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Trusted Cluster based Optimal Multi-sink Repositioning Technique for WSNs using Improved Bull Optimization and Clonal Selection Algorithm

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Abstract:
Wireless Sensor Networks (WSNs) are networking devices, which are sending, receiving information and monitoring the data through the sink node. Sink node of WSNs are collect and forwarded, centralized the all data, also called base station. There are some issues are leads to affect the function of sink nodes they are, quality of service (QoS), high bandwidth demand, high energy consumption, provisioning, compressing techniques, data processing also cross-layer design. If these issues are may affect the whole system, it may create node failure. To overcome these problems, we propose a TC-OMSR technique for reduce that issues and increases node parameters. A trusted cluster based optimal multi-sink repositioning technique (TC-OMSR) is proposed using improved Bull optimization and clonal selection algorithm. In TC-OMSR technique, first we introduce an Improved Bull Optimization for efficient cluster formation based on the basic behavior of sensor nodes. Then, we illustrate Clonal Selection Algorithm to compute the trust of each node based on multiple constraints are energy consumption, network lifetime, mobility and received signal strength. From computed trust values, the highest trust value owned sensor node is considered as CH in the cluster. Finally, the execution of proposed TC-OMSR technique is compared along the existing techniques with regards to delay, network lifetime, delivery ratio, energy consumption, throughput and false positive rate.

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1. Introduction

Wireless sensor network (WSN) understand an unavoidable disseminated system to make an insightful domain and in charge of detecting just as for the main stage of handling [1]. Sensor systems are profoundly disseminated systems of little, easily handled device, which is can be sends the enormous number of signals to the earth through the sensor nodes. Also, which is supports of physical parameters, for example, temperature, weight or relative dampness [2][3]. Every hub of the sensor system comprises of three subsystems: the sensor subsystem which detects the earth, the handling subsystem which plays out the nearby calculations on the detected information and correspondence subsystem which is in charge of the message trade with neighboring sensor hubs [4]. While singular sensors have restricted detecting locale, preparing force and vitality, organizing a bigger number of sensors offers ascend to a powerful, solid and exact sensor system covering a more extensive area [5]. Ideal hub situation is a difficult issue that has been demonstrated to be NP-Hard for the vast majority of

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the details of sensor arrangement [6]. There are several heuristics were proposed for final optimal solutions. In any case, the setting of these advancement techniques is essentially static as in surveying the nature of applicant positions depends on an auxiliary quality metric, for example, separation, arrange network and additionally putting together the examination with respect to a fixed topology [7]. Then again, a few plans have upheld dynamic modification of hubs' area since the optimality of the underlying positions may end up void during the activity of the system relying upon the system state and different outer components [8]. To know the continuous data on the sink position is the significant test is that the sensor hubs. We need an estimation system is required at each bounce to improve the adequacy of WSN. Sending of hubs in the system depends free of measurements that base the condition of the system or it accept an example of system tasks, which stays unaltered all through the system lifetime. It is intricate to finding an effective procedure for ideal passage area.

Circulated relay situating ways to deal with assurance arrange recuperation for divided WSNs by limiting the development cost of the hand-off hubs. Power based methodology extends the system bit by bit with the organization of extra transfers. In the game-theoretic methodology, the parcel to be associated with is dictated by the pioneer hand-off hubs dependent on the likelihood dispersion work (pdf) of the segments [9]. A multi-arrange dynamical RN situation arrangement is utilized to lead the RNs to their time-changing improved positions. Dynamical transfer hub position arrangement (DRNS) depends on the utilization of molecule swarm advancement (PSO) calculations and enlivened by model prescient control (MPC) systems following a bi-target improvement methodology [10]. An arbitrary challenge-based bunching (RCC) is steadier than the customary grouping techniques like Lower ID (LID) [11]. An adjusted Poisson PMF articulation is relied upon spatial and transient angles are consolidated dependent on interim ideas and it is approving the dynamic fluffy c-implies calculation Two as the most productive groups development conspire [12]. Two conveyed hand-off hub situating ways to deal with assurance organize recuperation for apportioned WSNs by the development cost of the hand-off hubs. Recuperation continues with the segment having the following most elevated need until system is totally recouped by arriving at the framework wide extraordinary Nash harmony [16]. Sea observing is testing a direct result of lack of ability to anticipate hub areas. What's more, which is important to maximize the utilization of energy by the procedure of hub arrangement since hub vitality is constrained and utilization of energy of hub portability is high [14]. WSNs have a few tribulations on various strategies, for example, arrangement, inclusion, trust model, time synchronization, middleware, adaptation to non-critical failure and the rest [13].The DCR depends on halfway system data including topological over-head related with every hub. The choice of befitting hubs to be moved during fell development is done deliberately by utilizing halfway system data with the end goal that the migration and message over declined [19]. Geometric Skeleton based Reconnection approach (GSR) that adventures the state of the organization territory to reestablish network to an apportioned WSN in a disseminate way. GSR decays the sending territory into its relating two-dimensional skeleton layout, along which portable transfers are populated by the enduring disjoint fragments to restore availability [18]. Advanced 3-D arrangement with Lifetime Constraint (O3DwLC), for hand-off hubs in natural applications. The technique improves organize availability, while guarantying explicit system lifetime and constrained expense [17]. The moderation of sink hub powerlessness in a strategic WSN utilizing responsive course muddling and issue of ensuring the sink hub through a typical system known as k-obscurity. To accomplish k-obscurity, can utilize a particular directing convention intended to work inside the requirements of WSN protocol IEEE 802.15 and 6LoWPAN[20].

