Journal of Theoretical and Applied Information Technology
15th July 2023. Vol.101. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

GAME THEORY BASED EFFICIENT ROUTING PROTOCOL IN MOBILE WIRELESS SENSOR NETWORK USING ADVANCED LEARNING MECHANISM

KAMALINDER KAUR[1*], SANDEEP KANG[2]

[1, 2]Department of CSE, Chandigarh University, Punjab, India

[1]*er.kamalinder@gmail.com, [2]sandeepkang.cse@cumail.in

ABSTRACT

Mobile Wireless Sensor Network (MWSN) plays a paramount role in controlling, monitoring, and collecting the required information from the sensors. MWSN consumes less energy and controls the lifespan of the network. The main challenge of using the MWSNs is the use of a routing mechanism, aimed to transfer the sensor information to the sink. In this paper, a novel Game theory (GT) based Routing Protocol (RP) in an MWSN has been developed. The proposed protocol is abbreviated as GT-RP in which fault tolerance has been achieved by offering alternative routes to pass the data when the existing route includes the presence of a fault. The game theory model has been improved further to route the data and then Machine Learning based Q-learning technique has been applied for the selection of alternative routes to maximize the data throughput rate and PDR with minimum delay. The improvement shown by the simulation results is (∼ 5.3%)for the PDR, (∼ 13.24%) for throughput and (∼ 6.48%) for delay against existing techniques.

Keywords: *MWSN, Mobility, Game Theory, Machine Learning, Routing Protocol.*

1. INTRODUCTION

Wireless Sensor Network (WSN) is a growing technology that uses the concept of mobility for various applications. Mobile WSN (MWSN)refers to the ability of nodes to change their position or location after the initial deployment [1]. MWSN comprises two components: Mobile sink, and Mobile Sensor Nodes (MSN) that have the ability to move to and fro within the mobile network as shown in Figure 1. Specifically, there are three parts of MSN:

- Sensing subsystem: This subsystem has been used for data acquisition by collecting data from the nearby environment.
- Processing subsystem: This subsystem is used to process and store the local data.
- Wireless Communication subsystem: This subsystem has been used for data transmission.

More specifically, conventional studies introduced the concept of mobility in the WSN which is advantageous due to wider benefits to the customers in terms of scalability, better network performance, bandwidth coverage, and efficient usage of resources [2]. Additionally, MWSNs consume less energy and control the lifespan of the network.

Figure 1 shows the sensor nodes, mobile agent, and WSN. The sensor nodes deployed randomly can easily communicate with each other and the other devices. The mobile agents have access to move anywhere, are responsible for managing and collecting the sensed data, and then are further passed to the access point[3]. Several emerging applications employ mobility in WSN, such as security, medical, intrusion detection, wildlife monitoring, environment mapping, traffic monitoring, etc. [4–5]. However, MWSNs have also been employed in an emergency situation as Unmanned Aerial Vehicles (UAV) for rescue and search operations and the monitoring of artifacts for medical purposes[6-7].

Themain challenge of using the MWSNs is the use of a routing mechanism aimed at transferring the sensor information to the sink. Routing is the process of transferring data packets from one end to

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the other, or end-to-end delivery. This is a non-trivial process.

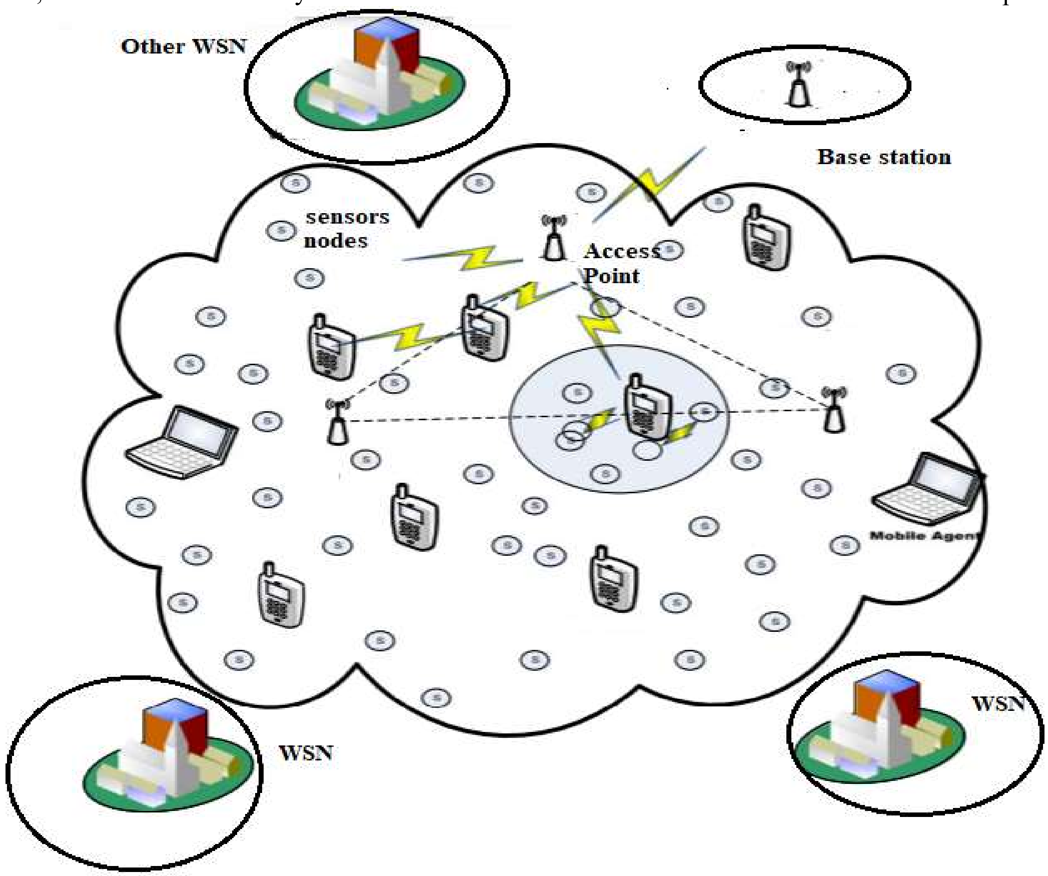


Figure 1: A typical MWSN

as it is associated with limited resources such asenergy, bandwidth, cost, and node mobility.

The main challenge of using the MWSNs is the use of a routing mechanism, aimed to transfer the sensor information to the sink. Routing is the process of transferring data packets from one end to other or say end to end delivery. This is a non-trivial process as it is associated with limited resources such as energy, bandwidth, cost, and node mobility. The network delay is another issue that increases due to long routes but short routes also drain the power due to the connection of intermediate nodes, thus leading to network partitioning. Therefore, sensor nodes are equipped with limited energy supply and minimum energy consumption. Thus, it is crucial in the MWSN for the efficient use of resources. In the past, researchers have employed Machine Learning (ML)based approach for route optimization [8]. However, some researchers focussed on developing the clustering-based adaptive RP for the efficient use of resource [5].

