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Optimized routing technique for IoT enabled software-defined heterogeneous WSNs using genetic mutation based PSO

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ABSTRACT

Now a days, emerging trends in the field of wireless sensor networks (WSNs) tend to work on more complex scenarios and flexible network models as the conventional WSN systems that are based on a classical arrangement of sensors. Generally, these networks have different limitations such as control node election, data aggregation, load balancing during data collection etc. The load balancing depends on the effective routing techniques which provide an optimum path to transmit the data such that the minimum amount of energy should be consumed. The control nodes are responsible for assigning the task and data transmission in the cluster-based routing techniques and the selection of the control node is an NP-hard problem. To resolve this problem, an adaptive particle swarm optimization (PSO) ensemble with genetic mutation-based routing is proposed to select control nodes for IoT based software-defined WSN. The proposed algorithm plays a significant role in selecting the control nodes by considering energy and distance parameters. The proposed work is implemented for the heterogeneous networks having different computing power accompanied by single and multiple sinks. The experiment was carried out on the scale of the performance matrix such as fitness value, stability period, average residual energy, etc. The simulation result of the proposed algorithm outperforms over other algorithms under the different arrangements of the network.

1. Introduction

A wireless network typically consists of several individual entities and is considered as the backbone of sensing in a remote and harsh environmental location where human intervention is not possible. The sensing task is independent of location and the sensors may have to operate in a harsh environment where the wired network can be frequently damaged and can't be repaired. The wireless sensor network (WSN) consists of a chip-based electronic module called a sensor node to monitor and cooperatively share the collected data to the control station or server. The main station typically called a base station, control server, or sink node which can observe and analyzed the data. The radio signals are the medium of communication between the sensors. Every sensor nodes are having limited storage capacity, processing intelligence, communication bandwidth along with the non-replaceable battery [1]. As the wide effect of advancement in the micro-electro-mechanical System (MEMS) technology it has boosted the density of sensors for deployment. The WSNs are not just decreased the cost, maintenance, and delay in deployment but also effective for any environment where human reach is impossible. The sensors used to recognize or monitor an assortment of environmental parameters such as light, noise, pressure, temperature, humidity, soil composition, air or water quality, traits of an object such as size, weight, position, speed, and direction [2, 3]. The origin of sensor networks is said to be motivated by military applications which range from small ground surveillance of the battlefield for target detection to large deep ocean monitoring. Furthermore, this system is adopted by many application domains listed as environmental monitoring, health care applications etc.

The sensor networks are evolved as an intelligent system for monitoring and sensing as software-defined sensor networking (SDSN) and the Internet of Things (IoT). A software-defined-wireless sensor network (SDWSN) comprises of the software-defined sensor nodes that can progressively reconfigure and their functions as well as properties by stacking various projects on request concurring ongoing detecting demands. SDWSN nodes outfitted with a few unique kinds of sensors can attempt an assortment of detecting errands as per sent and enacted programs because of the revolution of 5G networks and the mobile communication integrated with the sensor Nodes. SDWSNs empower

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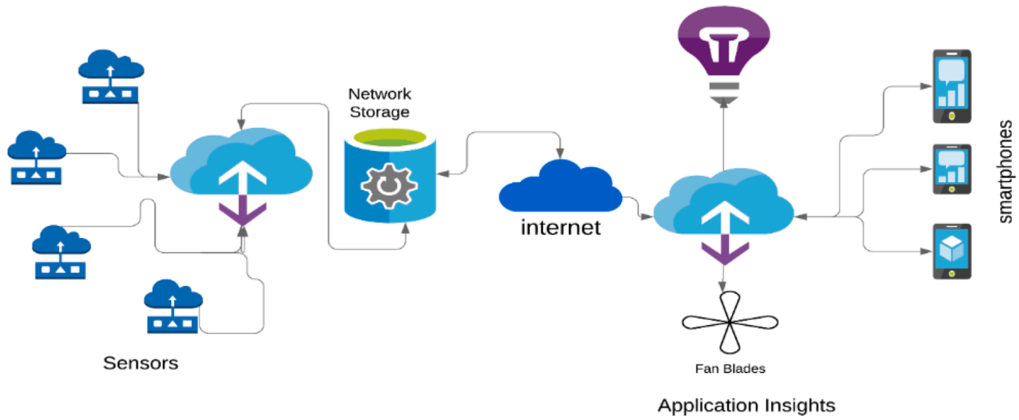

Fig. 1. **IoT Supported SDSWSN Architecture.**

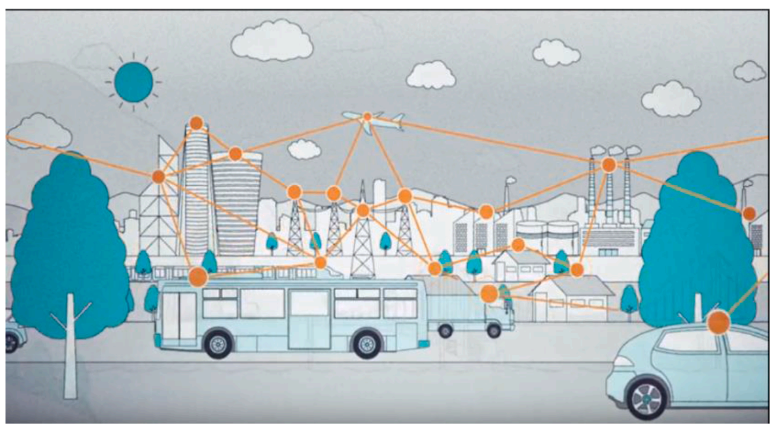

Fig. 2. Devices range from ordinary household objects, vehicles to sophisticated industrial tools that are connected via the internet

control of the program in the network and virtualization of the network hardware by separate the control plane and information plane [3]. In software-defined networks, control knowledge is taken out from information grid gadgets and executed sensibly brought together controller (network working framework, can be shaped by circulated bunches), which interfaces with information plane gadgets through given standard model interfaces. The network administrators run programs on the controller to naturally oversee information plane gadgets and enhance network performance efficiently and prolonged. These engineering empower enacted control plans to create an alterable detecting system, making the streamlined model network deployable on board in wireless networks, which makes the eventual fate of software-defined WSNs brilliant. In many applications, the effective deployment of sensors is performed in the harsh periphery, which makes sensor node replacement a complex, inexpensive, and challenging work. In this manner, in numerous situations, wireless senor nodes should work without battery substitution for a significant period. Therefore, energy efficiency is essential for SDWSNs. The features of SDWSN is the directly programmable, agile abstracting control plane, centrally managed, programmatically configured, open standards-based vendor allows network administrators to automatically and dynamically manage and control a large number of the network [4].