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Contributions of this paper are, we propose a trusted cluster based optimal multi-sink repositioning technique (TC-OMSR) for WSNs utilizing improved Bull optimization and clonal selection algorithm. Initially, we introduce an Improved Bull Optimization for efficient cluster formation based on the basic behavior of sensor nodes. Second, we compute the trust of each node depends on multiple constraints by using of clonal selection algorithm. Finally, we compare the result of proposed TC-OMSR technique with the existing techniques in terms of delay, consumption of energy, network lifetime, false positive rate and delivery ratio also throughput.

The manuscript is organized as pursues: In part I, we expressed analysis of various techniques of sink node repositioning for WSNs. In part II explains the issues of sink node repositioning of WSNs assume on illustrative example, In addition, we analyzed problems of previous methods and system model pursues section III. We illustrated about proposed algorithm in part IV. In part V, discuss implementation aspects and results. We outline the major conclusions of this paper in section IV.

2. Related Works

There are lots of researches have been presented in sink node repositioning of WSNs. Some latest research relevant to cluster based optimal multi-sink repositioning of WSNs using variety techniques. Kemal et.al [21] have exhibited, the capability of entryway repositioning for improved system execution as far as delay, energy and throughput and address issues identified with when should the passage be migrated, where it is moved to and how to deal with its movement without negative impact on information traffic additionally two methodologies that factor in the rush hour gridlock design for deciding another area of the portal for streamlined correspondence timelines and energy separately. Niayesh et.al [22] have displayed, WSNs depends clustering ,the Cluster Heads (CH) situated around Base Station (BS) devour more vitality and fumes their vitality supplies quicker than different ones which prompts vitality gap issue and untimely system passing. Muralitharan et.al [23] have proposed, The utilization of improved clustering methods and various versatile sinks along groups and remain in each group for a constrained so journ time determined by first algorithm. Saeidet. al [24] have proposed, LEACH algorithm (low energy adaptive clustering hierarchy) is a productive grouping calculation where hubs inside a bunch send their information to another head of cluster. Hossein et.al [25] have displayed, Base station (BS) situating is a viable technique for improving the presentation of remote sensor system. Muhammad et.al [26] have exhibited, for social event significant data in Mobile sensor organize, the between sensor availability speaks to an indispensable job. Hubs inside these sorts of systems look at different parts of a region of intrigue. Prerana et.al [27] have introduced, sink repositioning system for extending the system lifetime. Prasenjit et.al [28] have concentrated on the issue of enduring system disappointments seen by sent sensor hubs in a WSN and propose a novel grouping calculation for WSNs, named Distributed Energy Efficient Heterogeneous Clustering (DEEHC) that chooses bunch heads as per the lingering vitality of conveyed sensor hubs with the guide of an timer, which is represents secondary. Andrea et.al [29] have concentrated on the issue on topologies based on clustering for WSNs with a few sinks considered.

3. Problem methodology and System model

This part expresses trusted cluster based optimal multi-sink repositioning technique for WSNs using and (TC-OMSR). By following this, we were described about improved Bull optimization Algorithm, clonal selection algorithm.

