF RELATED WORK

Protocol	Objective	Advantages	Disadvantages
MWCD [21]	Improve energy efficiency and optimize wireless charging path	(1). Minimizes duplicate data transmission (2). High PDR due to dynamic data transmission	(1). Low performance when the number of nodes are high in the network. (2). No mechanism presented to

			handle the higher energy consumption
UCMC [22]	Charging Path Planning and Uneven Cluster Formation	(1). High data delivery and network lifetime due to unequal cluster formation (2). Charging to sensor nodes is less effort	(1). Energy information of sensors are not considered in routing so that the optimum path consumes more energy (2). Lower data rate when nodes deployment is sparse and duplicate retransmission of packets are possible
SPT-EBR [23]	Joint Routing and Energy Harvesting for shortest path construction	(1). Optimal forwarder is selected for data transmission (2). Energy harvesting capacity is added	(1). Energy harvesting is random and thus number of active nodes are very less after smaller network rounds (2). Simultaneous routing and rerouting of data packets maximizes the bandwidth consumption of the network.
NO-BBA [24]	Buffer battery aware scheduling and energy harvesting	(1). No need of control packets transmission (2). Highly scalable	(1). Algorithm proposed is more complex (2). High energy consumption
Routing WRSN [25]	Data aggregation via CH and routing of packets	(1). Provides effective clustering mechanism for aggregated data transmission (2). Algorithm used for clustering is more simple	(1). Random CH selection consumes more energy consumption (2). Frequent re-clustering is possible that increases energy and time consumption
CH rotation [26]	Double chain markov model for energy harvesting	(1). It is suited for various applications (2). Location awareness scheme is added	(1). Rerouting of data packets in the route to the BS increases the transmission delay (2). Not suitable for large scale environment
MAC Protocol [27]	Improve QoS and energy efficiency	(1). Recharge ability is very high (2). Node position is known at each round	(1). Increases data drop rate which is not suited for real-time data sensing applications (2). Increases complexity of each sensor node and the rate of mathematical calculations are high
La-CTP [28]	Loop aware energy harvesting and data collection	(1). Single node events data processing is less complicated	(1). When the BS is located far away from the network, then it is not effective
Critical Index Computation [29]	Critical index based charging demand achievement	(1). More centralized and organized network processing (2). It is easy to notice any failure or demand in network	(1). Node density based critical index increases packet losses (2). Loss of raw periodical data which could be useful for other purpose
SBCS [30]	Energy improvement by mobile charger traveling	(1). Processing is lightweight (2). Simple for specific application	(1). Limited node bandwidth availability (2). Less network lifetime and replenishment
IGRC [31]	Shortest path prediction for different charging points	(1). Delay for transmission is lesser (2). Available charging points are high	(1). Propagation delay increases in the network (2). Manual node selection for path planning is not effective
	Energy level and energy	(1). Less energy wastage	(1). Large communication hops

2-hop clustering [32]	harvesting level improvement	(2). High nodes available for route selection	availability increases overhead (2). High charging time due to scattered sensor deployment
Optimum CH selection [33]	Solar energy harvesting for energy and traffic aware packets transmission	(1). Traffic is evaluated in network periodically (2) Less overhead in data transmission	(1). Data aggregation is very challenge in sparse and dense environment (2). Possibility of enlarge the network is not possible
K-means [34]	Optimum route selection for energy harvesting	(1). Less overhead and complexity (2). Harvesting energy for sensors in a simple way	(1). If node failures in data transmission, PDR is affected and high energy wastage is a significant drawback
FWA-ATF [35]	Improve energy efficiency via recharging of sensor nodes	(1). Clustering improves energy efficiency (2). Route is predicted to improve PDR (3). Congestion control is achieved (4). Context specific solution is given for the sensor nodes (5). Cluster formation is executed periodically	(1). Some of the nodes are isolated in network and thus cluster formation is not effective (2). Topology is very random and hence increases latency and redundant paths for data transmission (3). Even though it is shortest path, end-to-end delay is large in data transmission

III. PROBLEM STATEMENT

In this section, we formulate the research problems on path planning for MWC based on [36], [37], [38], [39] and [40] and then analyze the shortcomings of previous works and the traveling distance of the MWC is large and energy consumption of all nodes is high. In WRSN, it must be optimized to minimize the travel of charging device since it follows random movement which takes large time consumption to charge all nodes. In order to effectively charge all sensors in network, the moving distance of MWC should be optimum and hence more energy transferred to nodes in a minimum time.

$$O_{(1)} = \min_{total} \sum_{i=1}^{n} DN_i \& \min_{total} \sum_{i=1}^{n} EC_i (1)$$

$$O_{(2)} = \max_{total} \sum_{i=1}^{n} NL_i (2)$$

Eqn. () describes the proposed model must minimize the energy consumption and the number of dead nodes and maximize the network lifetime. Further, if the residual energy of a sensor is less than the charging threshold, the CH initiate energy charging request to WCE via BS. Hence, the appropriate charging threshold must be defined in CH for all nodes act as the CM. By traversing optimum path for all nodes to the WCE, the rate of energy consumption of CH is maximized.Authors in [36] jointly consider the energy supply and routing path selection algorithm to maximize the network lifetime. Here wireless charging is performed when a node has lower energy. For that charging time and speed also calculated to charge that node. Route selection is performed based on residual energy level and charging factor. Wireless charging is optimized to minimize the travel of charging device since it follows random movement which takes large time consumption to charge all nodes. A fuzzy logic based duty cycling procedure [37] to improve energy efficiency in energy harvesting WSN. Here the network is constructed as tree and the aggregator node is presented in root position. All other sensor nodes are arranged in hierarchical format. Further duty cycling is performed based on residual energy, predicted harvesting energy, and expected residual energy. A tree based network construction leads to hotspot problem in the nodes that are positioned nearer to the root node. Scheduling without consideration of node position degrades the data transmission efficiency since if the first level nodes are assigned with large duty cycle then the data is not able to reach the root node. In [38], network is constructed with two layers. The first layer comprises charging points (CPs) and the second layer comprises sensor nodes. The sensor nodes are recharged from CPs through wireless energy transfer technique. In order to save energy consumption, each node makes own decision on duty cycle. If a node has lower residual energy, then that node switches to sleep state. The significant problems in this work are follows,

- Decentralized duty cycling affects the data transmission in the network
- Scheduling based on residual energy is not sufficient for energy harvesting networks (energy harvesting characteristics must be considered)

Authors in [39] designed renewable WSN with wireless portable charging device (WPCD) which recharges the sensor nodes starting from rest station. This paper focuses on routing path optimization for WPCD and data transmission. For identifying optimal route for wireless charging, Nodal A* algorithm is proposed. Data transmission is performed by SARSA which is a reinforcement learning algorithm. The main limitations of this work are follows,

- Charging path selection by nodal A* algorithm is a time consuming process and it is not suitable for large scale network
- Only charges the data in pre-defined path which means the emergency node gets energy as per the schedule.The network is split into equal cells and each cell has CH. However, with static sink node equal cluster formation introduces hotspot problem
- Route selection by SARSA algorithm leads to local optimal solutions and considering residual energy alone is not efficient and it leads to data loss.

A cluster based routing algorithm for wireless rechargeable sensor networks [40]. The network is designed with mobile sink node and mobile wireless charging device. Initially, the network is segregated into multiple clusters by k-means algorithm. Then wireless charging is performed in each cluster. For inter-cluster and intra-cluster routing, distance metric is considered.

- In k-means algorithm, number of clusters and initial centroid selection is more important which may result in non-optimal clusters
- Random CH selection is not efficient since it has to aggregate the data from all cluster members
- Inter-cluster communication by greedy algorithm considers distance metric for routing. However, absence of optimal route selection leads to data loss

Moreover, we design a Synthesized Energy-Efficient Approach (SynE2A) in a novel Chess-board based WRSN network design for the above issues solving. Hence, we achieved our joint objective is to improve the charging quality and to improve the network lifetime.

IV. SYSTEM MODEL

This section describes each algorithm presented for energy consumption reduction and network lifetime improvement. The explanation of SynE2A is initiated with network model and assumptions and each algorithm used for process is presented in individual subsection.

A. System Overview

In this paper, we consider a set of sensors which are denoted as S_i disseminated to the network. Network is assumed to be 2D and the coordinates of sensor node is $s_i$is x_i, y_i. In WRSN, base station (BS) is fixed which is a sink node for gathering data from all sensor nodes. We assume that BS is unlimited that does not restrict any data transmission like sensor nodes. Therefore, any sensor s_i can be communicated to other node s_j within its transmission range. Each sensor is equipped with a specific battery ε_{max} and the initial energy of sensor s_i is $\varepsilon_{i,t}$ which denotes the residual energy of node s_i at time t. All sensors in network is divided into clusters and sensor data collected in clusters are transmitted to BS by multi-hop fashion in an optimum manner. Fig 1 represents the overall system model in WRSN.