The new advancement in the field of SDWSN and communication technology such as 5G has opened the gate of traditional wireless sensor technology to a very extent. The wireless sensors, cloud computing, artificial intelligence, and other supporting technologies have set-up collectively a new paradigm of information processing as shown in Fig. 1 because of the real-time integration of the data this transformation has increased the demand for this prototype. It's an arrangement consisting of interrelated computing and processing devices, mechanical units, computerized equipment, that can move and process the information over the system without human intervention. It includes artificial intelligence as well as the design making from the aggregation of the collected data. IoT is an innovation that can lead the communication of the devices to the next level and it doesn't limit to the senor network. It evolves more like smart systems having intelligence, for example, industrial robots, home automation systems. where the house-hold devices have chip-based programming [4]. They can communicate within themselves and execute the desired task as per human intelligence, based on the sensing environment. Take your smart fitness band, having some sensor to check your heart rate once you come from the morning walk. It will automatically trace and sends the information to all household devices. They can adjust themselves according to the current biological condition of the person like to drop- down or raise the room temperature. In recent years the notion is shifted towards the Internet of things.

The wireless sensor network is seen as its integral part of the IoT system. Several developments are going on based on the concept of IoT such as smart cities, driverless cars, automated industrial equipment, and many more [5]. The demand for IoT increases because of the real-time integration of data. IoT infrastructure has also compelled the dense structure of Wireless Sensor Network (WSN). The Internet of Things (IoT) describes the network of physical objects "things" connected over the Internet.

Fig. 2 demonstrates a scenario where IoT plays a major role. A shopping app will be linked to a smart fridge, which could able to determine what food is required (based on preceding consumption and present monitoring) and send the grocery listing straight to a person's phone. It might be possible the smart fridge could order commodities automatically without any human intercommunication. In the Internet of Things, devices have sensors and software that facilitate the collection and exchange of data through the internet.

1.1. Motivation

Monitoring is considered a crucial task in every domain of technology. Advancement in sensors makes ease to monitor the harsh or unattainable environment. The IoT and 5G technology are seen as the emerging technology of this era according to the gartners curve which can help in the advancement and upgradation of the current wireless sensor network. It will change the way of communication and will highly impact sensor technology. Although any technology is having its limitations and constraints. The IoT enabled software-defined sensor network comes with limited potential power or battery which might be non-replaceable in a most deployment scenario. Efficient energy consumption can use to tackle this problem and helps to prolong the network lifetime. From the studies, it shows that effective routing techniques can lead to a better energy consumption model with this motivation an energy-efficient routing technique for such IoT enabled software-defined wireless sensor network is proposed. The contribution of the proposed work is given as followed:

- ü A Genetic mutation-based particle swarm optimization is proposed for selecting the control nodes for the heterogeneous SDWSN were the energy heterogeneity of sensors is taken into consideration.
- ü The proposed fitness function is based on the energy and distance parameter of control nodes, control sink, and the common node. The heterogeneity factor is also added for a better tradeoff.
- ü The proposed method is applied to three-tier distributed energy heterogeneity in terms of potential power for the heterogeneous network.
- ü The proposed work first implemented for a single sink heterogeneous model and further it is tested over a multiple sink heterogeneous model.
- ü In this work, an adaptive inertia tuner having dynamic convergence property based on (δ) seed value is proposed.
- ü The comparative analysis of proposed work is done on the performance matrix such as fitness value, stability period, dead and alive nodes, average residual energy, the packet sent to CS and inertia weight.

Rest of the paper organized as follows: Section 2 discusses the literature review of the paper. The conventional PSO is discussed in Section 3. Section 4 discusses the system and energy dissipation model and the proposed method is discussed in Section 5. The simulation results and their analysis is given in Section 6 and the paper is concluded in Section 7.

2. Literature review

Minimizing power consumption is an important objective in a wireless sensor network (WSN) where one of the possible ways to achieve this objective is efficient routing for data transmission. The energy balance in communication is the significant innovations to extend the lifetime of software defined wireless sensor networks. Although the effectiveness of a particular routing algorithm mainly depends on the capabilities of the sensor nodes, control node, and the dedicated application requirements. Clustering plays a very vital role in energy balancing between the control server, control nodes, and normal nodes. The clustering-based routing algorithms can be considered as the most sophisticated categories which maintain load balancing among all types of nodes. It can be seen as the master-slave models where common nodes as a slave unit in the network will send the data to control nodes, control server working as the master. The traditional clustering based routing techniques have always focus on the selection of the control nodes (CN). The selection of control nodes in various routing techniques depends on the different formulation and the parameter. The proposed algorithm solves the art of state over the different clustering based routing techniques which are having deployment ranges from classical WSN, the software-defined network and to the newly adopted internet of things.

Heinzelman et al. introduced a classical clustered oriented routing algorithm namely "low energy adaptive clustering hierarchy" abbreviated as LEACH [6]. This algorithm operates dynamically and this is very first of its kind of protocol. LEACH has adopted a probabilistic, hierarchical, one hop and distributed protocol approach. This technique used a randomization strategy in the distribution of energy between the nodes of SDWSN by the selection of local control nodes rotationally. This paper discussed that the LEACH protocol executed in two-phase, which are set-up phase and a steady phase respectively. The control node selection starts at every sensor node based on some probability-based random number. Although this method having some limitation as it ignores other parameters for selection of the control node, hence its leads to unbalance distribution of CNs. Also if the control node is far away from the control server then energy depletion is more so the distance plays an important role in control node selection. Heinzelman et al. proposed the LEACH-C, which is a centralized cluster-based routing protocol. As the LEACH was one of the liked protocol in the industry which somewhat tends toward the centralized model of selecting the control node, many research tries to find out modified LEACH version which different control nodes selection strategy. Although this method suffered due to poor network grouping and leads to a hotspot problem [7]. Ran et al. introduced LEACH-FL, a fuzzy logic-based two-level hierarchical control node selection techniques [8] where the probability of selecting the control nodes is calculated by considering the fuzzy logic. Also, this method evades energy parameter consideration due to which energy-centric efficiency is not obtained. Younis et al. in earlies after LEACH, introduced "HEED" A hybrid approach that is energy efficient and having a distributed strategy based clustering. It included residual energy as the parameter for control node selection. There work concluded that apart from the residual energy their intra-cluster communication cost help to minimize the energy consumption and have a part in joining the nodes in the clusters. The main advantage of this methodology is to exploit the multiple transmission energy availabilities at the sensor level [9]. Since the HEED clustering adopted a secondary parameter for cluster selection, it cannot give the guarantee for optimal control node selection in term of minimizing energy consumption and prolonging the lifetime of the network. Xiaorong et al. proposed the Hausdorff clustering mechanism for WSN [10]. It considered the node location, network connectivity and communication effectiveness as the parameter for control node selection. The main task starts here now the role of the control node is to optimally schedule among the cluster members. Since the technique used is comprised of the greedy based algorithm it comes with the time complexity which might take a long time to execute the algorithm.