3.1 Problem methodology

Pushpalatha et.al [30] have proposed, For ready to transfers the data through sensor or mobile nodes, clustering technique alive distance and energy methodology is used, which are closes to both sensor

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and sink node. For clustering the nodes, in this work using Weight K-means algorithm. Also, pushpalatha et.al using optimal cluster head selection technology for data transfer without node failure also finds energy consumption and bandwidth utilizing the cat swarm optimization algorithm also it can used for find the sink node and resource optimization. This research work is implementedand evaluated in terms of varying performance measures also which is analysis the security level, energy utilization, false positive rate and delivery ratio also this method not suitable for enormous sink repositioning. From [21]-[31], there are varieties of techniques are used for repositioning the sink nodes for WSNs, with and without clustering. Almost all techniques are only focus on energy efficiency and node failures. There are no techniques for covers the all issues like high energy consumption, high energy demand, nodes failures and network failures. To overcome those problems, a trusted cluster based optimal multi-sink repositioning technique (TC-OMSR) is proposed using improved Bull optimization and CSA.

1. In TC-OMSR technique, first we introduce an improved Bull optimization for efficient cluster formation based on the basic behavior of sensor nodes.
2. Then, we illustrate clonal selection algorithm (CSA) to compute the trust of each node based on multiple constraints are energy consumption, network lifetime, mobility and received signal strength.
3. From computed trust values, the highest trust value owned sensor node is considered as CH in the cluster. Finally, the result of proposed TC-OMSR technique is contrasted along existing techniques in terms of delay, energy consumption, network lifetime, delivery ratio, throughput and false positive rate.

3.2 System Model

The proposed TC-OMSR scheme is shown in figure.1. Here the main function of proposed TC-OMSR scheme is sink node repositioning with develops the energy consumption, network lifetime and delivery ration , through put and false positive rate with higher efficiency than existing techniques. Initially, the sensor nodes are clustering by using of Improved Bull Optimization Algorithm (IBOA). Then, we select the cluster head based on highest trust values of each clustering nodes also selects the source and destination of nodes from clustering group by using of proposed Clonal Selection Algorithm (CSA) and finally, the data transfer between the source and destination, the transmission is occurs through the cluster head. In figure 1 , showing the source and destination, cluster head. Using of proposed TC-OMSR scheme, we can reduce the energy consumption and delay and increases the network lifetime and delivery ratio, through put also positive rate.

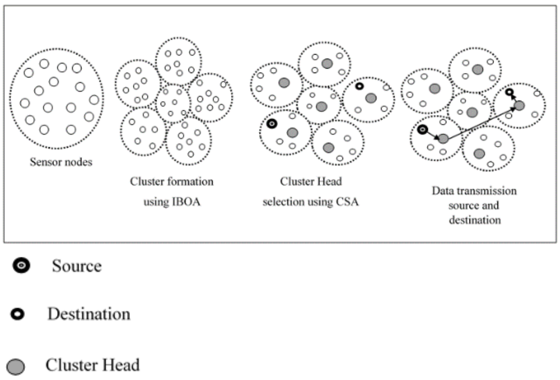

Figure1. Proposed TC-OMSR scheme

4. Trusted cluster based optimal multi-sink repositioning technique for WSNs using improved Bull optimization and clonal selection algorithm

4.1 Clustering Formation using Improved Bull Optimization

The IBOA proposed in this paper is a developmental calculation utilizing for structure the proficient grouping dependent on the essential conduct of hubs. The BOA is creating dependent on conduct of bull or wild oxen. The calculation starts by instating the number of inhabitants in wild oxen. It does this by doling out an irregular area to each bison inside the hunt space. Next, it refreshes each wild bull wellness in connection to the objective and along these lines learn the crowd's best creature ($best_{\max.k}$) and every bison individual best ($best_{ini.k}$). In each stage, that the health is better than the group's general most prominent, it saves it as the gathering's most extraordinary ($best_{\max.k}$). Next, the estimation invigorates the region of the wild bulls using Equation (1). After this, it insists the improvement or for the most part of the principle bull ($best_{\max.k}$).

The sound and conduct of wild bull k (k=1, 2, 3… n) which moves the bison to proceed onward to investigate other touching territories since where they are by and by is hazardous or needs adequate field is spoken to by w. k and wild ox sound which requests that the creatures remain on to misuse the present area since it has enough field and is sheltered is spoken to by m. k.