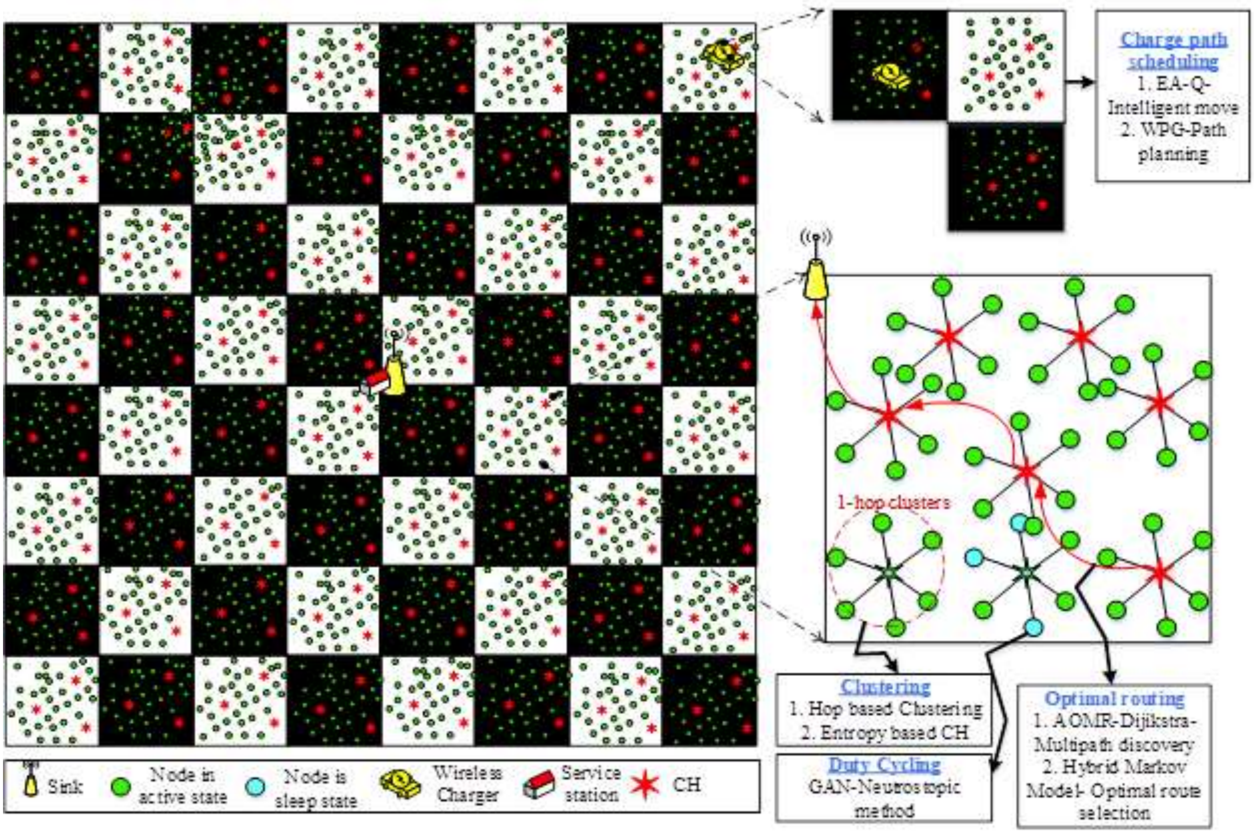


Fig.1. System Model

Energy Consumption Model: In WRSN, sensors are utilized to sense, generate, relay, collect and process data from various sources and forward them to the destination nodes.

All sensors in WRSN are arranged in a graph $G\ (V, E)$ on which V represents the total number of nodes, and E denotes the sum of edges that communicates with the vertex V. In the network, sensors are deployed in a compact way. Sensor nodes are constrained by the Computational Power, Energy, And Memory, etc. Hence, the large number of sensor nodes are not deployed, which leads to huge overhead. In this sub-section, we discuss the energy model for WSN. The aim of designing this model is to minimize the energy constraints and we considers the energy model with $k - bits$ of packet over the distance d, which is given as follows:

$$E_{TX}(k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2 & d < d_s \\ kE_{elec} + k\varepsilon_{mp}d^4 & d \geq d_s \end{cases} \qquad (3)$$

Where ε_{mp} represents the multipath energy loss, ε_{fs} represents the free space energy loss, d denotes the distance between the source node to the destination node. $E_{elec}$is the node energy dissipation, and d_s represents the cross over distance. It is expressed by follows:

$$d_S = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \qquad (4)$$

The amount of received energy is computed by the following

$E_{RX}\ (k) = \ kE_{elec}$ (5)

In this way, the node energy consumption for packet transmission and receive is computed in the network layer.

Energy Harvesting Model: For every time interval of sensor nodes, the total harvested energy is computed between time t and $t + T$ as follows.

$$\varepsilon(t_i\ to\ t_i + T) = \ \varepsilon_t(n) + \tau \int_{t_i}^{t_i+T} \varepsilon_h(n,t)dt - \int_{t_i}^{t_i+T} \varepsilon_l(n,t)dt \qquad (6)$$

Where t_i represents energy of the sensor at initial time t_1, energy harvested at time interval T and leakage of energy in this time interval. The factor τ is the efficiency of charging and all sensors consist of storage buffer for storing harvested energy.

B. Unequal Cluster Formation

We construct our network as a chess-board with white and shaded blocks. Each block represents cell in the network. Thus the network has 8×8 cells in the network and the clusters are formed in each cell. Then the cells are assigned to a rank value based on the distance with sink node. Based on the rank value, the Hop Aware Cluster (HAC) formation algorithm is proposed to form 1-hop, 2-hop, 3-hop, and 4-hop clusters. In each cluster optimal CH is selected by Compound Entropy Determination (ComED) method. Herein the entropy value is formed based on Residual Energy, Average Distance, Charged Time Variance, and Mobility.

Residual Energy (RE): It represents the current energy level of sensor nodes. As assumed, all nodes have same initial energy (ε_i) and the energy level is varied over a time period. For node S_i the RE is computed as follows

$$RES(S_i) = \varepsilon_i - DE (7)$$

Where DE represents the dissipated energy value over a time period. The fitness function used in CoMED is defined as follows:

$$f_{i,j} = \frac{RES_j \times D_j \times (mob_j - 1) \times CV_j}{\sum_{k \in S_i} (RES_k \times D_k \times (mob_k - 1) \times CV_j)} (8)$$

Where S_i is the neighbors of node i, E_j represents the residual energy of the neighbor j of the sensor node i, CV_j is the charging covarianace of the sensor node j, D_j represents the multiplicative inverse of the distance between the sensor j and the BS and mob_j is the mobility of the sensor node.

C. Adaptive Duty-cycling

It is necessary to turn off the radio of the sensor nodes to minimize the energy consumption due to idle listening. Thus we propose an adaptive duty cycling method called Neural-Neutrosophic based Flexible Duty-Cycling (N2-FlexDC) scheme. Here Neutroshopic algorithm is integrated with Generative Adversarial Network (GAN) to assign optimal time slots for sensor nodes. The N2-FlexDC is performed based on the$RES_{S(i)}$, Expected Energy Level$Ex_{e(i)}$, and Current Buffer Level$CR_{B(i)}$.In this process, all CMs in the cluster are assigned with the optimum time slots. Splitting of total available time slots and scheduling is implemented by the N2-FlexDC algorithm. Table II (a) summarizes the GAN hyper parameters used in this paper and Table II (b) illustrates the different modes of sensor nodes.

TABLE.II (A)
CHOICE OF GAN HYPER PARAMETERS

Activation function	Relu, Leaky Relu, Sigm, Tanh
Batch normalization	TRUE, FALSE
Max pooling	TRUE, FALSE
Number of Convolutional Layers	1, 2, 3
Number of Dense Layers	1, 2, 3
Dropout	TRUE, FALSE
Kernel Size	3,5
Number of neurons	16, 32, 64, 128, 256, 512, 1024, 4096
Number of Kernels	1, 4, 16, 64, 256

TABLE II (B)
MODES OF SENSOR NODES

Modes	**State of Sensor Node**	**Process Performed**	**Potentiality**
Mode 1	Sleep State	Turned Off radio	Elimination of idle listening
Mode 2	Listening State	Sensing and Data Aggregation	Event detection
Mode 3	Transmitting State	Transmit data to CH	Minimized number of Transmission

In this paper, we follow MAC scheduling process for CMs to reduce the unnecessary energy consumption that is noticed in overhearing and idle listening states. CH in each cluster is responsible for time slots allocation by using N2FlexDC protocol. When all CMs in the cluster are assigned with sleep slots then there is an issue as communication interruption among nodes. Hence, slots assigned to nodes properly according to the energy consumption and buffer strength of node. There are three types of modes are assigned to the nodes which are denoted in Table 3 In the following, we presented the algorithm description of N2-FlexDC protocol implemented in this paper.

Algorithm N2-FlexDC Protocol
Input: 'k' number of clusters as $C = \{C_1, C_2, .., C_k\}$
Output: Sleep/Active scheduling
1. Begin
2. Obtain total time slot T
3. Divide $T = \{T_1, T_2, .., T_t\}$
4. Set schedule
$T_1 \rightarrow Mode\ 1$;
$T_2 \rightarrow Mode\ 2$;
$T_3 \rightarrow Mode\ 3$;
5. For each $C_k \in C$
Find $Sl = \{sl_1, sl_2, \dots sl_k\}$
Find $RES_{S(i)}, Ex_{e(i),CR_{B(i)}} \leftarrow Sl$
6. For each $CM \in C_I$ with X nodes
7. Assign $\left(X - \frac{X}{2}\right) \rightarrow Schedule$
8. End for
9. End for
10. End

D. Inter-Cluster Routing

In mobile sensor network, link stability varies over time period. Thus it is necessary to find optimal route for data transmission. We perform novel on-demand routing protocol based on Adhoc On-Demand Distance Vector (AODV) protocol. Our proposed routing protocol is named as Tri-Cohesive Multipath Backup Routing (Tri-CoMBR) protocol. In this protocol, three significant algorithms are combined to select optimal route in the sensor environment. Herein Adhoc On demand Multipath Route (AOMR) and Dijkstra's algorithms are integrated to discover multiple paths for data transmission. From that multiple paths, optimal path and a backup path is selected by Hybrid Markov Model (HMD) by considering Energy LevelRES, Congestion MetricCM, Link StabilityLS, Distance$S$, and Hop Count HC.