Singh et al. discussed PSO-C swarm intelligence based optimization algorithm is known as particle swarm optimization which simulates the social deportment of the group of birds, fish to find the food particle in global search space [11]. In this work, the aim is to localized control nodes surrounding the center density. The PSO-based method is to localize the head nodes around the center of cluster density. However, it reduces distance among the clusters. Moreover, the congestion and the retransmission processing for packets have an adverse effect over the lifetime of the sensor network lifetime. Wang et al. discussed a variable dimension based PSO i.e. VD-PSO. The VD-PSO double the number of tryst points over the dimension of each particle and save the coordinates of control nodes [12]. The evolutionary proceeding helps in obtaining the shortest path as optimal. Because of the unpredictability in the number of tryst points, the dimension of particles is diverse. Xiang et al. proposed NWPSO which is a variant of PSO [13]. It uses the concept of fitness function by considering the distance and the energy transmission within a common node, control node and the control server. Notably, it depends on the variance on inertia function as a non-linear weight to select the control nodes from the network. It has taken inertia as the parameter for the modification in the base PSO it proven more flexible in term of modification. Fitness function doesn't consider the effect of distance between control nodes and sink node which play a vital role in the fitness of particle in PSO.

Mohemed et al. addressed the issue of the energy hole problem that occurred by routing protocol which leads to the early termination of network existence [14]. This is due to the uneven tradeoff between distance and energy. The author suggested OHCR as on-hole children reconnection and On-hole alert for local and global nature. Whereas the said method has been affected by topology reformation overhead. Ahmed et al. introduced a novel particle swarm optimization algorithm for dynamic WSNs to hasten packet transfer and decrease energy losses [15]. The Euclidean metric plays a vital role in particle positioning along. The proposed PSO variant is executed in three stages where the distance between non dominated solutions and particle positioned using Euclidean metrics are taken into consideration for the calculation of personal and global solutions. As this method have accelerated packet transfer rate but packet loss rate has not been improved which leads to the consumption of more energy by retransmission of packets. Kumar et al. proposed integration of the genetic algorithm with the PSO for performance enhancement of the network [16]. It proposed a fork and join model for the selection of control nodes from the sensors. This paper has traces of different parameter consideration for the control node selection. Like it has a randomized way for the selection of CNs in each iteration and it effectively converges particles using adaptively changing the inertia weight function. This plays a vital role in updating the direction of swarms. Although Energy and distance trade-off not balanced while fitness calculation. Jothikumar et al. presented an EODC protocol in which energy optimization is implemented over Dynamic clustering using the PSO technique [17]. The fitness value is calculated over parameter consideration of node location, link quality, the energy of inactive and active node. Manhattan distance is used in the computation of fitness value which is carried out at the base station of the network. Although the sole purpose of EODC is to minimize energy consumption and an increase in the number of packet transmission. The shortest path is identified based on the energy of the route which can lead to uneven clustering and energy balancing is affected in extreme cases.

Ruan et al. used PSO by uneven dynamically selection of clustering for multi-hop routing for WSN, and the result shows it has achieved energy consumption in a more balanced way and prolongs the network lifetime [18]. PSO has played an important role to provide a scalable, efficient and modern protocol approach for the dynamic working of the network. Multiple cluster creation leads to congestion issue which increases the waiting time for packet and consumes high energy. Wang et al. discussed a routing scheme using a variant of PSO for heterogeneous WSN [19]. An energy center searching using particle swarm optimization (EC-PSO) is introduced. This method helps to avoid the energy hole problem. In this approach, cluster head selection is using a geometric method. Notably, it executes in two steps in the first step cluster head is selected using a geometric method while in the second phase cluster head selection will follow the PSO algorithm for choosing nodes that are at resembling distance to energy centers. Further for data communication, a greedy algorithm is used for creating a chain or tree. The greedy approach along with two-level clustering increases costs over computation time since the greedy algorithm is not always efficient. Pavani et al. introduced SCBPR a secure cluster-based routing protocol using PSO for making cluster head selection more secure [20]. The proposed method was formatted based on a hexagonal sensor network, this work focuses on clustering along with the security of cluster heads. The main issue which is brief in this method is the establishment of a secure routing path for packet transmission and minimal energy consumption in a packet transfer. However, this security mechanism has put overload of checksums, encryption and decryption by which the packet drop rate is increased and put up the adverse effect of energy consumption.

Tlholiso et al presented a multi-hop particle swarm optimization based routing algorithm for WSN using the concept of energy reaping [21]. This technique uses the worst-performing node of the network to prolong the network lifetime. The worst node which has the lowest energy is pushed into the halt state where it's been idle for the time being until its energy is higher in comparison to other nodes. This method tries to balance the equality of energy consumption within the network and increases the stability period of the network. While this method does not give an effective routing path as it doesn't consider the distance between different entities of the network like the distance between common nodes, control node, and sink node which play an important role in the network [21]. Bouyer et al. presented a combined K-Harmonic Means clustering method with an enhanced Cuckoo Search and particle swarm optimization [22]. Cuckoo Search is intended to the global optimum solution using the Levy flight method by adjusting radius dynamically and astutely. Therefore, it is faster than the standard cuckoo search. Cuckoo Search is effected with PSO to evade falling into local optima. This method solves the local optima problem of KHM with notable development in efficiency and stability. In the fitness function calculation, it does not consider the node density, which results in a higher cost of execution. Sha et al. discussed a type of low-latency data gathering method with multi-sink for sensor networks [23]. It divides the network into several virtual regions consisting of three or less data gathering units and the leader of each region is selected according to its residual energy as well as the distance to all of the other nodes. Only the leaders in each region need to communicate with the mobile Sinks which have effectively reduced energy consumption and the end-to-end delay.

The proposed work based on the particle swarm optimization and genetic mutation-based routing technique for IoT based software-defined WSNs. The proposed algorithm executes in two-phased where the first phase is stabilization. In this phase, the network aims to select the optimal number of control nodes among all the common nodes based on the merit of fitness value. Since the fitness value calculation is based on distance and energy parameters it can be seen as the utmost pragmatic scenario for effective control node selection. The second phase is energy dissipation in which the sensor nodes simulate the real-time energy dissipation model given, which used to calculate the estimated stability period of the simulated network.