1.1 Challenges

Mobility in WSN endows with significant challenges for energy-efficient routing as illustrated:

The development of a technique for globally addressing sensor node (SN) deployment is not possible on a wider level. Thus, leading to fostering overhead maintenance[2].

Since MWSN is dynamic in nature, node mobility encompasses the change in links and node location, thus making routing difficult.

Sensor nodes have limited energy and storage capacities. Thus, frequent depletion of energy leads to network partitioning. Moreover, nodes drop out of the network due to the dynamic nature of the network topology.

Generation of data by multiple sensors at the same time due to any event results in data traffic. This traffic needs to be aggregated for efficient

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

utilization of bandwidth and to make the network energy efficient.

Sensor nodes are usually application-specific and thus assigning requirements need to change with application.

Data is collected based on location and thus it is important to determine the position of sensor nodes and thus, need to design the routing protocol, which must be adaptable.

There is a need to set a good threshold for SNs to save energy, time delay, and transfer the sensed data. Thus, limiting unnecessary transmission saves energy.

1.2 Routing Protocols in MWSN

In the past, several Routing Protocols (RP) have been designed based on design issues, and criteria. But, none of the existing RP reaches perfection due to the limitations as each one was designed for a specific application[5]. The taxonomy of RP for MWSN is given in Figure 2. The routing mechanism for MWSN has been classified based on the network structure, energy efficient technique, and state of information.

1.3 RP based on network structure

The protocols are comprised of three types: Direct communication, Flat, and hierarchal routing[2]. In direct communication routing, there is direct communication between the sink and sensor nodes. If the area is large, then the battery power of SNs drains very quickly and thus collision also surges. Therefore, this type of routing is very less used in WSN. The flat-based routing assigns the same work to all the deployed nodes. It is very effective, simple, and efficient for a small area. It is further classified as Opportunistic routing and best path routing. The best path routing is optimal as it fits to detect the best

path and then forward the message to the next node. The hierarchical routing divides the nodes into clusters dynamically and thus forms the superclusters. The data aggregation has been done by the cluster head and thus saves energy and data consumption. Such type of routing is further divided into three parts flat, cluster, and zone-based hierarchy[5].

1.4 RP based on Energy Efficiency

Energy efficient RP is based on the consumption of energy by the sensor nodes. The SNs consume their battery during the transfer of information in an active state but also consume energy to listen to any request under the idle state. Thus, this protocol minimizes the energy either in an active or inactive state. The other protocol needs to save energy by switching its operation to a sleep mode that saves a large amount of energy [5].

In this section, SNs need to be mobile and thus, RPs support the management of mobility. The mobility-based RP is categorized as a routing process that takes place when the sink is mobile. When nodes act as a relay, then routing takes place. When all the SNs are mobile and a few SNs are stationary then routing takes place.

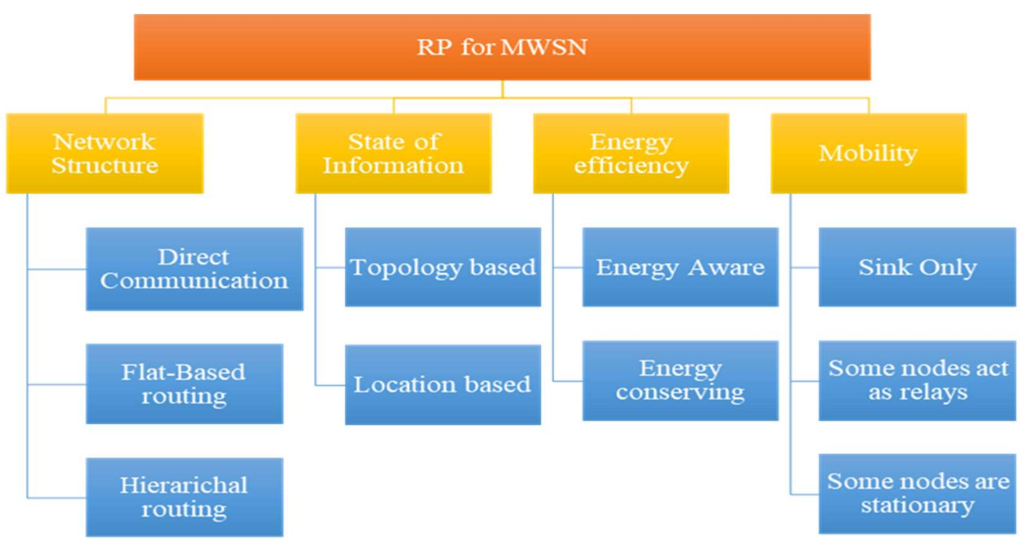


Figure 2: Taxonomy of RP for MSN

1.5 RP based on mobility

In recent years, researchers proposed the various machine learning based RP's for MWSN. Prakash 2021 presented a review based on ML – hierarchical. RP to determine the lifetime of the wireless sensor network. The study employed energy-efficient schemes to improve the lifetime of the WSN [8]. A wide range of ML-based RP is defined in the literature such as Distributed Regression (DR), Reinforcement Learning (RL), and map-based protocols [9]. These protocols enable the SNs to learn and make effective decisions by responding to changes in the environment.

Esmaeili et al. 2022 combined the ML technique with the metaheuristic approach for adaptive routing. A combined model was presented for efficient routing in the clustered WSN [10]. The study used the Genetic Algorithm (GA) for automatic tuning and performance metrics in terms of lifetime, aggregation factor, and a number of nodes. The best routes had been estimated using the classification approach in which the developed model was trained as per configuration and also adapted as a clustering protocol. Further, practitioners proposed the game theory-based energy efficient clustering protocol for WSN [11-12]. The results are efficient but limited to improving the lifetime of the sensor network. The main aim of this paper is to develop an adaptive ML-based routing protocol which is further enhanced with the help of game theory based architecture in which energy efficient routing protocol has been incorporatedin order to find the alternative route at the fault occurrence in the pre-defined route. It further helps to extent the network lifetime and unwanted minimize energy wastage.

1.6 Structure of the Paper

The paper begins with the introduction of MWSN followed by the challenges and RP used in WSN based on different aspects. Section 2 includes the detailed review of the state of art techniques using the different optimization and machine learning techniques. The further section 3 discusses the research methodology based on Game theory and Q-learning. The section 4 provides the results and discussion and finally, a comparative analysis is presented for robustness. At the last, section 5 concludes the paper and discuss the future direction.

2. RELATED WORK

In recent years, WSN practitioners presented several techniques that illustrated the use of RP for various applications. MWSN-RPs are influenced by the WSN and mobile ad-hoc network (MANET) protocols, sharing limitations in terms of energy, bandwidth, and cost. Additionally, WSN functioned like an MWSN, routing the data from SNs to a single sink. But WSN is generally considered static, and thus, unable to cope with mobility. But, MANETs works with the concept of mobility, thus allowingthe source destination communication between the SNs. But this encompasses the additional overhead issue that is not considered for the MWSN. Nowadays emerging applications demand minimum delays with a high PDR. To achieve this, many routing protocols have been designed for MWSN, and current literature highlighting the implementation of RP for MWSN is illustrated in this section.