(ii). Link Stability: It defines the stability of link between N_i and sink node. It can be expressed as follows

$$LS = \frac{Radius}{(dis(S_i, BS))} \quad (9)$$

Here $Radius$ represente the communication range of S_i.

(iii). Distance: Euclidean distance is computed for two nodes (source and nearby sensor node) in order to compute the distance between both CHs. The distance between CH_1 and CH_2 is computed as,

$$D(CH_1, CH_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \qquad (10)$$

wherex_1, y_1 and x_2, y_2 represents the coordinates of CH_1 and CH_2 respectively

(iv). **Hop count (HP):**HP defines the number of hops between S_i and BS.

By using all metrics optimal nodes are selected. At first, the weight value is computed for all nodes based on as follows,

$$W(S_i) = RES + CM + \left({LS + HP}/{dis(S_i, BS)} \right) \qquad (11)$$

The nodes are sorted in descending order based on weight value. Then the threshold value (μ) is computed based on the average weight value as follows,

$$\mu = \frac{(W(N_1) + W(N_2) + \cdots + W(N_n))}{n} (12)$$

The nodes which have weight value higher than threshold ($W > \mu$) are considered for second stage.

From the set of paths selected using weight values from Tri-CoMBR protocol, hybrid markov model is presented to choose the optimum path. Algorithm describes the optimum path selection by the hybrid Markov Model in which path cost is determine by the available nodes and their configuration in the selected multiple paths.

Algorithm Hybrid Markov Model
Input: Multiple possible paths
Output: Optimal path
1: **Begin**
2: Find all possible paths ($\aleph = \{\boldsymbol{Path_1}, \boldsymbol{Path_2}, \ldots, \boldsymbol{Path_Y}\}$.)
3: **For** each path
4: Find $\boldsymbol{RES}$
5: Find $\boldsymbol{D}$
6: Find $\boldsymbol{PathCost}$
7: Sort all paths based on $\boldsymbol{PathCost}$
8: **If** ($\boldsymbol{PathCost}_{\complement} < \boldsymbol{PathCost}_{c\in\aleph, c\neq\complement}$)
9: $\boldsymbol{Path}_{\complement}$ →**Optimal Path**
10: Transmit data via $\boldsymbol{Path}_{\complement}$
11: **Else**
12: Move to next path
13: **End if**
14: **End for**
15: **End**

E. Charging Path Schedule

MWC charging for reducing the energy consumption is related to the distance and to improve the energy efficiency through MWC, the distance between the sensor node and MWC must be optimized. To reduce the energy waste, we considered the chessboard based network design and our MWC play the role of Queen in Chess that is it can decide to any next move. Hence, in this paper we select the next move for MWC based on the current and previous moves and then the traveling charging path is computed.

In our chess-board based network design, we incorporate intellectual moves by reinforcement learning algorithm for charge path schedule. From the service station, the Mobile Wireless Charge (MWC) decides the next move intellectually by Intelligent Q-Learning with Energy Awareness (IQL-EA) algorithm. The next move selection is performed based on the average energy consumption of the clusters in that cell, number of clusters in the cell, and expected energy consumption of the cell. After the move, the charging is path is determined by Weighted Planar Graph (WPG). In this manner, the charging schedule is optimized in our work.

Based on the previous discussion about MWC, different traveling charging paths result in different traveling distance between the sensor nodes to the MWC. The time of charging and battery capacity spent for sensor node is different for different traveling paths. The traveling path of MWC not only affects the energy wastage rate, but also increases the charging time of each sensor. For that, traveling path is optimized using weighted planar graph.

We model the distribution of sensors in a WPG which is a graph $G(V, E)$. Here $V = \{v_1, v_2, \ldots v_n\}$ denotes the set of nodes position and E is the set of edges. We defined the energy cost for MWC for traveling a node from i to j (i.e. EC_{ij}), we have,

$EC_{ij} = k \times x_{ij}$ (13)

Where x_{ij} is the distance between $i$and j,k is the constant variable. To solve the traveling path distance, energy consumption and time issues, the weighted planar graph is constructed. The detail of the proposed algorithm is given in Algorithm.

Algorithm 1: Weighted Planar Graph Algorithm	
Input: $[x_i, y_i]$, $0 \leq i \leq n_p$ (next move)	
Output: Traveling path for charging by MWC	
1.	Begin
2.	For n_p at x_i, y_i
3.	Compute the distance between each cluster (received requests) and the BS
4.	Sort the distance and energy in ascending order
5.	Choose $cluster\ c_{count}$ which is near to the BS.
//The initial value of count is 1	
6.	Compute the distance and energy of the balance clusters from the $cluster\ c_{count}$
7.	Choose the cluster $c_{count+1}$ which is closest to the cluster c_{count}, c_{count}= $Count + 1$
8.	Repeat step 3 until $count = n_c$ // number of clusters selected
9.	The MWC drive from Cn_c to the BS.
10.	End for
11.	End

Algorithm 1 description is follows: for the proposed weighted planar graph we taken into count one sample example that is there are five nodes to be charged in the clusters over the time. Firstly, we compute the residual energy of each cluster, and then the sorted order of clusters is $c_1 < c_2 < c_5 < c_4 < c_3$. Considering the residual energy c_1 is selected first. Then distance between the clusters to the MWC's current position is computed. Next, clusters are sorted in ascending order by distance values from the previous order. Therefore, the clusters are $c_5 < c_2 < c_4 < c_3 < c_1$. The final arrangement is taken into account for charging and the travel path is follows $c_5 < c_1 < c_2 < c_3 < c_4$. Fig 2 illustrates the weighted planar graph construction and the charging path for MWC.

In this paper, we studied the wireless charging issue in WRSN and this issue is addressed by two kinds of principles as (1). No node is dead in the network due to the energy replenishment problem and (2). Seek for efficient charging by reducing energy, distance and time of charging operations. A dynamic path charging scheme is introduced in this paper which is done by the Queen Move in Chessboard. Chraging threshold is defined by clusters in network. When the the energy of clusters are lower than the threshold value, then charging operation is incorporated. CH will send the charging reqeust to MWC via BS. The Chraging time of MWC is computed by follows,

$$CT_{S(i)} = CT_{S(i-1)} + ct_{s(i)} + \tau_{s(i)} \quad (14)$$

Where $CT_{S(i-1)}$ represents the charging time of node $s(i-1)$, $ct_{s(i)}$ is the time duration for MWC traverse from node $CT_{S(i-1)}$ to $CT_{S(i)}$. The charging path is dynamic and thus $ct_{s(i)}$ is changed over the time. Assume that distance from node $S(i)$ to $S(i-1)$is $D(i)$, then $ct_{s(i)}$ is computed by,

$$ct_{s(i)} = \frac{D_i}{S} (15)$$

Where $\tau_{s(i)}$ is the time duration for MWC achieve the energy replenishment for the node $S(i)$ and the charging time for node $S(i)$ is computed by,

$$\tau_{s(i)} = \frac{\varepsilon_{o(s(i))} - RES_{s(i)} - (\tau_{s(i)} + ct_{s(i)}) \times R_{\varepsilon(s(i))}}{P_C \cdot \beta} (16)$$

Where $\varepsilon_{o(s(i))}$ is the original energy level for sensor $s(i)$, $RES_{s(i)}$ is the residual energy of node $s_{(i)}$ at the charging request time, $R_{\varepsilon(s(i))}$ is the energy consumption for node $s(i)$, P_C is the power required for charging by MWC and the charging variable is β which is $0 < \beta < 1$.