Mathematically, the democratic equations which determines the movement of the buffalos is:

$$(m.k+1 = m.k + la_1(best_{\max.k} - w.k) + la_2(best_{ini} - w.k) \quad (1)$$

The law based Equation (1) has three principle parts, in particular, the memory part $(m.k+1)$ which means that the creatures know that they have migrated from their previous situations (m,k) to another one. This means that their broad memory limit which is an indispensable device in their transient way of life. The subsequent part speaks to the helpful characteristics of the creatures. $la_1(best_{\max.k} - w.k)$ The bull is phenomenal communicators and can follow the area of the best wild ox in every emphasis. The last piece of this condition $la_2(best_{\max.k} - w.k)$ draws out the excellent knowledge of these creatures. They can tell their past best gainful area in contrast with their present position.

Initialization of population

The populace for tackling an improvement issue with d measurements is made with the quantity of N and d-dimensional people. Since there is no data about the arrangement from the start, the underlying populace is arbitrarily created inside the arrangement space as indicated by Equation (12),

$$X_{nm} = X^{\max}{}_m - r \times \left(X^{\max}{}_m - X^{\min}{}_m\right) \quad (2)$$

Here, i = 1….N; j = 1….d N is the amount of individuals, d is the amount of dimensions for certain problems, and r is a randomly chosen parameter in [0, 1].

Irregular people are made uniquely at the underlying stage. At different stages, these people are improved.

Updating the fitness function

The important parameter of this bull algorithm is fitness function. After updates the bull location (which is represents in algorithm 1), we update the fitness function of bull in equation (3),

$$w.k+1 = \frac{(w.k + m.k)}{\pm 0.5} \quad (3)$$

Finding best individuals

The reason for existing is to discover better people by doing research around the estimations of the quality in the proposed calculation. For the answer for push ahead rapidly and effectively and to dispose of nearby minima, this procedure must assume a functioning job. Every individual is changed by above procedures,

$$V_{nm} = \begin{cases} X_{nm} + w \times r_1 \times X_{nm}, r_2 \le 0.5 \\ X_{nm} - w \times r_1 \times X_{nm}, otherwise \end{cases} \quad (4)$$

Where, new estimation (V_{nm})of the element with m^{th} dimension of the individual (n^{th}) is the quality estimation of the component of individual, r1 and r2 are arbitrarily picked qualities in [0, 1], and w is the latency weight.

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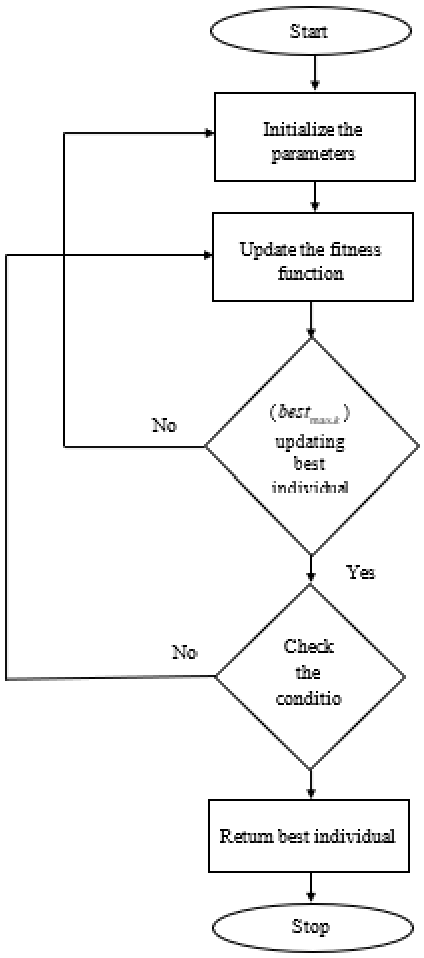

Figure 2. Process of Improvement Bull Optimization

On the off chance that there is no improvement in various cycle, the calculation re-instates the whole crowd. If the best bison is improving its positions, the calculation verifies whether the halting model is come to. If our best buffalo fitness ( ) meets our exit criteria, it ends the run and provides the location vector as the solution to the given problem. Some of the high points of this new algorithm are its ease of implementation, ability to search both locally and globally at the same time, use of relatively few parameters, flexibility and fast rate of convergence. The Algorithm flowchart is presented in Figure.