2.1 Game theory-based Routing Protocol for MWS

Wang et al. 2019 developed a novel RP that was presented for the optimal distribution of nodes and selection of cluster heads. The study introduces the concept of compressive sensing and also determines the cluster size, hot-spot problem, and energy consumption. In addition, the energy consumed due to the movement of nodes and the lifespan of WSN is also computed. The developed protocol had been evaluated by computing the number of nodes, and simulation time. The model was faced issue related to computation period in which spatial-temporal coefficient makes the network complex [13].

Prem Kumar et al. 2019 proposed an Ad-hoc on-demand (AODV) routing protocol based on GT in a WSN. The optimal path is computed from source to destination end by combining the AODV with GT. NS2 simulation environment was created to validate the results and lifetime was improved to 35% in comparison to existing techniques. Additionally, the throughput of the proposed system was also revamped that enhance the network performance and data security. The proposed system was applicable to defence applications and 5G systems. In complex condition, designed network was vulnerable to data security[14].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Thandapani et al. 2020 proposed a game theory-based clustering technique to optimize the energy through the appropriate selection of the cluster head and routing protocol. The multipath routing used avoids the problem of hotspots and improves the energy of the network. The authors proposed the three-tier network model, energy model, and cluster game has been modelled [15].

$$Total energy consumed(E_T) = E_M + E_P \tag{1}$$

When, S_M of a node $= (rpm \times$ diameter of the wheel$\times \pi)/60\ m/s$. Where, S_M signifies the mobility speed, E_M is the mobility energy, and E_P is the primary energy of the node. Thus, performance metrics such as Packet Delivery Ratio (PDR), mobility speed, average residual energy consumed, number of nodes, and simulation time had been measured. Further, the hot spot issue is also considered to determine the delay in comparison to simulation time. The game theory clustering algorithm is advantageous but it is difficult to implement for a hybrid structure[15].

Raj et al. 2020developed a distributed technique based on GT and enhanced ACO to route the mobile sink and data gathering. The study combines both techniques to attain the optimal solution and choose the best path. The presented study managed the data efficiently and provides a wiser trajectory that not only improves the lifetime but also saves the energy in the network. The study shows promising results in reducing the delay and enhancing the lifetime but issue related to loss of packet raised in faulty scenarios [16].

Premananda et al. 2021developed a coalition GT-based Hierarchical RP to optimize the WSN issues. The studies used the clustering technique for the selection of optimum cluster head and compute the probability ensuring an even distribution of energy. However, the problem of battery optimization of nodes is also considered to increase the network lifetime. The study formulated the WSN as a coalition GT with which three different phases start-up phase, configuration phase, and steady phase. An initial phase is used to collect the local data followed by the formation of a cluster head and then transmission of collected data in the last phase. The performance evaluation had been determined using the network lifetime, number of alive nodes, number of cluster heads, total energy consumed, and energy level of nodes. Thus, promising results were shown but such algorithms were not applicable for dynamic networks and faced the latency issue[17].

2.1 Bio-inspired optimization technique based RP for MWSN

Farzana et al. 2017 proposed an Ant-based RP to estimate the reliable path using quality and delay of link. The authors developed the reinforcement algorithm for the link quality and thus the routing table was maintained for each node. Further, data utility had been estimated and Space Division Multiple Access (SDMA) technique was applied to collect the data from the SNs. The simulation experiments had been carried out to compute the delay, delivery ratio, overhead, residual energy, and packet drop rate. The outcomes show that the reliability of the proposed system improved due to a reduction in packet drop rate and delay in comparison to existing protocols but the problem of cluster overhead troubles the model in complex scenarios[18].

Khabiri et al. 2017 proposed a cuckoo search-based energy-aware clustering RP to acquire the best efficiency by selecting optimal cluster heads. The implemented technique was based on four different criteria, namely residual energy of nodes, cluster-cluster distance, source-to-base station distance, and cluster distances. The proposed method includes the network model and energy consumption model based on the cuckoo optimization technique. The outcomes were further measured in terms of the number of alive nodes, network energy, data packets received, and minimum energy consumed by the nodes. The results were further compared with the Low Energy Adaptive Clustering Hierarchical (LEACH) and other existing techniques to show superiority but model was costly in practical scenarios[19].

Wang et al. 2022 implemented a hybrid model using the FA and ACO to develop the clustering-based RP that maximizes the lifetime of the network. A novel cluster-based model had been developed to select the cluster head and network clustering optimized using the FA. The cluster heads were further dispersed using the decision domain and then inter-cluster routing had been established using the improved ACO technique. Further, the authors improved the network throughput using the polling control mechanism that also balances the energy consumption of the proposed model. The outcomes show that network lifetime and throughput had been improved by the issue related to latency still exist[20].

2.2 Routing Protocol for Sensor Network

Sarma et al. 2016 presented a hierarchical cluster-based RP considering the energy requirements and re-clustering time. The proposed study includes the appropriate selection of the cluster head ensuring optimal use of energy and channel panel. The protocol was reliable and ensured that the best throughput was achieved. Further, network topology had been considered to use alternative paths for data transmission. The simulation results show that energy efficiency, lifetime, and throughput had been achieved but latency issues remained in complex conditions [21].

Singh & Verma 2017proposed an energy-efficient routing protocol to improve the lifespan of the network. The study is based on adaptive threshold routing using the concept of weighted probability. The proposed RP employed the Network model and Radio energy model. The former model forms the cluster and selects the cluster head. However, the threshold function was defined for each head. The latter model computed the energy during the data transfer process. The performance metric used to evaluate the hierarchical RP is total data packets, residual energy, and the alive nodes. The promising results had been achieved but unable to protect the network from noisy signals, especially cluster nodes [22].

Rady et al. 2018 proposed a genetic algorithm based on hierarchical RP to revamp the stability and lifetime of the network. Generally, MWSN is dynamic, thus more complicated than the WSN. The increase in complexity also consumes more energy due to the interconnection of nodes. Therefore, the main idea of the author was to determine the mobility of nodes through the selection of cluster heads in an optimal manner. The proposed algorithm is used to find the location by minimizing the energy and thus, experiment results prove the superiority of the proposed GA in comparison to existing protocols but model have the problem of packet dropwhich needs to be addressed [23].

Oladayo, & Ashraf 2019 proposed a secure RP for MWSN considering the conditions limited resources, and dynamic state. The authors discuss the MWSN issues such as lack of assurance, data delivery due to sensors mobility, nodes low power, and issues related to security. The outcomes show that the proposed solution not only improves secure data delivery but also ensures the reliability of the network. Formal and informal analyses had been carried out to enhance the security level of the developed protocol. Further, cost analysis also had been done to compute the overall cost of the secure RP. But model face problem related to the loss of packet during routing [24].