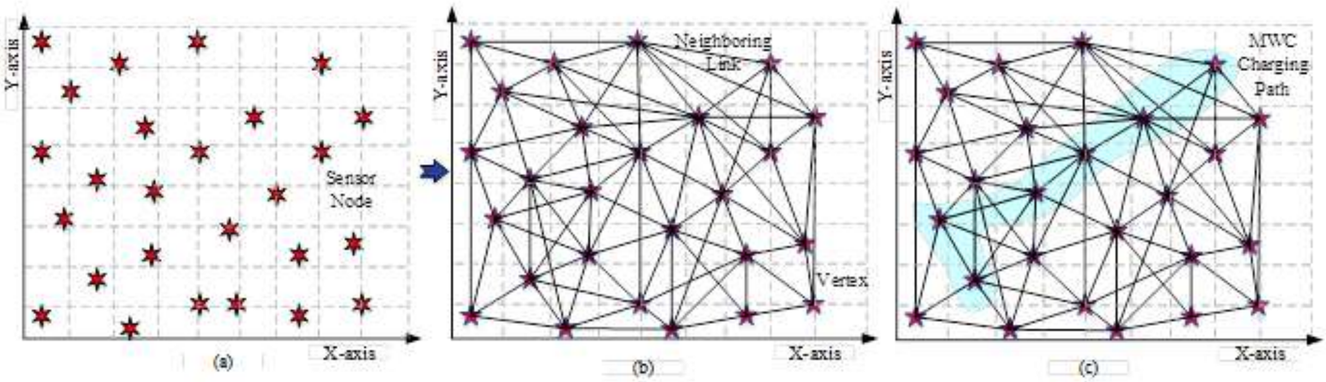
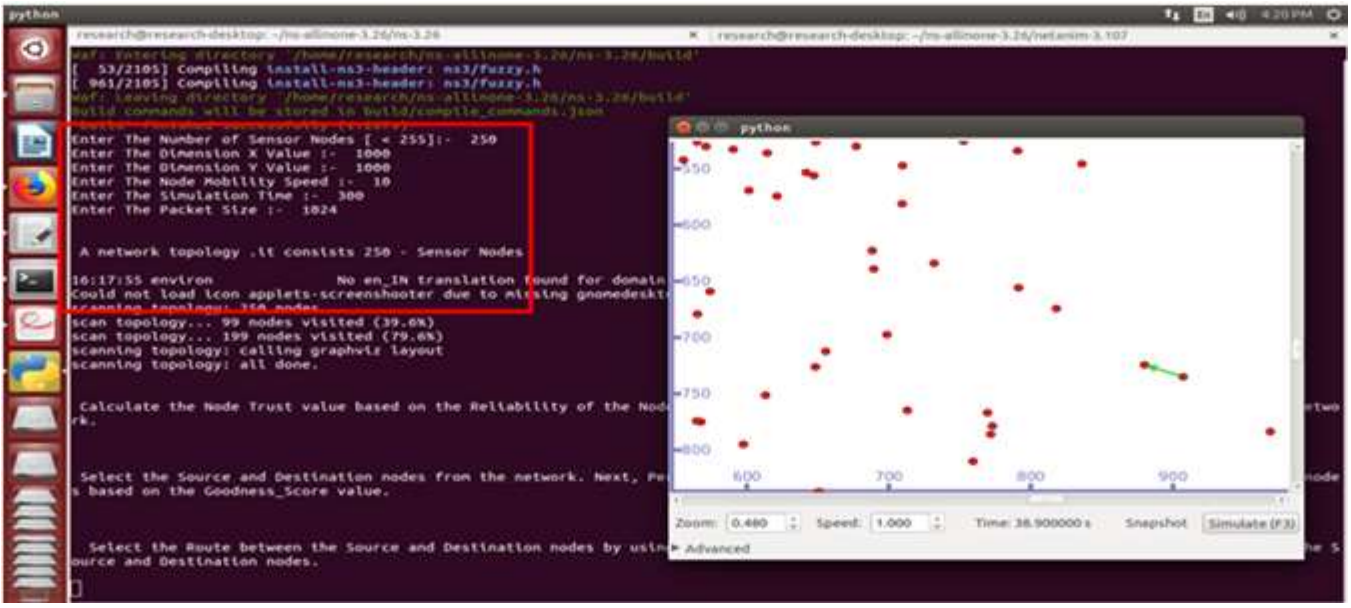


Fig 2 (a).Nodes Deployment, (b).Weighted Planar Graph Construction and (c). MWC Charging Path Prediction

V. EXPERIMENTAL RESULTS & DISCUSSION

This section deals with the evaluation of the proposed SynE2A in terms of performance metrics. Thus, extensive simulations are carried out to measure the efficiency of the SynE2A. In this paper, we aim to implement SynE2A for the following objectives.

- **Lifetime of Network:** Optimization of memory, power and energy makes a WSN more efficient and effective for a longer time
- **Energy Efficiency:** energy efficient data structure that optimizes the network performance (QoS) in different regions. We implemented various solutions to solve this issue.



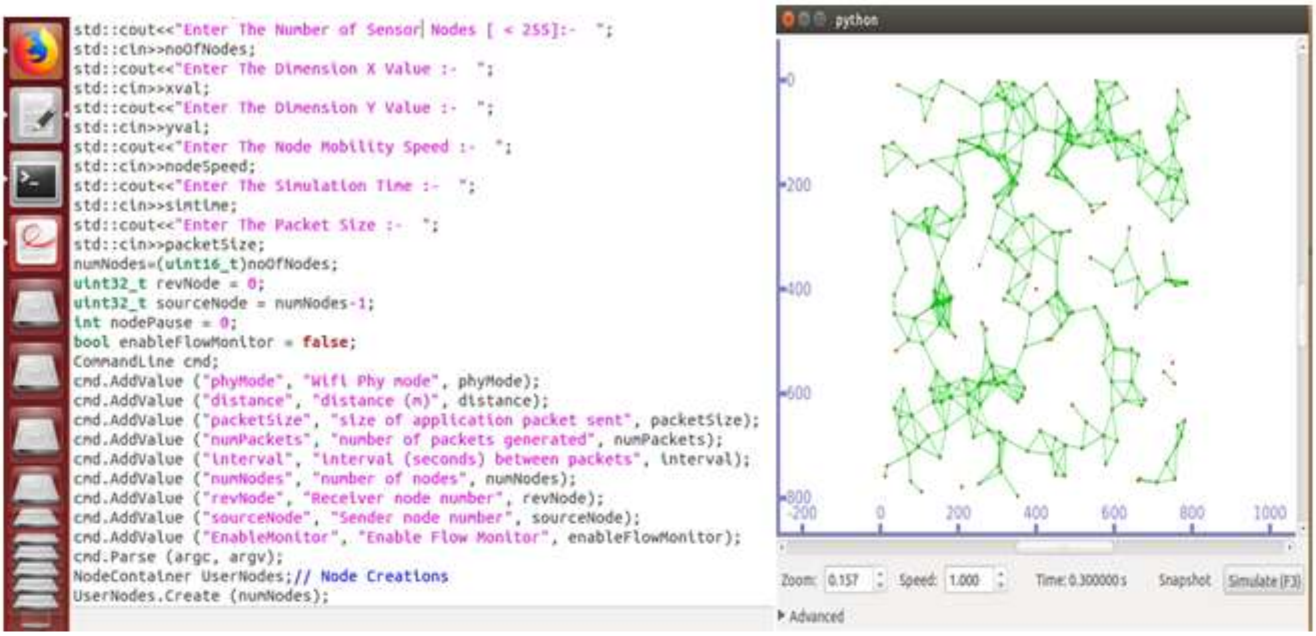


Fig.3. Simulation Diagram

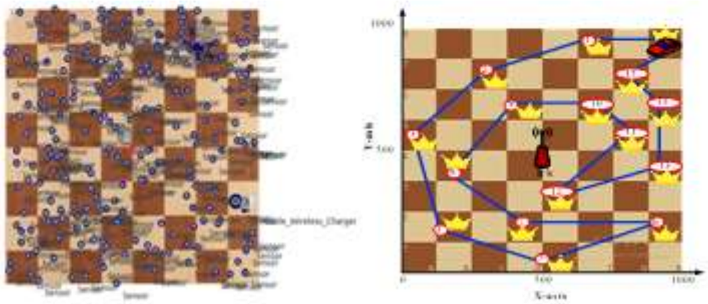
A. *Simulation Configuration*

The proposed SynE2A model is simulated and tested using NS3.26 simulator. NS3 is the most suitable simulator that supports different network configuration. Thus, the proposed SynE2A model is tested using NS3 simulator. The NS3 simulator is installed and operated over Ubuntu 14.04 LTS OS. Fig 3 describes the simulation diagram of the proposed scheme.

TABLE III
SIMULATION PARAMETERS

Parameters		Value
Simulation Area		$1000 \times 1000m$
Number of Sensors		250
Number of Sink / BS		1
Mobility Model of Sink		Random Waypoint
Initial Energy of nodes		750J
Number of Packets		1000
Number of Retransmissions		7 (Max)
Packet Size		1024bytes
Packet Interval		10μS
Sensor Communication Range		300m
Data Rate		88Mbps (Max)
Number of Slots		16
Slot Duration		10μS
Total Energy of MWC		10000J
Power out rate MWC		5J/S
Moving energy consumption rate of MWC		0.3J/m
Speed of MWC		5m/s
Markov model	$Mean$	0.7
	SD	0.2
	Range	0-1.0
	Number of Iteration	100
Number of Rounds		1000
Simulation Time		100s
Number of Clusters		10 -- 15
No of Packets		10 -100 per second

In table III, the simulation parameters considered in our SynE2A is illustrated. The simulation testbed for the above parameters is represented in fig.4. Fig 5 describes the smart agriculture in WRSN environment.



(a) (b)

Fig 4 (a).Chessboard Design (b). Moving Path of MWC

Application Scenario (Smart Agriculture):

Our proposed model is testing over the smart agriculture applications. For sensing, and transmission of agriculture information, various agriculture sensors are used that are follows,

- *Accelerometers:* These devices are used to detect the activity, motion and intrusion of the farm.
- *Temperature and Humidity Sensors:* It's used to know about the air monitoring, livestock and soil monitoring and livestock healthcare monitoring. We tested DHT11sensor for crop field monitoring and it consists of Decimal and Integral parts of relative humidity and temperature.
- *Pressure Sensor:* This type of sensor finds the atmospheric pressure i.e. eventually utilized for measuring altitude.
- *Soil Moisture Sensor:* It measures the moisture level of soil and if the soil is dry then it detects low level.
- *Salinity Sensor:* The salt water intrusion is detected using BC548 IC. If the saline water enters into the water tank, then the probe passes electricity since salt water is a good conductor.
- *Water Level Sensor:* BC548 transistor is used for water level monitoring and sends the water level information to the sink node. Table IV illustrates the readings for various sensors from Day 1 to Day 6.