3. Conventional PSO

In 1995 Kennedy et al. introduce a population-based metaheuristic global search optimization technique known as Particle Swarm optimization. Originally they were working to develop a model to describe the social behavior of creatures like a flock of birds and a school of fishes. However, their model was capable to do optimization test so they proposed a new optimization technique. This optimization inspired by the behavior of social creatures to find food particles in the global search space. Certainly, it mimics the navigation pattern which aims to find the best solution by Communication and learning between them [21]. The PSO works in a multidimensional search space were each particle initially consists of two entities i.e. position vector and velocity vector. The initial position of the particles is considered as the potential solution. After PSO starts its functionality the particles opt to moves towards the food location or global minima iteratively. In every iteration, optimal personal best as pbest and global best as gbest is the best solution which is calculated using effective fitness function helps the particles to converge toward the food. The particle which succeeded in reaching towards the food particle is entitled to communicate its opted path or best solution to other particles so that other particle will able to update their position vector and velocity vector toward food particle. All particles move continuously towards the best solution by updating their respective pbest and gbest solution. As the PSO terminated on some defined condition all the particles are reached nearby to an optimal

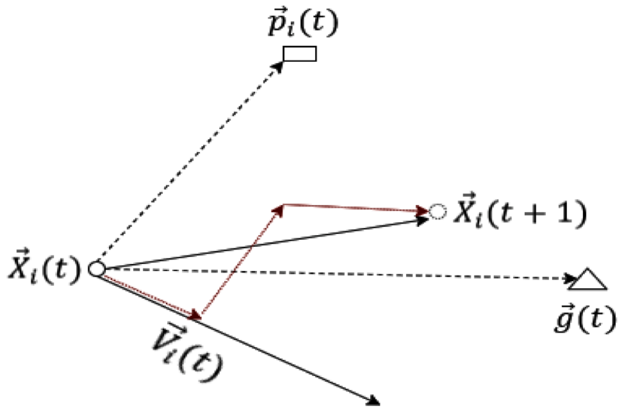

Fig. 3. particle movement from location *X (t)* to *X (t+1)*

solution [22].

The PSO initialized with a defined N number of random particle and each particle is being allocated with initial position and velocity vector as shown in Fig. 3. Where $\overrightarrow{X}_i^j$ represents the position vector for i^{th} particle ($1 \leq i \leq p$) in j^{th}dimension at 0^{th}generation and its formulated by equation (1)

$$X_j^i(0) = X_{min} + (X_{max} - X_{min}) \times r \tag{1}$$

The $X_{min}$is initialized with value 0.0 and X_{max}initialized with 4.0 were r is the random number between 0 and 1 to assign the randomize location to the particle. Velocity vector $\overrightarrow{V}_i(t)$ also defined in the same way as to position vector, the velocity of i^{th} particle in j^{th} dimension at 0^{th} generation is formulated using equation (2)

$$V_j^i(0) = V_{min} + (V_{max} - V_{min}) \times r \tag{2}$$

The value of $V_{min}$and V_{max} are assigned -4.0 and 4.0 respectively were r is the random number between 0 and 1. This value is used in specifying the limits of the given multidimensional search area concerning the randomly calculated position and velocity [23]. The position of $\overrightarrow{X}_i(t)$particle is getting renewed in each $t+1$ iteration as shown in fig. the position $\overrightarrow{X}_i(t+1)$ is calculated using the updation rule. In PSO position and velocity is updated using the following formula which consists of previous communicated learning of particles. Velocity update rule PSO:

$$V(t) = \omega \times V_i(t-1) + c1 \times r1(Pbest_i(t-1) - X_i(t-1)) + c2 \times r2(Gbest - X_i(t-1)) \tag{3}$$

Position update rule PSO.

$$X_j^i(t) = X_i(t-1) + V_i(t) \tag{4}$$

Genetic Mutation Operator (GMO): Genetic algorithm is having different feature were the mutation operator is one of its feature used to restrain the genetic diversity along with best feature selection for its successive generation. It remodels the sequence of particles of the current state. Here it will first divide the particles, then a two-step swap mutation operator is applied. Within the process rationally selected two positions are swapped and the remaining position arranged as per the sequence. This method ensures the legal heirs or child with the best sequence while restraining their characteristics [13].

4. System and energy dissipation model

An IoT supported software-defined WSN model is observed as an operational WSN architecture as a digraphGn = (V, L) [11]. In the given model *V* specifies the vertex set, which having Software-defined WSNs or common nodes, control nodes (CNs), and the control server (CS) or sinks node. They are randomly distributed within the specific monitoring area. The L in the Graph specifies the collection of directed transmission or communication link that is dedicated to the transmission of the collected data from common nodes to the control node (CN) and the control server [19]. The assumptions of the SDWSN environment are listed as follows.

- Ø IoT derived SDWSNs committed to detecting various sensing targets like temperature, moistness, etc. are randomly disseminated inside the equivalent geological area of the SDWSN.
- Ø The participating IoT enabled SDWSNs must have a universal identification number (UIN) [13].
- Ø Each unit in the IoT deployment having SDWSN capabilities is dedicated to sensing the collect the data from the surrounding environment and send that data to the control node (CN), control server (CS) [20]. Whether it's a normal sensor unit or the dedicated sensor unit, each SDWSNs have equal capability.
- Ø In the unattainable deployment, all units including the control node are equipped with a non-replaceable battery. The energy distribution within all nodes is fairly allocated.
- Ø Traditional network configuration suggests that the control server is having external energy resources since it's the dedicated server to carry out all processing of the network [14].
- Ø The proposed network only considered a heterogeneous environment with a predefined amount of energy. It considered 3-tire heterogeneity by consisting of *n* number of sensor nodes where tire-3 nodes have more initial energy than the tire-2 nodes which further have higher initial energy than tire-1 nodes. The proportion of normal nodes in the network is highest with advanced nodes having the least count.