Bashar 2019 presented an efficient secure RP for MWSN using the Ant Lion optimizer ensuring multi-tier routing. The study includes the encryption and decryption technique with cryptography in a spherical structure. The proposed structure saves power and controls the overutilization of energy. The performance metrics in terms of throughput, PDR, energy consumption, network lifetime, and the delay had been measured. The issues related to data security and overhead needed to be addressed in future studies [25].

Chen et al. 2021developed a reservation-based RP especially for multipath in which data was transmitted on a priority basis. The study includes the packet scheduling model used to provide differential services and schedule the packets in an appropriate queue, the proposed study also solves the problem of load balancing. The authors consider the different scenarios: considering a different number of nodes, delay-sensitive data, normal data, traffic consideration, and verification of the proposed algorithm. The proposed study had been compared with the existing study and the results guaranteed outperforms in terms of PDR, and delay but challenges related to network lifetime not been addressed optimally [26].

2.3 Comparison of routing protocols for MWSN

In this section, RP for MWSN is compared to determine the effectiveness and superiority of the proposed system. The different RP developed in the literature has been analyzed and then strengths and weakness highlighted in Table 1.

Table 1: Literature Survey

Author	Technique	Strength	Weakness
(Masoud et al., 2019) [27]	Hybrid clustering RP using the graph theory	The performance of the system was improved and the network lifetime was enhanced by 10%.	The study is limited as the authors are unable to deploy the protocol using real nodes.
(Zhang & Yan, 2019) [28]	Energy efficient clustering formation RP algorithm for the mobile nodes	Reduction in energy dissipation and improvement in PDR	The study was limited to obtaining the optimal clusters in a real environment.
(Yarinezhad, 2019) [29]	Routing algorithm using multi-rink infrastructure	Reduction in energy consumption, prolonging the network lifetime, and delay	The authors are unable to detect the faulty nodes and recover the path for optimal transmission of data.
(Rajesh & Jaya, 2020) [30]	An energy-efficient mathematical model for MWSN, secured cluster head protocol	The outcomes in terms of normal energy utilizedand number of active nodes. The study shows that about 59%, 38%, and 17% of additional information was obtained in comparison to the existing approach.	The proposed solution was erroneous and unreliable during the computation of cost and energy.
(Kumaran, &Chinnadurai, 2021) [31]	Ad-hoc sensor RP for MWSN	The outcomes show that PDR, average energy consumption, and end-to-end delay were improved.	The study depicts limited results when the number of nodes increases and thus the performance of the system degrades.
(Almesaeed & Jedidi, 2021) [32]	RP adapting the mobility of SNs named Dynamic Directional RP (DDR)	The proposed RP improved the network lifetime by about 13% and also enhances the PDR, and energy consumption. However, maintenance of shorter routes was improved by 33% in comparison to the LEACH protocol.	The search angle was changed in the discovery phase and this result needs to configure the protocol dynamically which slowed down the system performance.
(Rajesh & Jaya, 2022) [33]	Secured clustering algorithm using the secret key that is dynamic in nature	The Monte-Carlo simulation was done and results show that packet received, end-to-end delay, security analysis, and packet loss were improved.	The study provides in-efficient results due to the complex formation of cluster routing.

Journal of Theoretical and Applied Information Technology
15th July 2023. Vol.101. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.4 Problem analysis

In the existing literature, different methods have been examined related to energy-efficient routing protocols [27-33] as discussed in Table 1. The issue related to the faulty route has been raised. To solve this problem, various strategies have been employed, but finding the optimal route for minimizing the packet drop remains a challenge. Hence, an innovative strategy is required to address the issue related to energy-efficient packet transfer and improve the overall network lifetime. To resolve this issue, the proposed framework is designed to improve efficiency while transmitting packets using an optimal alternative route in the event of a fault occurrence on the existing route. The proposed GT-RP approach has an edge over the existing techniques in order to discover the optimal alternative route and improve the overall throughput and latency during packet transfer to the desired destination with an improved lifespan of the network.

3. RESEARCH METHODOLOGY

In this section, the authors have proposed a novel Game theory-based routing protocol in an MWSN. In the proposed model, the sensor nodes and base station both are mobile. The proposed protocol is called GT-RP in which fault tolerance has been achieved by offering alternative routes to pass the data when the existing route includes the presence of a fault as shown in Figure 3.

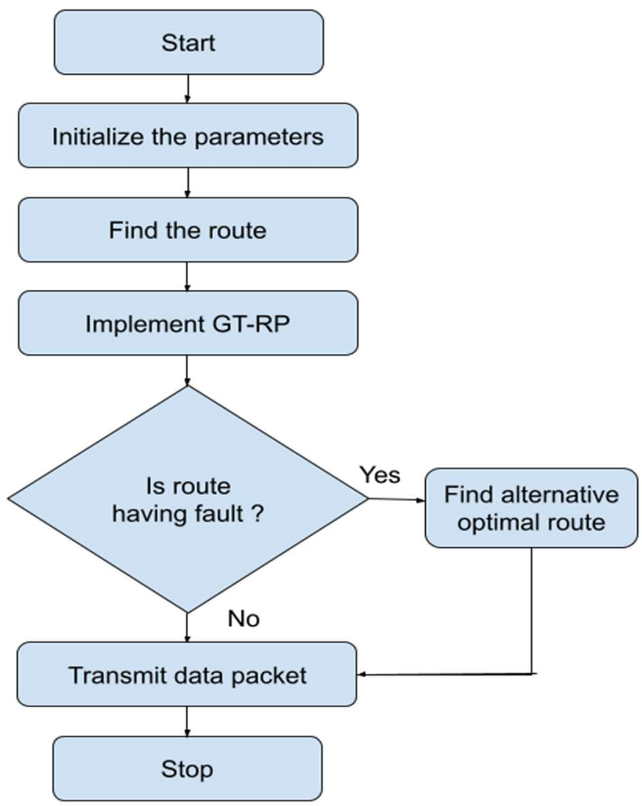


Figure 3: Conceptual Flowchart Of Proposed Work

The main aim of the proposed GT-RP is to extend the SN's lifetime. The implementation has been done in MATLAB, in which some alternative routes have been offered for the transmission of the packet when the current route has node failure. The proposed protocol maintains the efficiency of nodes and the route's reliability. In order to minimize energy consumption, the data packets have been passed or routed through the different hops. Additionally, some mobile nodes are intelligently scheduled in a low-power state. This is also called a dormant state, which means that the services of these SNs are not required at a particular instant. After some time, these nodes may perform a transition of the state from steady to active as per requirement. The transition of a state has been decided by the base station. This not only saves energy but also prolongs the battery life of the SNs.

Journal of Theoretical and Applied Information Technology
15th July 2023. Vol.101. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Further, the game theory model has been used to route the data, and then the ML based Q-learning technique has been applied further for the selection of alternative routes to maximize the data throughput rate and PDR with minimum delay. A hierarchical RP is based on the formation of cluster groups or heads named cluster heads (CH) and non-cluster heads (NCH).