The algorithm of improved bull optimization is following,

Algorithm 1	**Improved Bull Optimization**
Step 1	Initialization: Inconstantly place buffalos to nodes at the solution space $X_{nm} = X^{\max}{}_{m} - r \times \left(X^{\max}{}_{m} - X^{\min}{}_{m} \right)$ Here, i = 1….N; j = 1…..d N is the quantity of people, d is the quantity of measurements for specific issues, and r is an arbitrarily picked parameter in [0, 1].
Step 2	Update the fitness function of bull $w.k+1 = \frac{(w.k + m.k)}{\pm 0.5}$
Step 3	Update the location of buffalo k ($best_{\max .k}$ and $best_{ini.k}$) using (3) $w.k+1 = \frac{(w.k + m.k)}{\pm 0.5}$
Step 4	Is best individual is updating? Yes, go to step 5, if No, go to step 1
Step 5	If checking criteria is satisfied, continue step 6, else go to step 3
Step 7	Output best individual

4.2 Computation of each node based on multiple constraints using clonal selection Algorithm

The CSA is a hypothesis used to portray the working of gained resistance, explicitly the decent variety of antibodies used to guard the living being from invasion. This hypothesis proposed by Burnet, expressed that antibodies generation is the choice procedure activated by antigens as their adversaries The hypothesis indicates that the living being have a previous pool of heterogeneous antibodies that can perceive all antigens with some degree of particularity [3, 4, 6, 7]. A counter acting agent at that point synthetically ties to the antigen if its receptors coordinated to an antigen. This synthetically restricting makes the phone clone, duplicate and produce more cells with a similar receptor. During the cloning stage, cells hereditary changes happen and advance the match or liking with the antigen. This permits the coupling capacity of the cells to improve with time and introduction to the antigen.

Let we consider the optimization problem of one M-dimensional function optimization,

$$Q:\min F(N) \qquad (5)$$

Here, $N=[N_1,N_2,....,N_n], N_m \in [X_n,Y_m], m=[1,2,...,M]$. in the feeling of vaccination, the target work F (N) compares to antigens, while factors relate to elective Antibodies. Factors are encoded to the person. $V_i(i=1,2,....,N)$ of the cloning immune, and $V_i=[V_{i,1},V_{i,2},....V_{i,n}]$, N is the size of the population. So the optimization problem of (6) is translated into:

$$Q:\min F(N)=F[V_t(N_m)] \qquad (6)$$

Also, this CSA haves five steps, which is following

Step 1: Calculation produces a lot of up-and-comer programs (P), which comprises of the subset of memory cells (M) and the remaining groups (G).

Step 2: Calculation picks n-set of people P which are with high affinity.

$$P(m)=\{V_{m,1},V_{m,2}.........,V_{m,n}\} \qquad (7)$$

Step 3: P(m) can produce an new antibodies group during complete the cloning operation and cloning death and selection operation.

$$P(m+1)=\{V_{m+1},V_{m+1,2,}.....,V_{m+1,n}\} \qquad (8)$$

Step 4: we again update the antibodies gathering and structures the memory sets of cell M.

Step 5: For generates the new antibodies we can replace the antibodies, which have low affinity also have in candidate programs.

4.2.1 Cloning Operation

Here, we using cloning operator, in this operation we can using for population $V'=\{V_{m,1},V_{m,2}.........,V_{m,n}\}$, the cloning operation is,

$$T_C^{\ C}:\Theta(V)=[\Theta(V_1) \quad \Theta(V_2).......\Theta(V_m)]^T \ (9)$$

After cloning operation, the population can change by following equation (10),

$$V_i=\{V_{i1},V_{i2},......,V_{iq-1}\}, V_{ij}=X_i,\ j=1,2.....q_i-1 \ (10)$$

4.2.2 Immune Genetic Manipulation

The cloning algorithm varied, depends on maturity of close degree and diversity of antibodies on high frequency several of antibodies. Which have following two steps,

Variation: The variation of clonal algorithm based on antibodies and original antibodies of population is represented following equation,

$$P(T_m^{\ c}(V_t)=V'_t)=\begin{cases} p_{ij}>0 & V\in V_j \\ 0 & V_i\in V \end{cases} \quad (11)$$

Cross: In these criteria, the original antibodies are cross linked and employs the cloned antibodies,

$$T^C{}_c=(V_i,V_t)=V'_i \quad (V_i\in V_j \quad, V_t\in V\ , j=1,2,...,M) \ (12)$$