The proposed and existing sensor networks are deployed heterogeneity scenarios in terms of the preliminary energy of the nodes. The network consists of *n* number of sensor nodes. Here, three tiers of heterogeneity are considered i.e., advanced, intermediate, normal. In the proposed scenario the advanced nodes have high initial energy than the intermediate and normal nodes and the intermediate nodes have more preliminary energy than the normal nodes. E_{adv}, E_{int}, and E_{nrm} symbolize the energy of the number of advanced, intermediate, and normal nodes in the network, respectively. This energy consideration satisfies the inequality$E_{nrm} < E_{int} < E_{adv}$. In the present model, n_{nrm}, n_{int}, and n_{adv} signify the total number of advanced, intermediate, and normal nodes, respectively. The number of normal nodes is highest in the network and intermediate nodes are also more than the advanced nodes which satisfied the inequality $n_{nrm} > n_{int} > n_{adv}$. The E_0 describes the preliminary energy of nodes. The total energy of the network is represented by E_T. The intermediate and advanced nodes are Ψ and ω times higher energy than normal nodes. Ψ and ω describe the energy fraction of advanced and intermediate nodes, respectively. The q and q_o describe the proportion of advanced and intermediate nodes, respectively. The number of advanced, intermediate and normal nodes are n^*q, n^*q_o, and $n^*(1 - q - q_o)$, respectively. The energies of the E_{adv}, E_{int}, and E_{nrm} are as per the equations $E_o{}^*(1 + \omega)^*n_{adv}$, $E_o{}^*(1 + \Psi)^*n_{int}$, and $E_o{}^*n_{nrm}$ respectively. The preliminary energy of advanced nodes is more by a factor of (1 + ω) and by a factor of (1 + ψ) for intermediate nodes. The total energy of the 3 levels of a heterogeneous network is $E_T = E_{adv} + E_{int} + E_{nrm}$ where E_T is $E_o{}^*n^*(1 + \Psi^*q_o + q^*\omega)$.

Energy dissipation: The considered environment of IoT enabled SDWSN is the most widely adopted data transmission model which is based on the path loss concept and the model consists of both multipath (*Emp*), fading (d^4 power loss), and free space (*Efs*) (d^2 power loss) channel utilization. The energy consumption of the model depends on the distance (*d*) between two entities. The i^{th} the transmitter is having the (*Xi*, *Yi*) coordinate, and another j^{th}*the*receiver is having the coordinates (*Xj*, *Yj*). The distanced can be calculated by using the Euclidean distance Formula and is formulated as:

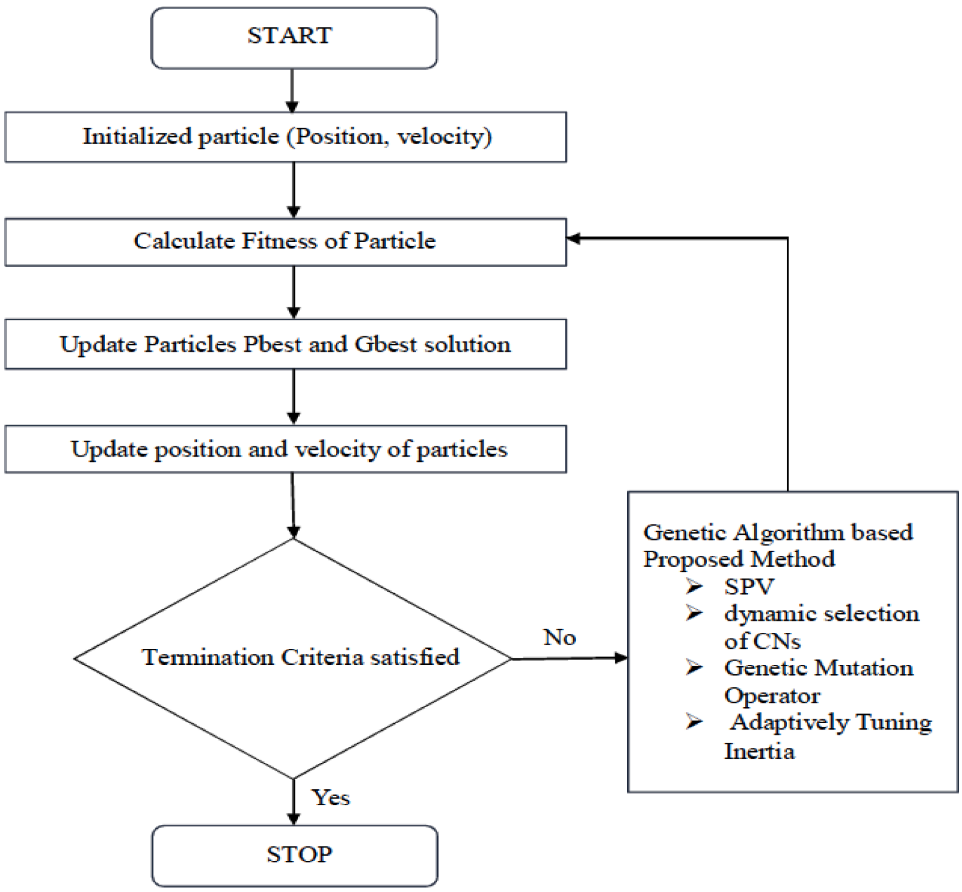

Fig. 4. workflow of the proposed method

$$\sqrt{(Xj - Xi)^2 + (Yj - Yi)^2} \tag{5}$$

In this work, we use the power control mechanism if the calculated d is lower than the threshold (d_0), then the free space model is used else multipath model is used to remunerate the path loss concept [11]. To send a l-bit message over the distance d, energy dissipation to transmit the data can be calculated for the common SDWSN node (E_{TXN_SDWSN}) is given as follows:

$$ETXN_{SDWSN(l,d)} = \begin{cases} k \times Eelec + k \times Efs \times d^2 & d \le d_0 \\ k \times Eelec + k \times Emp \times d^4 & d > d_0 \end{cases} \tag{6}$$

The energy transmission for the control node of l-bit data packet is as follow:

$$ETXN_{CN}(l,d) = \begin{cases} k \times (Eelec + E_{DA}) + k \times Efs \times d^2 & d \le d_0 \\ k \times (Eelec + E_{DA}) + k \times Emp \times d^4 & d > d_0 \end{cases} \tag{7}$$

The E_{TXN} is known for the energy required for transmission, control node consume energy E_{DA} for data aggregation whereas the distance between two sensor units of SDWSN or between nodes to the control server is defined by$d$. The energy dissipates per bit to run the transmitter, or a receiver circuit is defined by$Eelec$. It depends on various circumstances such as modulation, source coding, filtering, including signal spreading. Efs plus Emp depend on the transmitter amp model [13].

Here l is the packet size to be transmitted and d_0 is the threshold value for transmission distance and usually formulated as below

$$d_0 = \sqrt{\frac{Efs}{Emp}} \tag{8}$$

The radio transmitter consumes the following amount of energy to receive an l-bit message:

$$E_{RXN}(l) = l * E_{elec} \tag{9}$$

5. Proposed method: genetic mutation based particle swarm optimization (GMPSO)

The proposed method is highly motivated by nature-inspired routing techniques where the behavior of social creatures is mimicked. The routing techniques are said to be effective when these can transmit the data by selecting an effective route from source to destination. The clustering-based routing is one of its kind highly operated techniques that has shown progressive efficiency in terms of vitality/energy utilization, fault tolerance, and robustness. In clustering-based routing election of control nodes are termed as an NP-hard problem therefore the challenge remains to attain the solution for the present problem. Optimization is one of the solutions for the presently rising problem. There are different optimization techniques, some of them are motivated by nature-inspired social behavior of creatures like a flock of birds, school of fishes, naked mole-rat, ant colonization, and many more. The Genetic Algorithm is the domain that can use following the proposed optimization technique to efficiently determine the best solution. The genetic algorithm is inspired as the evolutionary algorithm which helps to evolve as a better solution by inheriting the fittest solution from each generation.