3.1 Game Theory-based RP

To construct the GT-RP, the following assumptions have been made:-

- There is a unique ID for each SN.
- After the deployment, the SN's location does not change.
- The location information of each SN has been contained in the sink.
- All the SNs deployed in the network have the same battery level that cannot be replenished. Moreover, there is not any energy limitation for the BS.
- The transmission power of each SN has been adjusted as per distance.

For the implementation of GT-RP, consider a network having 'M' number of nodes, 'T' actions and 'U_F' is the utility function. Therefore, GT=<M,T,U_F>. When the attributes of a homogenous cluster differed, then differences are known by the clusters and there is no coordination seen between them. Thus, mixed strategy equilibrium is noted in each node, and the probability of a cluster head less than one has been declared. The given situation is implemented as a mixed strategic game with the following facts. In the game strategy,

- Players: M Sensor nodes
- Actions: Each player in the given set of actions is the Cluster Head (CH) and Non-Cluster Head (NCH).
- Utility Function (U_f): The utilities of each player are represented as a payoff function which is '0' and cannot be declared to Cluster head, u-d_k declared to the player of only one node.

The payoff with (2×2) player for the above game is illustrated in Table 2.

The strategies applied are $(u - d_k, u - d_K)$ and (0,0) direct and these are not needed to explain. Moreover, these are not following the Nash equilibrium. The other conditions are balanced such as $(u - d_k, u)$ and $(u,\ u - d_k)$, said to be Nash equilibrium. An optimal selection of the Routing protocol which is energy efficient is the U_f of a game, which is given as $U_{F_{GT}}$ for the given SN as follows:

$$U_{F_{GT}} = \begin{cases} 0, if SN_{p,q} = NCH \\ u, if SN_q = CHand\ \forall i \in M, \quad SN_p = NCH \\ u - d_k, if SN_p = CHs.tu > d > 0 \end{cases} \quad (2)$$

The game utility is '0' if no either node 'p' or 'q' is interested in playing cluster head, and the utility of the player is '$u - d_k$' if node 'p' plays CH and node 'q' plays NCH and payoff is defined as 'u' in a case when at least one node play CH.

Table 2.GT-RP for (2×2) player

Player 1	Player 2	
	CH	NCH
CH	$u - d_k$, $u - d_k$	$u - d_k$,u
NCH	u, $u - d_k$	0,0

The proposed GT-RP has the same concept of rounds of LEACH protocol. There are three phases for each round start-up phase and steady-state phase as illustrated in Figure. The first phase describes the collection of information, the selection of CH, and the formation of the cluster. The last phase used for the transmission of data packets over the efficient route.

- Start-up phase

In this phase, the network is switched ON after the placement of nodes into their position and set-up of the base station. The base station transmits the 'hello' message first. The node received the information and then acknowledge it by broadcasting a 'hello' message over a selected route 'R' having a radius (r). The radius for the given network is defined as follows:-

$$N_A = m_{CH} \pi R^2 \quad (3)$$

The given equation can be deduced as:-

$$= \sqrt{\frac{N_A}{m_{CH}\pi}} \quad (4)$$

Where m_{CH} described as a number of CHs.

The node 'p' in the cluster 'q' computes the probability as per the given equation:-

$$p_n = 1 - \left(\left(\frac{c_M}{u}\right)\left(\frac{c_M \pm 1}{c_M}\right)^{m \pm 1}\right)^{\frac{M}{M-1}} \quad (5)$$

The probability of the node has been compared with the other node in the cluster and the node having the highest probability is selected as CH in the network. There are only 5% of nodes selected for the CH election and after the election process, the 'Hello' message is transmitted with the node ID number. The request to join with a member node with a high energy set to 0. Then, 'Join-Rep' is set to 1 to transfer the message and declared it as a member. When the CH message is received by the candidates then nomination has been withdrawn and the cluster has been formed by joining with a member node.

Steady-state phase

An event detected by every node has transmitted the data to the cluster head (CH)and then CH transmits the data to the base station. The prediction of maximum transfer of information over an efficient route and deletion of members that are not required prevents the energy. The pseudocode of the proposed algorithm is as follows:-

$Pseudocode of GT - RP$

$Input$: M, $number\ of\ nodes$
m_1, m_2: NodesamongM
U_F: NodeUtilityfunction
$p(m_1)$: a proability of the node m to be a m
O_K: Clustersinanoptimalnumber
Count: Count the number of times to be a CH.
Output:
$CH(m_1)$: the CH of a node m_1
Is CH (m_1): true if $CH(m_1) = m_1$
Function:
Transfer (data, radius);
Send (packets, node destination);
Compute the Probabilityas per equation 4
Initialization:
$U_F(m_1) \leftarrow m(CH, NCH)$
Is $CH(m_1) = False$;
$r \leftarrow 0$
% for every round of cluster%
if $\left(count == \frac{M}{O_K}\right)$
Is $CH(m_1) \leftarrow False$;
$p \leftarrow (0, 1)$;
else count $\leftarrow \frac{O_K}{M}$
end if
$p \leftarrow$ Probaility of nodes as per given equation
transmit (p, node)
For each $m \in M$
If $(p(m_1) > (m_2))$
$CH(m_1) \leftarrow U_F(m_1)$;
Is $CH(m_1) \leftarrow True$
Transmit(quit-selection-message, M)
else $CH(m_1) \leftarrow False$
$CH(m_2) \leftarrow U_F(m_2)$
End if
End for

The proposed algorithm used the idle-sleep method to transmit the information and balance the energy. In our algorithm, RP-based cluster head selection allows the node energy prediction and its mobility by finding the alternative path that is efficient and has less traffic. It also prevents the death of the nodes and members' deletion based on mobile node control which is predicted by the sink. The position of a new mobile node has been estimated by the sink which is assigned to the nearest cluster and thus, a member of the parent cluster.

3.2 Q-learning for the optimal selection

Q-learning is a reinforcement learning-based algorithm used to select the action-selection policy in an optimal manner. The Q value signifies the quality value that demonstrates the usefulness of a given action used to acquire the future reward. In this technique, temporal differences have been used to predict the expected Q-value without any knowledge of the particular environment in the form of episodes. It is generally defined using an agent and includes the set of states (E) and actions (T). An agent changes its position from one state to another state by performing an action t∈T. In order to learn and gain knowledge about the environment, an agent in E attracts T. The reward (W) given to the agent entirely depends upon the outcome.