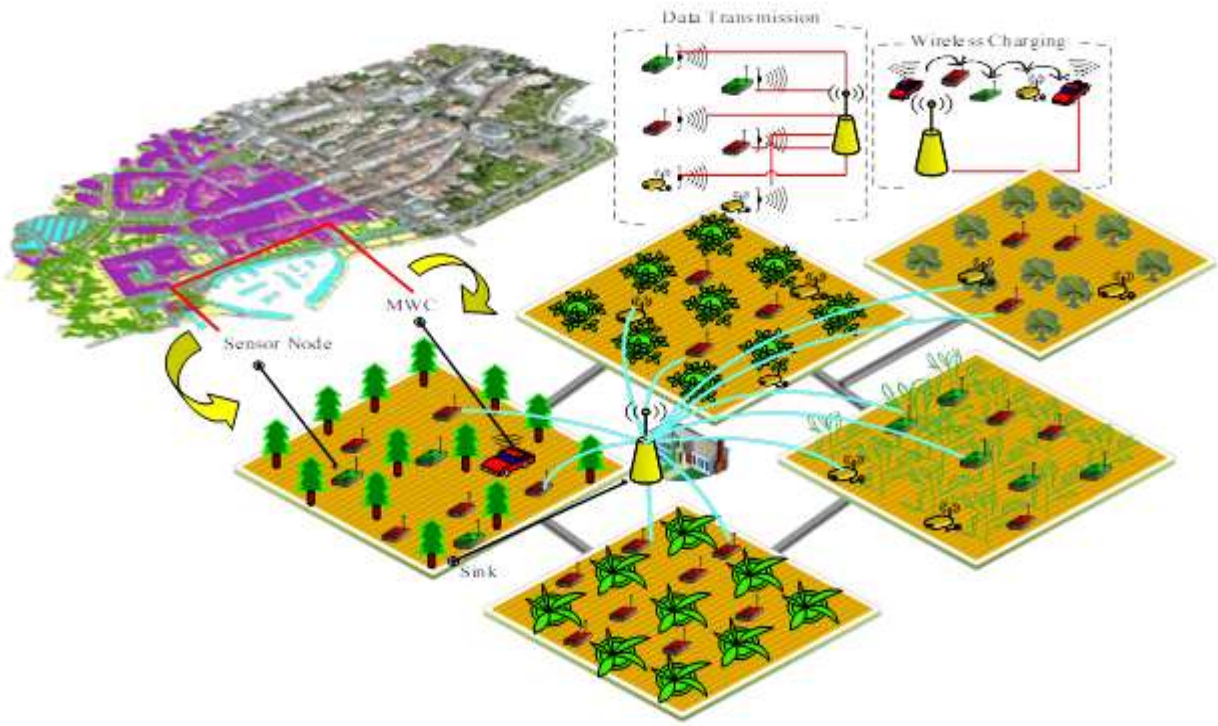


Fig.5. Smart Agriculture

TABLE IV
SENSED DATA IN AGRICULTURE BASED WRSN

Time	Environmental Temperature	Relative Humidity	Soil Moisture	Salinity Value (Water)	Salinity Value (Salty Water)
Range	27-32^{0}C	70-84%	1005 – 1019mV	40-42%	90-92%
Day 1	31.25^{0}C	71.2%	1005mV	40.02%	91.2%
Day 2	31.45^{0}C	72.3%	1011mV	41.25%	91.45%
Day 3	31.47^{0}C	82.36%	1019mV	41.08%	92%
Day 4	31.52^{0}C	82.56%	1009mV	41.57%	91.45%
Day 5	27.30^{0}C	83.45%	1012mV	41.47%	91.58%
Day 6	27.78^{0}C	70-84%	1013mV	40-42%	90-92%

Recently, smart agriculture appplication is faced by energy shortage problem. Solar battery assisted MWC is used to achieve higher charging in the areas of resource contrained sensor nodes. Both solar battery capacity and sensor nodes are monitored to improve the stability of smart agriculture application.

B. *Comparative Analysis*

In this subsection, the performance of the proposed SynE2A model is evaluated in terms of various performance metrics arriving time, energy consumption, PDR, throughput, delay and network lifetime. The comparison analysis is performed with the JESR [36], Balanced SS [38], K-CHRA [40], Firework-ANN [35], Fuzzy ADC [37] and the proposed SynE2A. Table V illustrates the comparative analysis of the proposed and previous works in terms of its process and demerits.

TABLE V
SUMMARY OF PROPOSED VS. PREVIOUS WORKS

Process	***JESR [36]***	***Fuzzy ADC [37]***	***Balanced SS [38]***	***K-CHRA [40]***	***SynE2A***
Clustering	×	✓	×	✓	✓
Routing	✓	×	×	✓	✓
Duty Cycling	×	✓	✓	×	✓
Charging Path	✓	✓	✓	✓	✓
Clustering scheme	-	Hierarchical Tree Construction Algorithm	-	K-means Algorithm	ComED by entropy function
Routing scheme	Routing Path Selection Algorithm	-	-	Greedy Algorithm	Tri-CoMBR protocol
MAC protocol	-	Fuzzy Algorithm		-	N2-FlexDC
Wireless Charging	Random Movement Algorithm	Random Movement	Charging Points based charging sensor nodes	Charging algorithm	IQL-EA and weighted planar graph
Demerits	• Higher time consumption for charging • Route selection without considering distance and link stability minimizes network lifetime and also PDR	• Energy consumption is high for aggregation of packets from lower nodes to the upper nodes • Time slots assignment is not optimum and fuzzy algorithm consumes more energy	• Time consumption is high for charging and also charging energy wastage is high • Adaptive duty cycle is not possible and it is possible to cause higher dead nodes	• Number of clusters are not optimal and result not optimal clusters • Random CH selection is not effective and not suited for dense environment	-
✓- Supported; ×- Not supported; - - Not proposed					

(1). Impact of Arriving Time of MWC

Arriving time of MWC is a vital metric in WRSN. It must be lesser to shows that the network has obtained a great performance in wireless charging. The performance of arriving time result that compared to the previous work is shown in fig.6

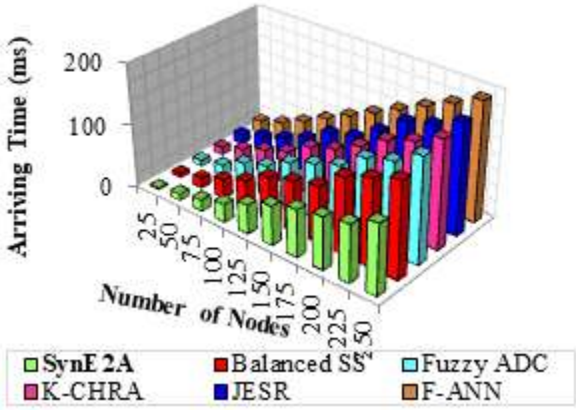


Fig.6.Arriving Time vs. Number of Nodes

(2). Impact of Energy Consumption

EC is a significant metric that amount of energy consumption by s_i which is formulated as,

$$EC = \sum_{n=1} CH_{\varepsilon}(n) + \sum_{m=1} CH_{\varepsilon}(m) \quad (17)$$

Where $CH_{\varepsilon}(n)$ is the amount of energy consumed by CH and $CH_{\varepsilon}(m)$ is denoted as the amount of energy used by CM.

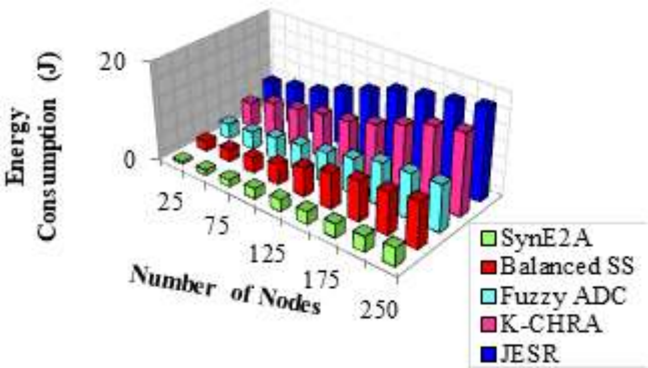


Fig.7.Energy Consumption vs. Number of Nodes

Energy consumption in the network plays pivotal role in network lifetime extension. The major objective of SynE2A model is to maximize the network lifetime by reducing the energy consumption.

Fig. 7, 8, 9 establishes the analysis of energy consumption on proposed and previous works by three kinds of terms such as number of nodes, charging rounds and number of clusters, respectively. The comparison shows that proposed SynE2A model minimizes the energy consumption over the network. In the presence of 100 sensor nodes the energy consumption over the network is 2J which is much lower than previous research works. The 2J represents the sum of energy consumed by every node in the network. When the number of nodes is increased then the energy consumption is also increased since in the presence of large number of nodes there will be large number of transmissions and receptions which consumes more energy. However, even in the presence of 250 nodes, proposed work provides only 3.5J (i.e.) 0.14J per node approximately. Thus the energy consumption is balanced in the proposed work to minimum amount. In prior works there is exponential increase in energy consumption is observed during simulations.