Algorithm: GMPSO
$k = 0$ Iteration Counter
$c1$, $c2$ =2 Social constant ;
N <= Number of particles ;
E_i<=Apply 3 tier energy heterogeneity and Assign Fc factor for each.
for each *ith*number particle ***do***

(*continued on next page*)

Table 1
Simulation Parameters used in the Heterogeneous network

Type	Parameter	Value
Network	Deployment Area (m)	100*100
	Location of Control sink (in case of single sink)	50*175
	Location of Control sink (in case of multiple sink)	(100,150), (200,100), (100,200), (150,100)
	Initial energy	1 J, 1.5 J, 2 J
	Number of nodes	100
	Constants	$q = 0.1$, $q_o = 0.2$, $\omega = 0.5$, $\Psi = 1.0$
Application	Data packet size	1000
	advertisement packet length	250
Radio model	*Eelec*	50 nJ/bit
	Efs	10pJ/bit/m^2
	Emp	0.0013 nJ/bit/m^4
	EDA	5nJ/bit/signal
	d_0	75m
Proposed model	IP	50
	Number of iteration	40
	C1	2
	C2	2
	t	25%
	The maximum value of ω	0.94
	Number of iteration	40

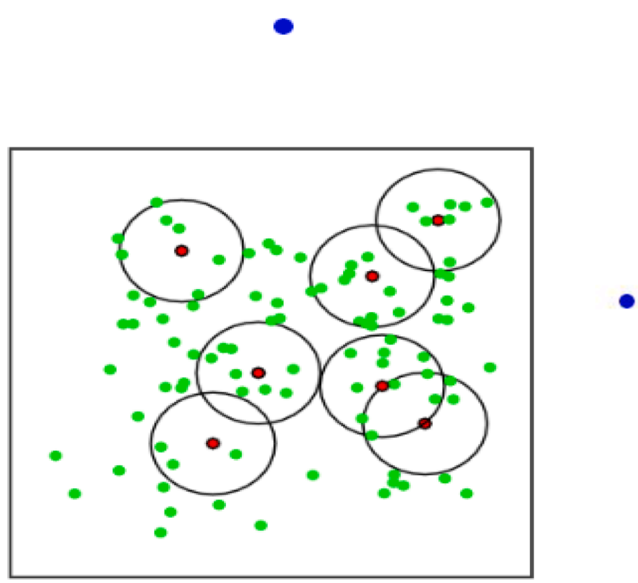

Fig. 5. Clustering using GM-PSO- for a single sink

(*continued*)

Arbitrarily assign position vector $\vec{X}_i^j(k)$ and velocity vector $V_j^i(k)$;
$rVar(i) = Random(minCN, maxCN)$
$S_i[k] = SPV_i[\vec{X}_i^j(k)]$
Find the heterogeneity factorFc for current particle.
Apply fitness function $fitness(S_i[k], rVar(i), Fc)$
$Pbest_{i=}\vec{X}_i^j(k)$
EndFor
$Gbest_i = max(Pbest)$;
While discontinuation criteria not satisfied ***do***
$K = k + 1$
$inertia_i = inertia_i - \delta \times inertia_i{*}Gbest_i$ (δ =seed value)
For each particle ***ido***
Update $\vec{X}_i^j(k)$
Update $\vec{V}_i^j(k)$
$S_i[k] = SPV_i[\vec{X}_i^j(k)]$
Forj = 1 to ***tdo***
$G_i(k) = GMO(S_i[k]), j(k))$

(*continued on next column*)

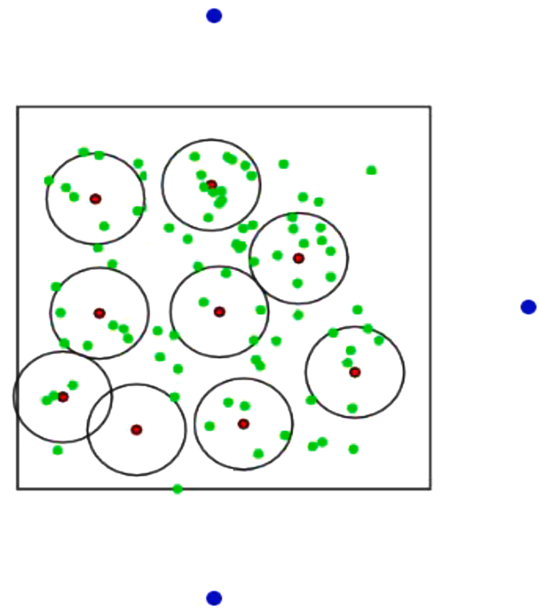

Fig. 6. Clustering using GM-PSO- for multiple sinks

(*continued*)

Apply fitness function $fitness(G_i[k], rVar(i))$
EndFor
$S_i[k] = MAX_{i=1} \leq_n Gbest_i(k)$ //Merge all offspring into fittest particle
Update $Pbest_i$, $Gbest_i$
EndFor
Project$gbest_i$particle
Endwhile

The IoT enabled SDWSN equipped with sensor nodes having two functionalities, i.e., nodes can collect and transmit the data to control nodes or base stations for further processing. The control nodes are selected from the common nodes. As following the workflow chart given in Fig. 4 the proposed GMPSO executed with a predefined number of N particles which is an individual network entity. Particles are generated randomly using equation 1 and 2 where X_i represents the position vector andV_i is the velocity vector of i^{th} particle at iteration t in j^{th} dimension. Every i^{th} particle attended with a random number (*rvar*) of control nodes. *rvar* is within a limit of the minimum (*minCN*) and maximum (*maxCN*) number of control nodes. Fori^{th} particle $rvar_i$ elements are considered as control nodes. The randomly generated position vector and a velocity vector of i^{th} particles are of continuous value. The sequence position vector $S_i(t)$ as discrete values are further generated by applying the smallest position value (SPV) rule over the corresponding position vector $X_i(t)$.The primary role of the SPV rule is to assign indexing for the position vector $X_i$of each randomize generated particle. Although this sequence position vector is used for the clustering .we pick first $rvar_i$ as control nodes from sequence vector indexes. After cluster nodes selection the control nodes CN_i are enumerated with their corresponding common nodes. This grouping is done by finding the closest control node for each common node. Further selected *rvar* used in Fitness calculation of each particle is which is performed by an effective fitness function given in equation 10. The fitness function formulated using different parameters of the network. We have taken distance and energy into consideration for the fitness calculation. Sequence position vector and $rvar_i$are evaluated using a defined fitness function for each particle of the swarm. The pbest and gbest solution for the swarm is updated based on the calculated fitness. After executing the defined process by the proposed method, it exhibits the gbest solution among all particles of each iteration. The number of iteration is one of the control parameters in the PSO, so after every iteration, PSO checks for the