In the proposed Q-learning-based MWSN routing, the agent is recognized as a network in which data flows from one end to the other end. The conventional single-agent technique includes a centralized network controller working as an agent that can analyze the environmental conditions and, thus can control the transmission of the packet of each mobile SN. Therefore, a large overhead is required by this agent but it is difficult to determine the network status in real-time.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

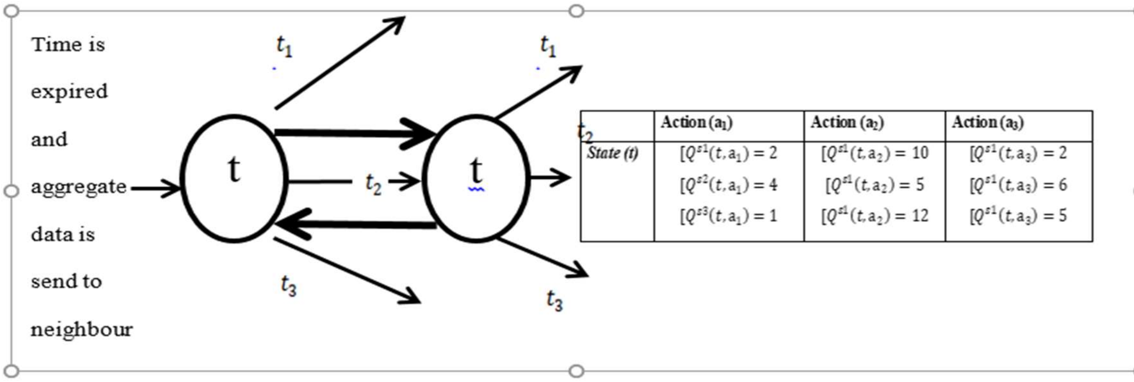


Figure 4: Proposed Q- learning process

In an MWSN, each mobile SN represents a state and data flow is an agent. Consider the waiting timer (W_T) of SN (j) expires, it is required to transfer the data to the neighboring node to forward the aggregated data. In such a case, the current state of SN is S_j; and the actions for that specific node is the list of all the associated nodes, and the next state of that particular node is S_k, to which data is a transferred from one state to another state. The state of the nodes and their actions are defined as follows:

$S_t = (t_1 \ , t_2 \ \ , \ldots \ldots , t_n)$

$$A_C = (a_1, a_2, \ldots \ldots, a_n), \quad A_j = \{a_j = t_j | t_j \epsilon N t_{sk}\} \tag{7}$$

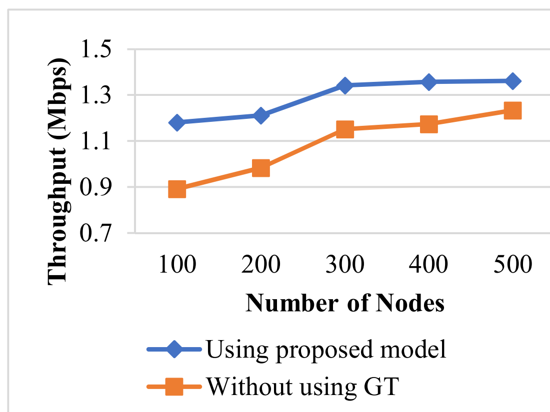
Let us consider that agent of a particular node chooses action (a) in the state (t), and reward (Rd) has been observed and the agent further entered into a new state (t'). The Q-value is updated as follows:-

$$Q(t, a) = (1 - \forall) Q(t, a) + \forall\{Rd + \gamma . Q(t', a)\} \tag{8}$$

In the given equation, ∀ is the learning rate of the node and γ is the important symbol that ensures future rewards. In the figure, there are different states for different actions and rewards generated as per the actions of the node.

Here, n is the count of SN and Nt_(sk)is the neighbor nodes of node s_k. In Q-learning, the best action has been determined using the Q-table in which action represented and returned the sum of present and estimated future rewards, whenever action has been performed on a particular node at a state t. This function is followed by the Bellman equation.

4. Results and Discussion



To verify and evaluate the behavior of the proposed model, the MATLAB tool is used. The performance metrics were computed to determine the robustness of the proposed technique and then further results are compared with the existing technique for superiority.

4.1 Performance Metrics

The performance is evaluated using the terms PDR, end-to-end delay, and throughput.

- **PDR**

It is an acronym for Packet to Delivery ratio. It is defined as the ratio of the number of input packets(P_I) to the number PDR of packets successfully received at the destination end (P_D)

$$PDR = \frac{P_I}{P_D} \tag{9}$$

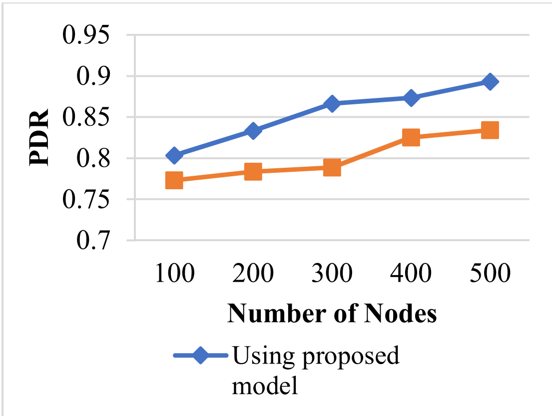


Figure 5 Computation Of PDR Vs Number Of Nodes With And Without Using The GT:

The Figure 5 shows that higher PDR is achieved using the proposed model and thus, shows the maximum delivery rate. The proposed model shows a PDR of 0.85% and without using the GT, it is 0.80%. Thus, the proposed protocol improved by 6.6% when using the game theory technique integrated with the machine learning technique.

- **Throughput**

It is used to measure the performance of the developed system. It is defined as the maximum rate to process the packets in the communication network. In other words, it is defined as the ratio of the success rate of data transfer over time. It is measured in bits per second (bps).The given graph shows that higher throughput is achieved using the proposed model and thus, shows the maximum performance of the proposed system.

Figure 6: Computation of throughput vs number of nodes with and without using the GT

Figure 6 shows the average throughput rate using the proposed model is1.291Mbps and without using the GT, it is 1.08 Mbps. Thus, the proposed protocol improved by 13.2% due to the use of game theory.

- **Delay**

It is defined as the maximum number of packets (Packets_Max) delivered over time. It is measured in milliseconds (ms).

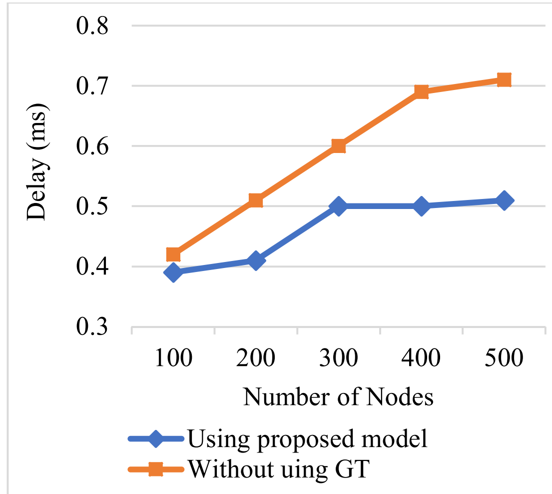


Figure 7: Computation Of Delay Vs Number Of Nodes With And Without Using The GT

The given graph shows the minimum delay achieved using the proposed model and thus, shows the improved performance of the proposed system. The average delay achieved using the proposed model is 0.4628 and without using the GT, it is 0.5994 ms. Thus, the proposed protocol improved the system performance by 22.7% due to the use of game theory approach.