4.2.3 Clonal Selection

We can mutates the antibodies, for all i (i=1,2,…,M),

$$Y=\{V_{ij}(m)|\max\ f(V_{ij}^{\ '}), j=1,2...q_{i-1}\} \ (13)$$

Y is probability, which is replace $V_i(m)\in\vec{V}(m)\ is\ F(V_i(m)\geq F(Y))$,

$$P_s^{\ m}(V_i\to Y)=\begin{cases} 1 \\ \exp\left(-\frac{F(V_i(m)-F(Y))}{X}\right) & F(V_i(m))\geq F(Y) \end{cases} \quad (14)$$

4.2.4 Clonal Death Operation

The clonal selection process are completes, the antibodies groups are,

$$P(m+1)=\{V_1(m+1),V_2(m+2),.....,V_i(m+1).....,V_M(m+1)\} \quad (15)$$

Here,

$$V'_i(m+1)=V_j(m+1)\in\vec{V}(m+1), i\neq j \ (16)$$

$$(V'_i(m+1)=F(V_j(m+1))=\max F(\vec{V}(m+1)).V_i^{\ i}(m+1) \ (17)$$

With probability of p_d, they $V_j(m+1)$ may die. The new antibodies are randomly generated by death strategies for replace, $V'_i(m+1)$ or $V'_j(m+1)$, which are used variation or cross over strategy and it can able to produce the new antibodies. Due to this effect, we can produce the antibodies, newly.

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$$P(m+1)=\{V_1(m+1),V_2(m+1),....,V_M(m+1)\} \quad (18)$$

The clonal selection algorithm is having clone operation, immune genetic setting also selection of main operators and clonal death operation are described in pseudo-code shown in below,

Algorithm 2	Clonal Selection Algorithm
Step 1	Create the underlying immunizer populace
Step 2	Update the fitness of every antibody;
Step 3	repeat
Step 4	for every antibody in do
Step 5	Cloning
Step 6	Hyper mutation
Step 7	Selection
Step 8	end for
Step 9	Until stop condition is satisfied

5. Simulation Results

The Network Simulator (NS2) is utilized to recreate the proposed believed bunch based ideal multi-sink repositioning (TC-OMSR) method. The presentation of steering convention is investigated by various testing situations with differing number of hubs and shifting number of rounds. The proposed trusted cluster based optimal multi-sink repositioning technique for WSN using improved Bull optimization and clonal selection algorithm. The improved bull optimization and clonal selection algorithm were compared with existing techniques of Linear programming formulation (LPF), Greedy maximum residual energy (GMRE) technique also, Lifetime and unwavering quality concerned ideal sink migration (LTRC-ORC). Our model is evaluated with different network scenarios with the NS2 tool. The mobile hubs are arbitrarily sent in the system with the 2000m × 2000m network area. We consider 50, 100, 150, 200 and 250 nodes that are randomly placed in a network scenario. The nodes relate to at least one neighbors so as to convey. The transmission range is fixed for each node. Path establishment between nodes is enabled by trust values evaluation using clonal selection algorithm. or on the other hand the examination of proposed steering is appeared in below graph.

Table 1 Network Simulator of TC-OMSR Settings

Parameters	Values assigned
Number of nodes	50, 100, 150, 200 & 250
Network area	2000mx2000m
Time Interval	0.005
Data rate	512Kb
Simulation time	2000.00ms
Initial energy	100
Packet size	400bytes
Routing protocol	TC-OMSR
Antenna	Omni antenna
Layer	LL Layer
MAC version	802.11
Mobility Model	Unstable
Traffic Type	CBR

5.1 Performance Analysis

Delay: The nodes are set from 50 to 250 randomly. In Fig.3 graph is plotted between delay and number of nodes. Delay was minimized from 80% of existing technique to 30% of proposed technique. Average End-to-end delay is calculated as the delay during the successful transmission of the packets from the source to the destination. The delay includes various delays such as queuing in the interface queue, latency in route discovery, delay in the retransmission, propagation delay and delay in transfer time. The end to end delay plays a major role in routing protocols. The proposed system reduces the delay drastically due to the selecting optimal path. This delay is the time duration for a packet to travel from the application layer of the source node to the destination node. Average End-to-end delay is calculated as the delay during the successful transmission of the packets from the source to the destination.