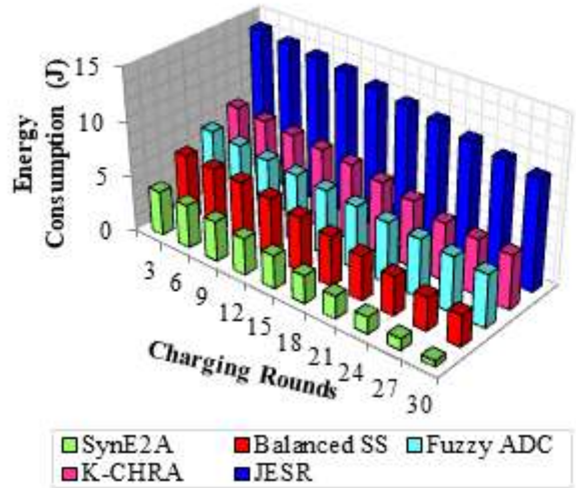


Fig.8.Energy Consumption vs. Charging Rounds

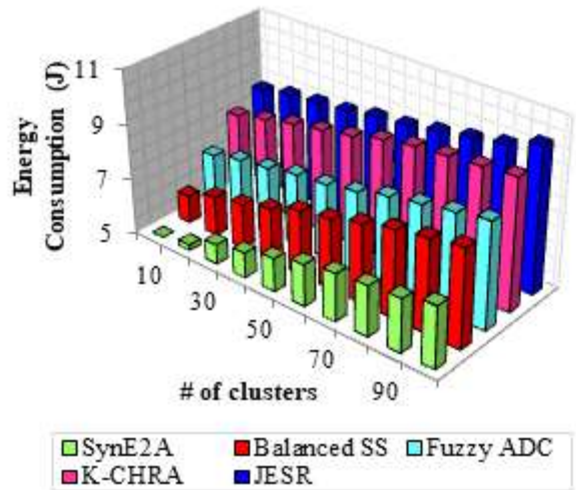


Fig.9.Energy Consumption vs. Number of Clusters

The energy consumption of the CH is generally higher in WSN and also in WRSNs. Fig 9 shows the comparison of the energy consumption of CH for 300 simulation rounds in different operation modes as sensing, transmission and reception. Compared to other algorithms in previous works, the energy consumption by proposed model is significantly minimized. This means that the performance of CH can work longer for performing various operations.

TABLE VI
ENERGY CONSUMPTION ANALYSIS

Methods	Number of Nodes	Charging Rounds	Number of Clusters
JESR	12.66 ±0.5	12.15±0.5	9.22±0.43
K-CHRA	10.35 ±0.3	6.505±0.3	8.975±0.34
Fuzzy ADC	6.18 ±0.4	5.875±0.4	7.885±0.42
Balanced SS	5.46 ±0.6	4.6±0.6	7.34±0.71
SynE2A	2.1 ±0.2	1.853±0.2	6.21±0.2

TableVI summarizes the energy consumption of entire network. It can be observed that energy consumption in SynE2A is lower than prior research works. The major reason behind this result is that the proposed uses energy efficient schemes as unequal cluster formation, adaptive duty cycling and inter class routing.

(3). Impact of Network Lifetime

A network lifetime is computed by the remaining energy level of a sensor based on its every round, which is formulated by follows.

$$Network\ Lifetime = \frac{RES_{s(i)}}{l\left(\varepsilon_{elec} + \propto D_{s(i)}^{BS}\right)} \qquad s(18)$$

Where RES_i is the energy level of node $s(i)$ and $D_{s(i)}^{BS}$ is the distance between the $s(i)th$ node to the BS. Network lifetime is a significant metric that demonstrates the efficiency of proposed SynE2A model. A value of this metric must be higher if the energy consumption over the network is minimized.

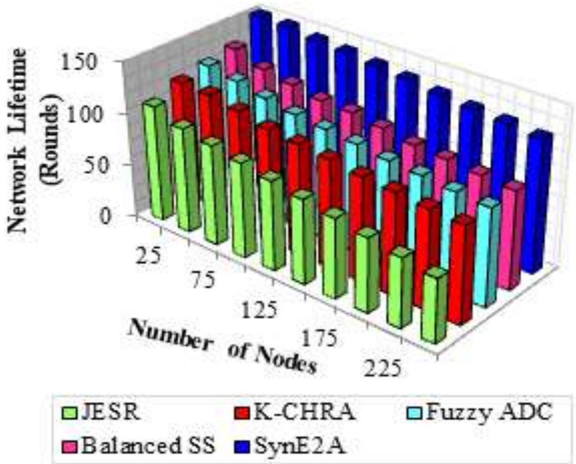


Fig.10.Network Lifetime vs. Number of Nodes

The number of nodes sensing, reception and transmission are keep at the same level in each period. A scheduling for adaptive duty cycling improves active nodes probability. Considering the cluster formation and energy efficient routing, network lifetime is balanced and defect of nodes are reduced.

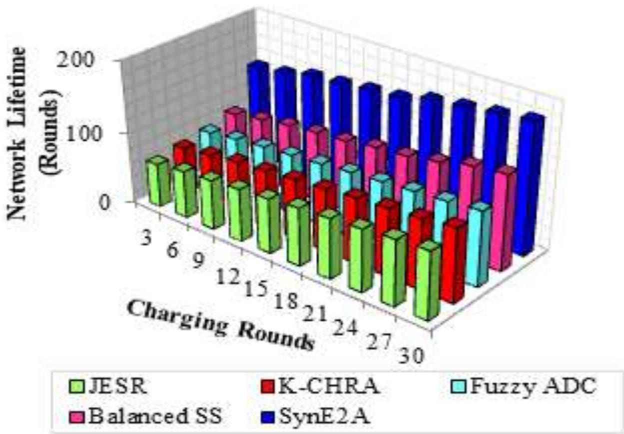


Fig.11.Network Lifetime vs. Charging Rounds

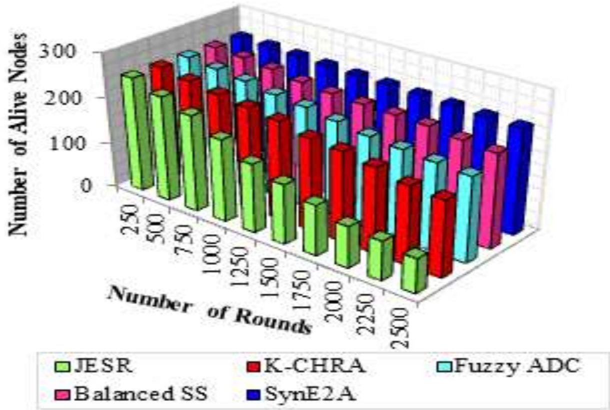


Fig.12.Number of Rounds vs. Number of Alive Nodes

Fig 10, 11, 12 illustrates the comparative analysis on network lifetime. This analysis indicates that the proposed SynE2A approach increases the network lifetime with increase in the number of nodes and also charging rounds. The network lifetime in proposed work in the presence of 50 nodes is 90 rounds which is relatively larger than existing works. Thus in proposed work, node early dead is prevented and the energy consumption is minimized. However, in prior approaches shows huge variation in network lifetime which confirms the computational overhead affects the network lifetime.

TABLE VII
NETWORK LIFETIME ANALYSIS

Methods	Number of Nodes	Charging Rounds	Number of Rounds
JESR	83±5	77±5	151±4
K-CHRA	105±3	83±3	207±4
Fuzzy ADC	106±4	86±4	215±5
Balanced SS	107±6	104±6	226±7
SynE2A	138±2	155±2	240±3

In table VII, average network lifetime is presented. This summarization shows that the proposed SynE2Amodel outperforms with all other techniques in term of network lifetime.

(4). **Impact of PDR**

PDR represents the number of packets sent to BS successfully with the total number of transferred from the source node and it is formulated as follows,

$$PDR = \frac{\sum \# \, of \, packets \, received}{\sum no \, of \, packets \, sent} \times 100\% \qquad (19)$$

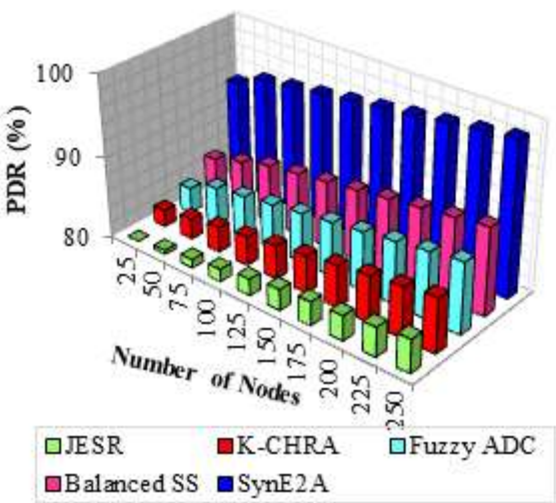


Fig.13.PDR vs. Number of Nodes

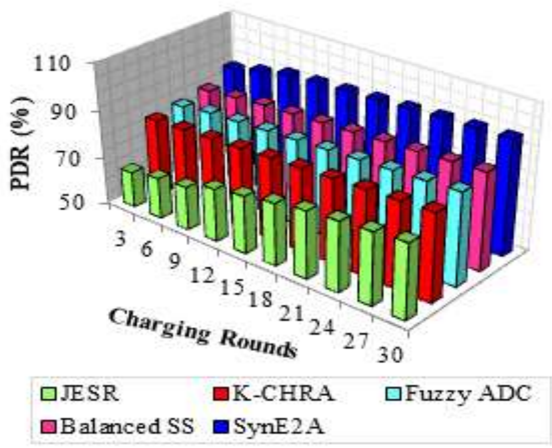


Fig.14.PDR vs. Charging Rounds

TABLE VIII
PDR ANALYSIS

Methods	Number of Nodes	Charging Rounds
JESR	82.08±0.4	74±0.5
K-CHRA	84.25±0.5	84±0.4
Fuzzy ADC	86.15±0.3	86±0.3
Balanced SS	88.1±0.6	88.1±0.2
SynE2A	96.15±0.2	95.5±0.1

PDR measures the amount of packets successfully delivered to the BS. This ratio is high when the data transmission is performed via optimum path and node consists of sufficient residual energy. Table VIII describes the PDR for the proposed and the previous works.