4.2 Comparative Analysis

In this section, a comparative analysis has been presented to determine the performance of the proposed study. The superiority of the proposed Routing Protocol was demonstrated by comparing it with the existing techniques. There are different simulation rounds performed in which different nodes are taken.

Table 3. Simulation Rounds

Number of Simulation Rounds	Number of nodes
2000 rounds	100
4000 rounds	200
6000 rounds	300
8000 rounds	400
10000 rounds	500

The proposed RP has been compared with the existing technique to validate the results.

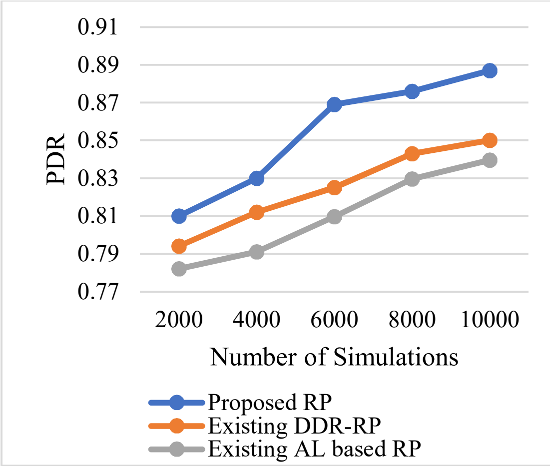


Figure 8: Computation Of PDR Using The Proposed Model And The Existing Technique

Figure 8 shows that the average value obtained using the proposed RP is 0.85% while that of the existing approach (DDR-RP) [32] is 0.82% and that of AL-based RP [25], it is 0.81%. Thus, 3% and 5.3% improvement have been seen in PDR in contrast to DDR-RP and AL-based RPrespectively.

Figure 9 shows the proposed RP has been compared with the existing technique to validate the results.

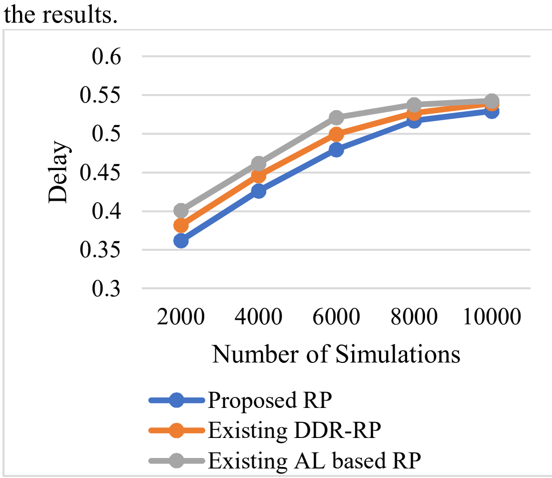


Figure 9: Computation Of End-To-End Delay Using The Proposed Model And The Existing Technique

The outcomes show that the average delay value obtained using the proposed RP is 0.4628 ms while that of the existing approach DDR-RP [32] is 0.4788ms and AL-based RP [25], is 0.4928ms. Thus, 3.45% and 6.48% improvement has been seen in computing the delay in contrast to DDR-RP and AL-based RP respectively.

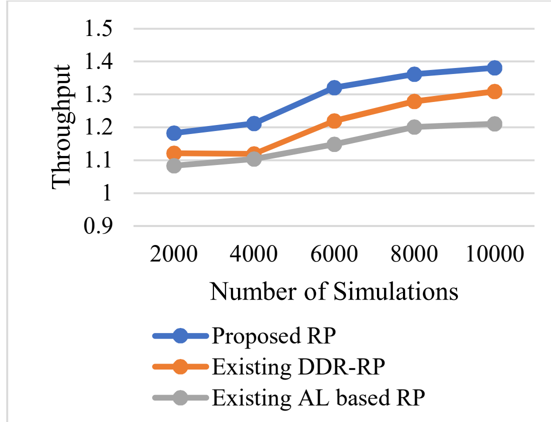


Figure 10: Computation Of End-To-End Throughput Using The Proposed Model And The Existing Technique

Figure 10 shows the proposed RP has beencompared with the existing technique to validate the results. The proposed model shows throughput using Routing Protocol of about 1.291Mbps and that of existing technique DDR-RP [32] is1.209Mbps and AL based RP [25] is 1.14Mbps. Thus, 6.78% and 13.24% improvement has been seen in computing the throughput against DDR-RP and AL-based RP respectively.

5. CONCLUSION

MWSN is the ability of nodes to change their position after their initial deployment. MWSN is dynamic in nature as node mobility encompasses changes in links and node location, making routing difficult.To facilitate the process, this paper attempts to develop a GT-RP based model for MWSN in order to find the optimal alternative route to pass the data due to the fault occurrence on the existing route. The simulation results demonstrate that the proposed model has shown an average improvement in the PDR of 3% and 5.3% against DDR-RP [32] and AL based RP [25] respectively. For throughput, the proposed model showed improvements of 6.78 and 13.24% against DDR-RP [32] and AL based RP [25] respectively. Finally, for delay, the suggested model showed improvements of 3.45% and 6.48% as compared to existing techniques, DDR-RP [32] and AL based RP [25] respectively. Further, the proposed model also improves the SN's lifetime due to the involvement of the Q-learning technique. In the future, the proposed GT-RP can be incorporated with swarm intelligence techniques in order to improve the decision-making process of route discovery and selection, which helps to improve the performance parameters.

REFERENCES:

[1] N. Mazumdar, S. Roy, A. Nag, and S. Nandi, "An adaptive hierarchical data dissemination mechanism for mobile data collector enabled dynamic wireless sensor network," *Journal of Network and Computer Applications*, vol. 186, 2021.p. 103097.

[2] S. Rajendra Prasad P., "Efficient Performance Analysis of Energy Aware on Demand Routing Protocol in Mobile Ad-Hoc Network," *Electronics and Communication Engineering-WILEY*, vol. 2,2019, pp. 1–14, , Accessed: Sep. 30, 2022. [Online]. Available: http://localhost/xmlui/handle/1/38

[3] K. Haseeb, N. Islam, A. Almogren, and I. U. Din, "Intrusion prevention framework for secure routing in WSN-based mobile Internet of Things," *Ieee Access*, vol. 7,2019, pp. 185496–185505.

[4] S. B. Sukhavasi, S. B. Sukhavasi, K. Elleithy, S. Abuzneid, and A. Elleithy, "CMOS image sensors in surveillance system applications," *Sensors*, vol. 21, no. 2, 2021.p. 488.

[5] Y. Tripathi, V. Kumar, and A. Prakash, "A robust energy-efficient cluster-based routing protocol for mobile wireless sensor network," in *Advances in VLSI, Communication, and Signal Processing*, Springer, 2020, pp. 61–69.