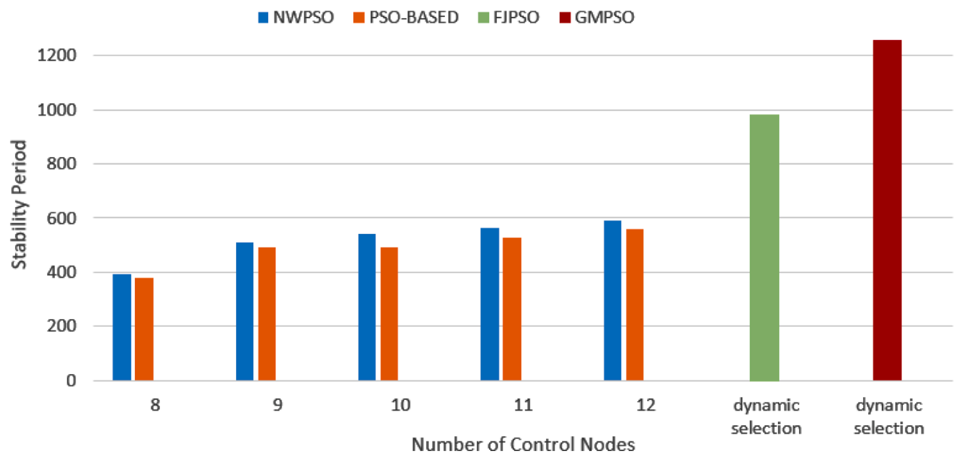

Fig. 7. Stability Period with respect to the Number of Control Nodes for Single Sink

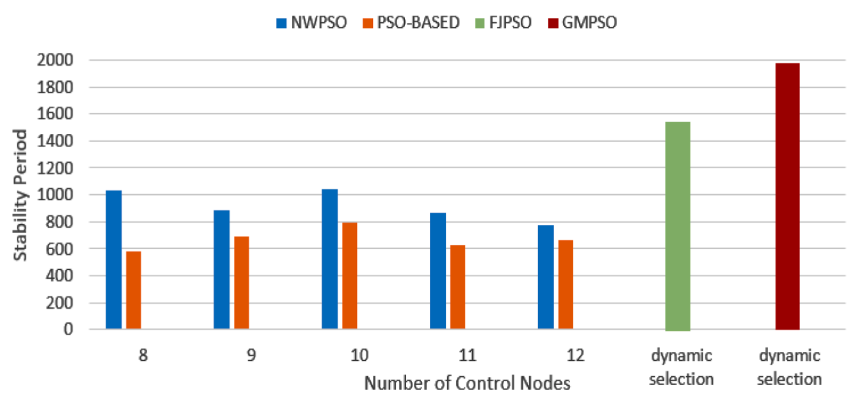

Fig. 8. Stability Period with respect to the Number of Control Nodes for Multiple Sink

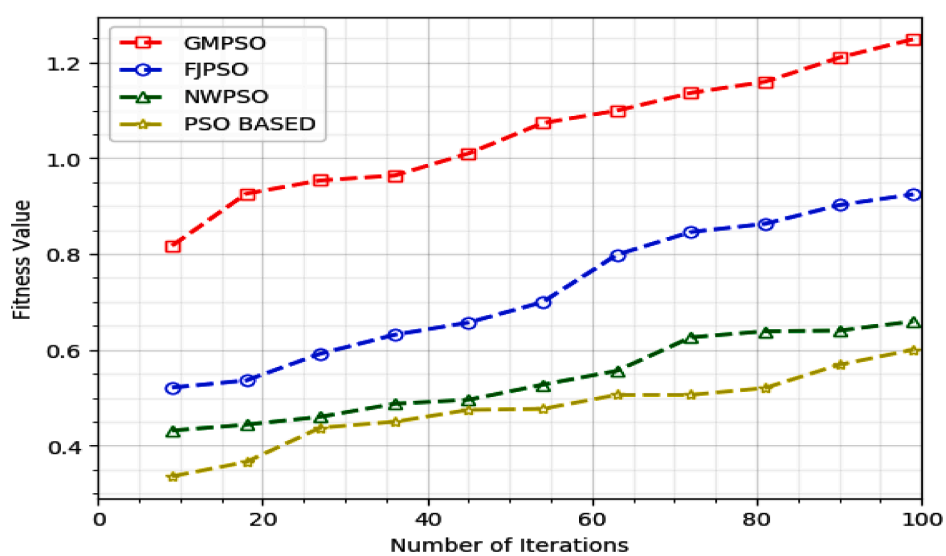

Fig. 9. Fitness value with respect to the Number of Iterations for Single Sink

satisfying criteria to discontinue the process.

Further, in consecutive processing, the updation of the position vector is done followed by updation of velocity vector using given equation 3. The formulation of the velocity vector in conventional PSO is having fixed inertia weight. Inertia weight plays an important role in the velocity updation of the particle, it is one of the control parameters. Large inertia weight facilitates greater global search and small inertia weight is facilitating greater local search therefore proposed method uses adaptively tuned inertia. In this approach at the beginning of the process, inertia weight is comparatively large. Which needs to be slow down in later iterations. We carry out this task by iteratively damping the inertia weight using equation 11. The newly generated velocity vector further used in equation 4 to update the corresponding particle position.