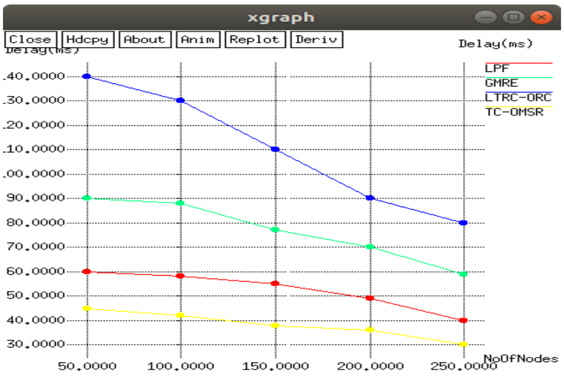

Fig. 3 Number of nodes versus delay

Energy Consumption: Fig.4 represents the energy consumption of proposed TC-OMSR technique and existing LTRC-ORC, GMRE, LPF model. When compare to previous protocol, we have minimized energy consumption level from 30% to 2%. Vitality utilization rate for sensors in a remote sensor system changes extraordinarily dependent on the conventions the sensors use for correspondences. Remote Sensor Network (WSN) is known to be an exceptionally asset obliged class of system where vitality utilization is one of the prime concerns. The main reasons for energy consumption are, for example, longer distance among the nodes and cluster head and that nodes randomly advertise themselves as cluster heads based on the energy level of the nodes.

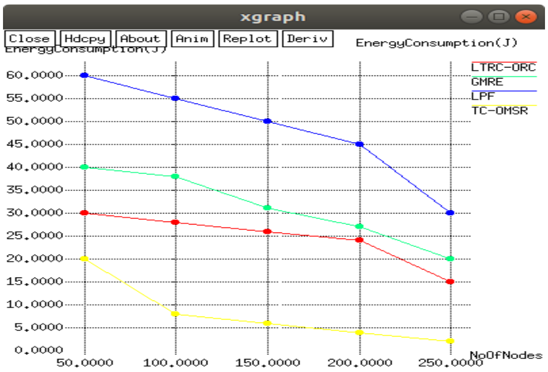

Fig. 4 Number of nodes versus energy consumption

Network Lifetime: The network lifetime was maximized from 20% to 60%. By choosing optimal path and trust node, we were increased lifetime of network in our proposed technique. We have compared our proposed TC-OMSR technique with existing model of LTRC-ORC, GMRE, LPF and graph were shown in Fig. 5

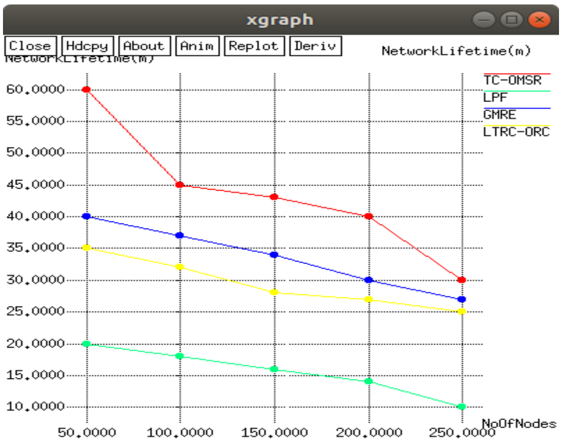

Fig. 5 Comparison graph of network lifetime with proposed and existing system

False Positive ratio: The false positive ratio was reduced from 60% of existing technique to 30% of our proposed TC-OMSR technique. Comparison graph was shown in below Fig.6.

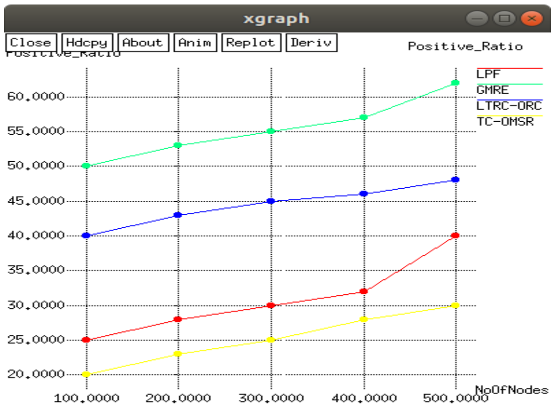

Fig. 6 Comparison of false positive rate with existing techniques

Throughput Ratio: The throughput ratio defines the rate of data packets received at a destination according to the number of packets generated by the source node for a specified period of time.