[6] G. Kadiravan *et al.*, "Metaheuristic clustering protocol for healthcare data collection in mobile wireless multimedia sensor networks," *Computers, Materials \& Continua*, vol. 66, no. 3, 2021, pp. 3215–3231.

[7] D. Popescu, F. Stoican, G. Stamatescu, O. Chenaru, and L. Ichim, "A survey of collaborative UAV--WSN systems for efficient monitoring," *Sensors*, vol. 19, no. 21, 2019, p. 4690.

[8] P. S. Prakash and others, "Machine Learning-Based Optimized Hierarchical Routing Protocols for WSN Lifetime: A Review," *Information Technology In Industry*, vol. 9, no. 2, 2021, pp. 289–307.

[9] C. Shivalingagowda, H. Ahmad, P. V. Y. Jayasree, and D. K. Sah, "Wireless Sensor Network Routing Protocols Using Machine Learning," in *Architectural Wireless Networks Solutions and Security Issues*, Springer, 2021, pp. 99–120.

[10] H. Esmaeili, B. M. Bidgoli, and V. Hakami, "CMML: Combined metaheuristic-machine learning for adaptable routing in clustered wireless sensor networks," *Applied Soft Computing*, vol. 118, 2022, p. 108477.

[11] N. Guruprasad and others, "Game Theory Based Routing Protocols and Their Efficiency in Improving the Lifetime of a Wireless Sensor Network," *Journal of Computational and Theoretical Nanoscience*, vol. 17, no. 9–10, 2020, pp. 4003–4006.

[12] X. Yan, C. Huang, J. Gan, and X. Wu, "Game Theory-Based Energy-Efficient Clustering Algorithm for Wireless Sensor Networks," *Sensors*, vol. 22, no. 2,2022, p. 478,

[13] Q. Wang, D. Lin, P. Yang, and Z. Zhang, "An energy-efficient compressive sensing-based clustering routing protocol for WSNs," *IEEE Sensors Journal*, vol. 19, no. 10, pp. 3950–3960, 2019.

[14] M. Premkumar, M. P. Chitra, X. A. Celestin, T. Kausalya, and M. N. N. Priya, "Game theory based Ad-hoc On Demand Distance Vector Routing Protocol to Extend the Wireless Sensor Networks Life Time," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, vol. 7, no. 3, 2019, pp. 463–471.

[15] P. Thandapani, M. Arunachalam, and D. Sundarraj, "An energy-efficient clustering and multipath routing for mobile wireless sensor network using game theory," *International Journal of Communication Systems*, vol. 33, no. 7, 2020, p. e4336.

[16] P. V Raj, A. M. Khedr, and Z. Al Aghbari, "Data gathering via mobile sink in WSNs using game theory and enhanced ant colony optimization," *Wireless Networks*, vol. 26, no. 4,2020, pp. 2983–2998.

[17] B. S. Premananda, N. K. Neti, K. P. Ashwin, and S. V Basu, "An energy-efficient, coalition game theory based hierarchical routing protocol for WSNs," *International Journal of Computers and Applications*, vol. 43, no. 3,2021 pp. 246–256.

[18] A. H. Fareen Farzana and S. Neduncheliyan, "Ant-based routing and QoS-effective data collection for mobile wireless sensor network," *Wireless Networks*, vol. 23, no. 6,2017, pp. 1697–1707.

[19] M. Khabiri and A. Ghaffari, "Energy-aware clustering-based routing in wireless sensor networks using cuckoo optimization algorithm," *Wireless Personal Communications*, vol. 98, no. 3,2018, pp. 2473–2495.

[20] Z. Wang, H. Ding, B. Li, L. Bao, Z. Yang, and Q. Liu, "Energy efficient cluster based routing protocol for WSN using firefly algorithm and ant colony optimization," *Wireless Personal*

Communications, pp. 1–34, 2022.

[21] H. K. Deva Sarma, R. Mall, and A. Kar, "E2R2: Energy-efficient and reliable routing for mobile wireless sensor networks," *IEEE Systems Journal*, vol. 10, no. 2, Jun. 2016,pp. 604–616, doi: 10.1109/JSYST.2015.2410592.

[22] R. Singh and A. K. Verma, "Energy efficient cross layer based adaptive threshold routing protocol for WSN," *AEU-International Journal of Electronics and Communications*, vol. 72,2017, pp. 166–173.

[23] A. Rady, N. Sabor, M. Shokair, and E.-S. M. El-Rabaie, "Mobility based genetic algorithm hierarchical routing protocol in mobile wireless sensor networks," in *2018 International Japan-Africa Conference on Electronics, Communications and Computations (JAC-ECC)*, 2018, pp. 83–86.

[24] O. Oladayo and A. Ashraf, "A secure and energy-aware routing protocol for optimal routing in mobile wireless sensor networks (MWSNs)," *International Journal of Sensors Wireless Communications and Control*, vol. 9, no. 4, 2019, pp. 507–520.

[25] A. Bashar, "Energy efficient multi-tier sustainable secure routing protocol for mobile wireless sensor networks," *J. Sustain. Wireless System*, vol. 1, no. 2,2019, pp. 87–102.

[26] Z. Chen, W. Zhou, S. Wu, and L. Cheng, "An on demand load balancing multi-path routing protocol for differentiated services in MWSN," *Computer Communications*, vol. 179, 2021, p. 296–306.

[27] M. Z. Masoud, Y. Jaradat, I. Jannoud, and M. A. Al Sibahee, "A hybrid clustering routing protocol based on machine learning and graph theory for energy conservation and hole detection in wireless sensor network," *International Journal of Distributed Sensor Networks*, vol. 15, no. 6,2019, p. 1550147719858231.

[28] J. Zhang and R. Yan, "Centralized energy-efficient clustering routing protocol for mobile nodes in wireless sensor networks," *IEEE Communications Letters*, vol. 23, no. 7,2019, pp. 1215–1218.

[29] R. Yarinezhad, "Reducing delay and prolonging the lifetime of wireless sensor network using efficient routing protocol based on mobile sink and virtual infrastructure," *Ad Hoc Networks*, vol. 84, 2019, pp. 42–55.

[30] D. Rajesh and T. Jaya, "A mathematical model for energy efficient secured CH clustering protocol for mobile wireless sensor network," *Wireless Personal Communications*, vol. 112, no. 1,2020, pp. 421–438.

[31] K. M. Kumaran and M. Chinnadurai, "A competent ad-hoc sensor routing protocol for energy efficiency in mobile wireless sensor networks," *Wireless Personal Communications*, vol. 116, no. 1, 2021, pp. 829–844.

[32] R. Almesaeed and A. Jedidi, "Dynamic directional routing for mobile wireless sensor networks," *Ad Hoc Networks*, vol. 110, 2021, p. 102301.

[33] D. Rajesh and T. Jaya, "Energy competent cluster-based secured CH routing EC2SR protocol for mobile wireless sensor network," *Concurrency and Computation: Practice and Experience*, vol. 34, no. 1, 2022, p. e6525.