In fig 13, 14 the comparison between proposed and previous research works is illustrated based on PDR. The analysis shows that proposed work achieves higher PDR than previous research works. When the number of nodes is increased, then the PDR is decreased. This is due to in the presence the large number of nodes, large number of packets is transmitted over the network. Thus all woks show the decrease PDR with increase in number of nodes. In JESR method, 40% of delivery ratio is decreased with increase in number nodes while in proposed work only less than 3% is decreased. This analysis shows that the proposed work can handle the large number of nodes without any packet loss.

TABLE IX
COMPARISON ON PDR

Work	Number of packets generated	Number of packets transmitted successfully	PDR
JESR	400	324	81.2
Fuzzy ADC	400	358	89.6
Balanced SS	400	382	95.44
K-CHRA	400	389	97.25
SynE2A	**400**	**394**	**98.5**

On this analysis, PDR of SynE2A is 98% is achieved which is nearly to reach 100% of PDR. This means that maximum numbers of packets are delivered successfully to the destination node. Previous works uses random routing scheme that does not effectively transmit packets from source to the destination node. However, our work is focused on minimizing energy consumption; we have developed an optimal route selection algorithm that ensures to increase PDR. Further, existing works does not schedule timeslots for packets transmission and slots are adequate to perform the packet transmission. Hence, we obtained the higher PDR. Table X summarizes the average delivery ratio obtained by previous and proposed work. The analysis shows that proposed IPbSR approach achieves nearly 90% of delivery ratio which is higher than prior works.

(5). Impact of Delay

As discussed in literature, majority of energy conservation schemes fail to achieve minimized delay. Involvement of optimum CH selection and routing of packets processes minimizes the delay in proposed work.

TABLE X
DELAY ANALYSIS

Methods	**Number of Nodes**	**No of packets / sec**
JESR	0.832±0.04	5.35±0.05
K-CHRA	1.94±0.05	9.5±0.04
Fuzzy ADC	2.12±0.04	12.2±0.03
Balanced SS	2.155±0.05	14.4±0.02
SynE2A	2.19±0.02	21.4±0.01

Fig 15 represents the comparison between end to end delay in the network. The analysis shows that proposed work achieves better results than previous research works. This analysis shows that reducing energy consumption alone is not sufficient to achieve minimized end to end delay. JESR method suffers from large delay upto11s due to ineffectual sleep scheduling. In the presence of 50 nodes, the delay experienced in SynE2A is 5s which is much lower than JESR method.Further, previous works only focuses on sleep scheduling and data transmission and other operations such as wireless charging by optimum path and energy efficient clustering are not considered. However, in proposed work the network performance in enhanced with the support of optimal CH selection, adaptive duty cycling and traveling path prediction. Thus delay in proposed work is lower than previous research works.

TableX summarizes the average delay results obtained for all research works. This analysis shows that proposed SynE2A model minimizes the end to end delay considerably. Thus proposed work is not only outperforms in energy efficiency but also in network performance.

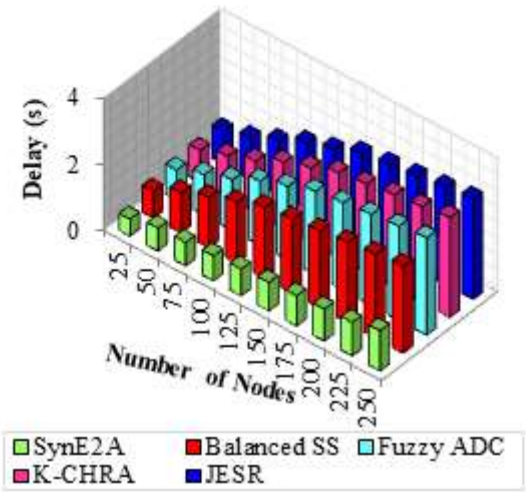


Fig.15.Delay vs. Number of Nodes

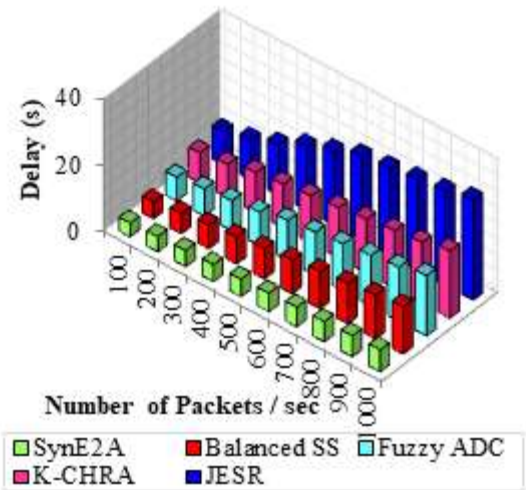


Fig.16.Delay vs. Number of Packets

(6). Impact of Throughput

Throughput is the sum of data transmitted to BS via clustered route which is formulated as follows,

$$Throughput = \frac{\#\ of\ packets\ sent * packet\ size}{Time} \qquad (20)$$

This parameter, throughput is defined based on its computation as the total number of packets transmitted towards the particular destination in accordance with the specified time. The design of routing and wireless charging reflects its performance in term of this throughput metric. The main objective of this proposed SynE2A is attained along with the measurement of throughput which is a network metric. Throughput metric is measured and plotted by comparing with previous research works as shown in fig 17. The performance of throughput observed from fig 18 is proved that the proposed SynE2A model is outperforms due to the planning of charging path and lightweight algorithms for clustering and routing improves the throughput of the overall network.

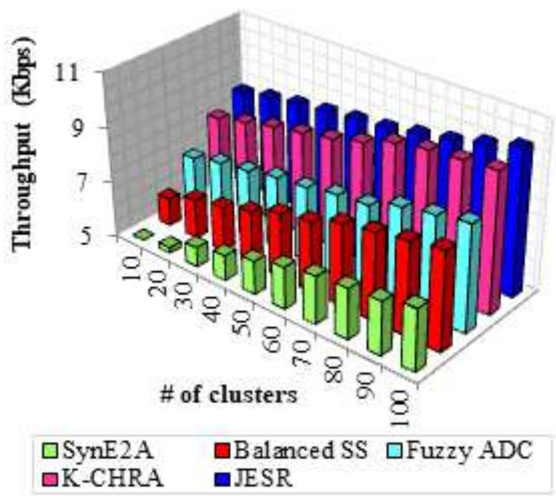


Fig.17.Throughput vs. Number of Clusters

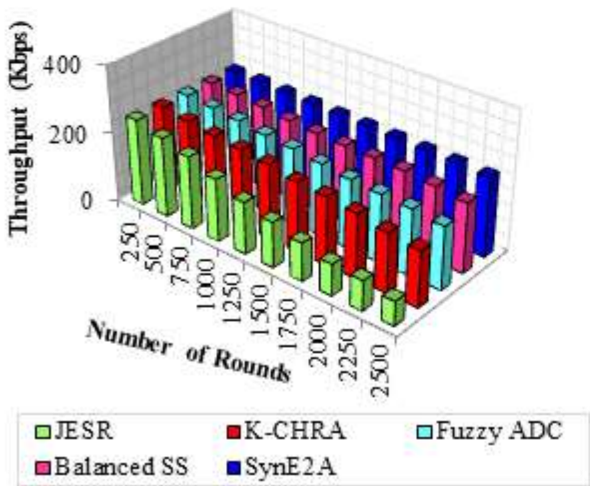


Fig.18.Throughput vs. Number of Rounds

TABLE XI
THROUGHPUT ANALYSIS

Methods	Number of Nodes	No of packets / sec
JESR	6.21±1	150.5±3
K-CHRA	7.35±0.5	206.8±4
Fuzzy ADC	7.86±0.9	215±3.5
Balanced SS	9.08±0.7	226±4
SynE2A	9.24±0.4	239±5

Table XI depicts the performance of throughput for the proposed and the previous works. From that, it is clear that the throughput in packets transmission is higher in the proposed SynE2A model.

The overall experimental evaluation shows that proposed work achieves better results in the aspects of energy efficiency, data delivery, network lifetime and wireless charging. Involvement of effectual node clustering, energy efficient routing, adaptive duty cycling, and wireless charging strategy improves the network lifetime and energy consumption performance. Time complexity of the SynE2Ais $O(\Delta) + O(m) + O(m) + O(\Delta + [d/R_c]$. This covered by the clustering, adaptive duty cycling, inter cluster routing, and wireless charging. The re-clustering and re-routing processes require the less frequent network changes, and it is mainly due to three reasons such as node death, node join and node movement.

VI. CONCLUSION

In this paper for maintaining the network QoS, energy efficiency, and prolong the lifetime of network, SynE2A model is proposed. To maintain the network performance in up to the level, we contributed four mechanisms. Unequal cluster formation by ComED achieves higher network lifetime performance since entropy value is dynamically computed to adjust the clusters count and number of nodes in each cluster. As a result, energy consumption is minimized. Similarly, adaptive duty cycling is implemented to turn off the radio when no operation involved. In this paper, GAN based duty cycle provides optimum slots for sensing, listening and idle. To further, reduce the energy consumption, optimum path is chosen by Tri-CoMBR protocol, which is a combination of AOMR and Dijsktra algorithm. Then, optimum route is selected by hybrid markov model. It is based on energy level, congestion metric, link stability and hop count. Then charging path schedule is proposed to find the intelligent move for MWC which decides the next move intellectually by IQL and also energy awareness is considered. From that move, weighted planar graph is constructed among the cluster of nodes to choose the traveling path.