$$Throughput\ Ratio = \frac{Received\ Data\ *8}{Data\ Transmission\ Period}$$

Fig. 7 shows the comparative analysis of throughput ratio of the proposed scheme with the existing, based on the values is given below. From the analysis, it is clearly shown that the proposed TC-OMSR has improved its throughput ratio to 9.5 % which is compared with the existing system

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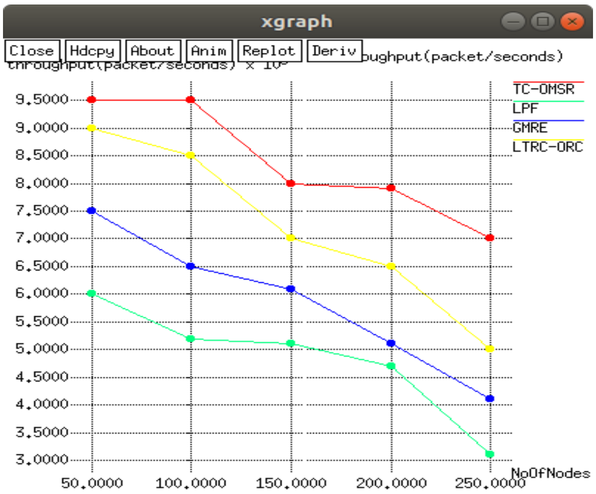

Fig.7 Number of nodes versus throughput

Packet Delivery Ratio (PDR): PDR were increased from 90% of existing technique to 99% of proposed technique. It is utilized to assess the nature of the system. It characterizes the proportion between the parcels got by the goal and the bundles produced by the source. It very well may be gotten by utilizing content, which produces the follow document and the outcome.

$$PDR = \frac{Received\ Packets}{Generated\ Packets} * 100$$

Packet Delivery Ratio is the proportion of the parcel conveyed effectively to the bundles produced at the source. The bundle misfortune rate is low if the Packet Delivery Ratio is high, which thusly prompts the more proficient steering convention. In any case, progressively interchanges, the directing convention which has high Packet Delivery Ratio may not be superior to the one with lower Packet Delivery Ratio, since the bundles which are shown up later than expected might be pointless despite the fact that these parcels are conveyed effectively to the goal. Comparison graph shown in Fig. 8.

Table 2 Comparison of Proposed and existing technique

Number of Nodes	Delivery Ratio			
	GMRE	**LPF**	**LTRC-ORC**	**Proposed (TC-OMSR)**
50	92	87	95	90
100	90	82	96	95
150	85	75	99	97
200	80	71	86	98
250	77	69	90	99

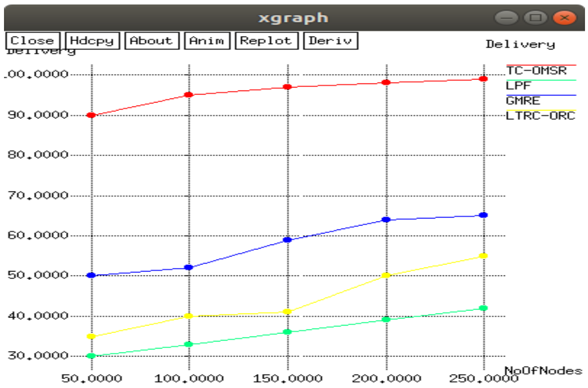

Fig. 8 Packet delivery ratio comparison with proposed and existing techniques

6. Conclusion

We proposed an trusted cluster based optimal multi-sink repositioning technique (TC-OMSR) for WSNs. proposed using Improved Bull Optimization and Clonal Selection Algorithm. By utilizing of Improved Bull Optimization Algorithm, we cluster every sensor node depend on their behaviors. Then we computed the multiple constraints are energy consumption, network lifetime, mobility and received signal strength of each nodes using of proposed Clonal Selection Algorithm. In addition, we have considered the highest trust values of sensor node as CH in cluster. The result of proposed TC-OMSR is establishes, the proposed TC-OMSR is gives high efficiency and perfect delay, energy consumption, false positive rate and network lifetime, delivery ratio, throughput to each node. Moreover, compared with the existing state-of-art techniques, the result and performance out of this proposed method is highly efficient.

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