Due to the limitation of sensors energy in harsh environment, total energy consumption (network level) and energy consumption (sensor level) is increases and thus, we deploy the optimum number of MWCs and achieve congestion free recharging tasks for large number of sensors in high coverage. To address the above issue, scheduling mechanism will be presented to avoid higher delay and battery consumption of MWCs. Further, mobile data collector (e.g. UAV) is presented for collection of critical and non-critical events. In addition, travel path planning for mobile data collector is focused.

REFERENCES

1. Feng, Y., Guo, L., Fu, X., & Liu, N. (2019). Efficient Mobile Energy Replenishment Scheme based on Hybrid Mode for Wireless Rechargeable Sensor Networks. IEEE Sensors Journal, 1–1.
2. Tian, M., Jiao, W., & Liu, J. (2020). The Charging Strategy of Mobile Charging Vehicles in Wireless Rechargeable Sensor Networks With Heterogeneous Sensors. IEEE Access, 8, 73096–73110.
3. Sha, C., Sun, Y., &Malekian, R. (2020). Research on Cost-Balanced Mobile Energy Replenishment Strategy for Wireless Rechargeable Sensor Networks. IEEE Transactions on Vehicular Technology, 1–1.
4. Chen, H., Li, X., & Zhao, F. (2016). A Reinforcement Learning-Based Sleep Scheduling Algorithm for Desired Area Coverage in Solar-Powered Wireless Sensor Networks. IEEE Sensors Journal, 16(8), 2763–2774.
5. Tian, M., Jiao, W., &Shen, G. (2020). The Charging Strategy Combining With the Node Sleep Mechanism in the Wireless Rechargeable Sensor Network. IEEE Access, 8, 197817-197827.
6. Liu, F., Lu, H., Wang, T., & Liu, Y. (2019). An Energy-Balanced Joint Routing and Charging Framework in Wireless Rechargeable Sensor Networks for Mobile Multimedia. IEEE Access, 7, 177637–177650.
7. Xiong, Y., Chen, G., Lu, M., Wan, X., Wu, M., & She, J. (2019). A Two-phase Lifetime-enhancing Method for Hybrid Energy-harvesting Wireless Sensor Network. IEEE Sensors Journal, 1–1.
8. Dong, Y., Li, S., Bao, G., & Wang, C. (2020). An Efficient Combined Charging Strategy for Large-scale Wireless Rechargeable Sensor Networks. IEEE Sensors Journal, 1–1.
9. Mo, L., Kritikakou, A., & He, S. (2019). Energy-Aware Multiple Mobile Chargers Coordination for Wireless Rechargeable Sensor Networks. IEEE Internet of Things Journal, 1–1.
10. Tsoumanis, G., Oikonomou, K., Aissa, S., &Stavrakakis, I. (2020). Energy and Distance Optimization in Rechargeable Wireless Sensor Networks. IEEE Transactions on Green Communications and Networking, 1–1.
11. Lu, Z., Fan, B., Cai, J., & Tang, L. (2020). J-RCA: A Joint Routing and Charging Algorithm with WCE Assisted Data Gathering in Wireless Rechargeable Sensor Networks. IEEE Sensors Journal, 1–1.

12. Gharaei, N., Al-Otaibi, Y. D., Butt, S. A., Malebary, S. J., Rahim, S., &Sahar, G. (2020). Energy-Efficient Tour Optimization of Wireless Mobile Chargers for Rechargeable Sensor Networks. IEEE Systems Journal, 1–10.
13. Cao, X., Xu, W., Liu, X., Peng, J., & Liu, T. (2020). A Deep Reinforcement Learning-Based On-Demand Charging Algorithm for Wireless Rechargeable Sensor Networks. Ad Hoc Networks, 102278.
14. Tomar, A., Muduli, L., & Jana, P. K. (2019). An efficient scheduling scheme for on-demand mobile charging in wireless rechargeable sensor networks. Pervasive and Mobile Computing, 101074.
15. Lin, C., Wang, K., Chu, Z., Wang, K., Deng, J., Obaidat, M. S., & Wu, G. (2018). Hybrid Charging Scheduling Schemes for Three-dimensional Underwater Wireless Rechargeable Sensor Networks. Journal of Systems and Software.
16. Sah, D. K., &Amgoth, T. (2020). Renewable Energy Harvesting Schemes in Wireless Sensor Networks: A Survey. Information Fusion.
17. Lyu, Z., Wei, Z., Pan, J., Chen, H., Xia, C., Han, J., & Shi, L. (2019). Periodic charging planning for a mobile WCE in wireless rechargeable sensor networks based on hybrid PSO and GA algorithm. Applied Soft Computing, 75, 388–403.
18. Liu, R.-S., & Chen, Y.-C. (2019). Robust Data Collection for Energy-Harvesting Wireless Sensor Networks. Computer Networks, 107025.
19. Sharma, H., Haque, A., &Jaffery, Z. A. (2019). Maximization of Wireless Sensor Network Lifetime using Solar Energy Harvesting for Smart Agriculture Monitoring. Ad Hoc Networks, 101966.
20. Mehta, D., &Saxena, S. (2020). MCH-EOR: Multi-objective Cluster Head based Energy-aware Optimized Routing Algorithm in Wireless Sensor Networks. Sustainable Computing: Informatics and Systems, 100406.
21. Wei, Z., Wang, L., Lyu, Z., Shi, L., Li, M., & Wei, X. (2018). A Multi-objective Algorithm for Joint Energy Replenishment and Data Collection in Wireless Rechargeable Sensor Networks. WASA.
22. Han, G., Guan, H., Wu, J., Chan, S., Shu, L., & Zhang, W. (2018). An Uneven Cluster-Based Mobile Charging Algorithm for Wireless Rechargeable Sensor Networks. IEEE Systems Journal, 1-12.
23. Yu, C., Tala't, M., Chiu, C., & Huang, C.L. (2019). Joint Balanced Routing and Energy Harvesting Strategy for Maximizing Network Lifetime in WSNs. Energies, 12.
24. Liu, Y., Lam, K., Han, S., & Chen, Q. (2019). Mobile data gathering and energy harvesting in rechargeable wireless sensor networks. Inf. Sci., 482, 189-209.
25. Lin, H., Bai, D., & Liu, Y. (2017). Maximum data collection rate routing for data gather trees with data aggregation in rechargeable wireless sensor networks. Cluster Computing, 22, 597-607.
26. Mahima, V., &Annamalai, C. (2019). A Novel Energy Harvesting: Cluster Head Rotation Scheme (EH-CHRS) for Green Wireless Sensor Network (GWSN). Wireless Personal Communications, 1-15.
27. Sarang, S., Drieberg, M., Awang, A., & Ahmad, R. (2018). A QoS MAC protocol for prioritized data in energy harvesting wireless sensor networks. Computer Networks, 144, 141-153.
28. Sun, G., Shang, X., &Zuo, Y. (2018). La-CTP: Loop-Aware Routing for Energy-Harvesting Wireless Sensor Networks. Sensors, 18.
29. Liu, H., Deng, Q., Tian, S., Peng, X., & Pei, T. (2018). Recharging Schedule for Mitigating Data Loss in Wireless Rechargeable Sensor Network. Sensors, 18.
30. Alkhalidi, S., Wang, D. & Al-Marhabi, Z.A.A. (2017). Sector-based Charging Schedule in Rechargeable Wireless Sensor Networks. KSII Transactions On Internet And Information Systems, 11(9), 4301-4319.
31. Yang, X., Han, G., Liu, L., Qian, A., & Zhang, W. (2017). IGRC: An improved grid-based joint routing and charging algorithm for wireless rechargeable sensor networks. Future Generation Comp. Syst., 92, 837-845.
32. Tanwar, S., Verma, S., &Tyagi, S. (2019). Energy Harvesting-Based Two-Hop Clustering for Wireless Mesh Network. Progress in Advanced Computing and Intelligent Engineering, 463-473.
33. Sharma, D., &Bhondekar, A.P. (2019). An Improved Cluster Head Selection in Routing for Solar Energy-Harvesting Multi-heterogeneous Wireless Sensor Networks. Wireless Personal Communications, 1-16.

34. Srinivasan, R., &Kannan, E. (2018). Energy Harvesting Based Efficient Routing Scheme for Wireless Sensor Network. Wireless Personal Communications, 101, 1457-1468.

35. Ali, A., Ming, Y., Si, T., Iram, S., &Chakraborty, S. (2018). Enhancement of RWSN Lifetime via Firework Clustering Algorithm Validated by ANN. Information, 9, 60.

36. Tang, L., Cai, J., Yan, J., & Zhou, Z. (2018). Joint Energy Supply and Routing Path Selection for Rechargeable Wireless Sensor Networks. Sensors, 18.

37. Mothku, S.K., & Rout, R.R. (2018). Fuzzy logic based adaptive duty cycling for sustainability in energy harvesting sensor actor networks. Journal of King Saud University –Computer and Information Sciences,.

38. Song, M., Lu, W., Peng, H., Xu, Z., &Hua, J. (2018). A Method of Balanced Sleep Scheduling in Renewable Wireless Sensor Networks. MLICOM, 293-302.

39. Aslam, N., Xia, K., &Hadi, M.U. (2019). Optimal Wireless Charging Inclusive of Intellectual Routing Based on SARSA Learning in Renewable Wireless Sensor Networks. IEEE Sensors Journal, 19, 8340-8351.

40. Wei, Z., Liu, F., Ding, X., Feng, L.H., Lyu, Z., Shi, L., &Ji, J. (2019). K-CHRA: A Clustering Hierarchical Routing Algorithm for Wireless Rechargeable Sensor Networks. IEEE Access, 7, 81859-81874.