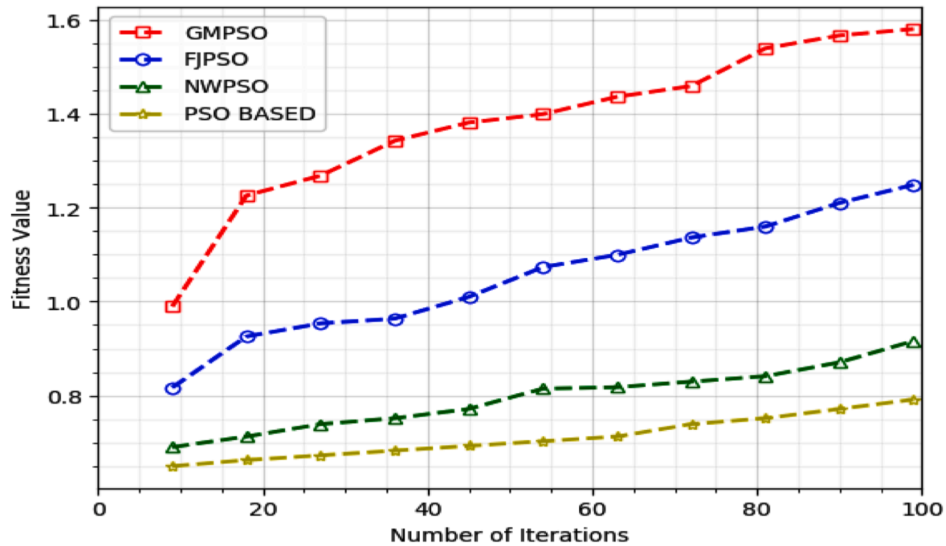

Fig. 10. Fitness value with respect to the Number of Iterations for Multiple Sink

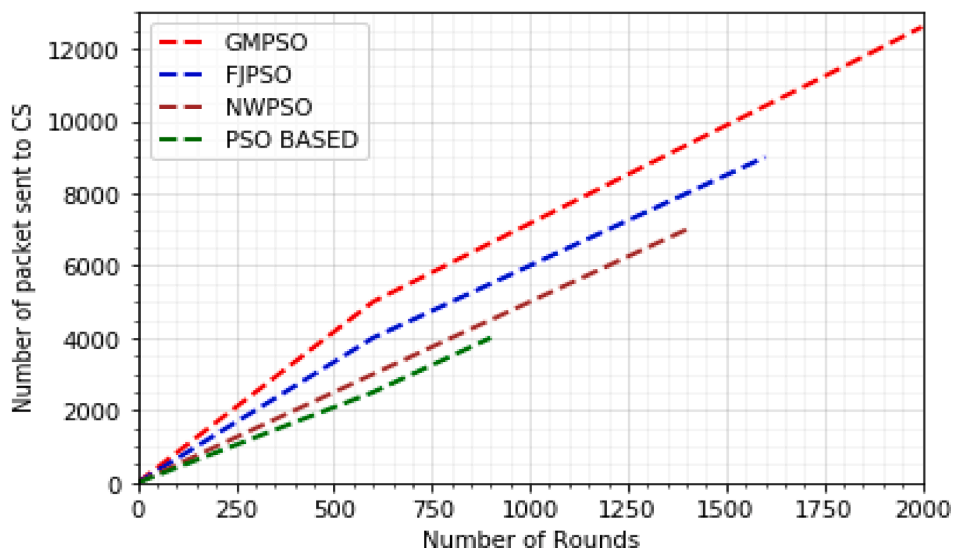

Fig. 11. Number of Packet Sent to CS with respect to the Number of Rounds for Single Sink

Now fork and merge model is starts to execute where the SPV rule is applied again on the newly updated particle to sustain the individual's restraint. In a fork, each particle induces to respective offspring (t % of initial population IP) accompanied by parent particle using genetic mutation. PSO does not have a selection operator whereas GA has a selection operator which helps other particles to evolve with the fittest particle. The genetic mutation operator GMO uses a two-point random mutation which is the selection feature of a genetic algorithm. The fittest particle will lead the solution toward a global solution. This genetically muted offspring particle is only differentiable over sequence position vector, there corresponding position and velocity vector are the same. Each offspring or sub-particle is having a corresponding control nodes sequence. GMO implemented with sequence position value accompanied by*rvar* number of CNs such that it should propagate the good feature of the fittest control node in the offspring. Further, the fitness function is applied over generated offspring to evaluate the fitness of each sub-particles. All the offspring and parent particles are joined in a single particle based on the merit of fitness value. This is the iterative process in each iteration the fittest particle is selected, and that particle will help to update the gbest and pbest solution for the given population till the termination criteria do not meet.

A single sink network is prone to more energy consumption. The transmission process will halt if the sink gets damaged or any failure related to the sink. Load balancing is not possible in this type of network; congestion is also a major issue. The use of multiple sinks can avoid this problem to some extends. The multiple sinks are deployed over a defined observation area. The workability of the proposed method is extended for multiple sinks.

5.1. Fitness function

The fitness function is considered as the prime factor for selecting control nodes in any metaheuristic routing algorithms. Parameters used for calculating fitness show the effectiveness of the fitness function. The fitness function should take the most realistic and effective parameter based formulation into consideration. As the pbest and gbest solution depend on the fitness value given by the fitness function and the proposed fitness function is based on the energy and distance parameter of control nodes, control sink, and the common node. The study shows that energy consumption and distance within these entities of networks plays

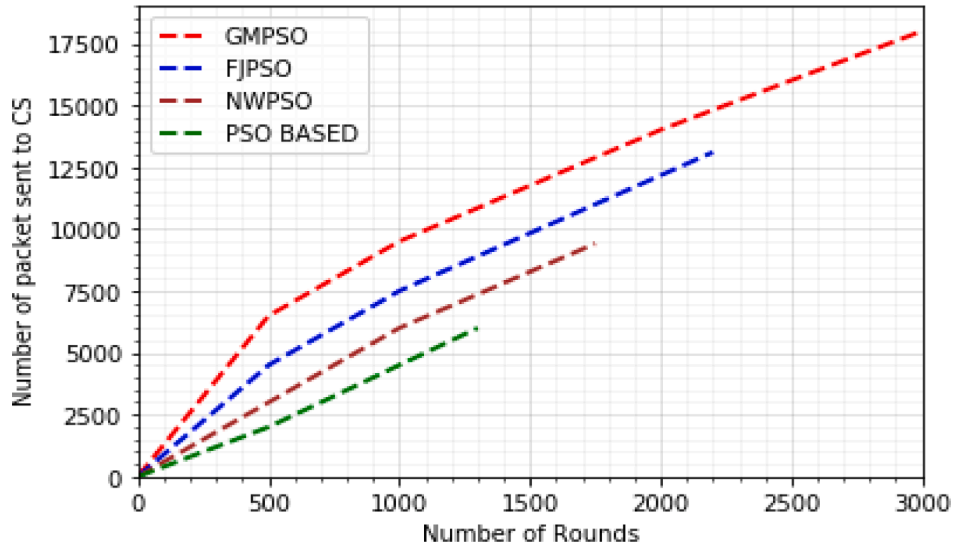

Fig. 12. Number of Packet Sent to CS with respect to the Number of Rounds for Multiple Sink

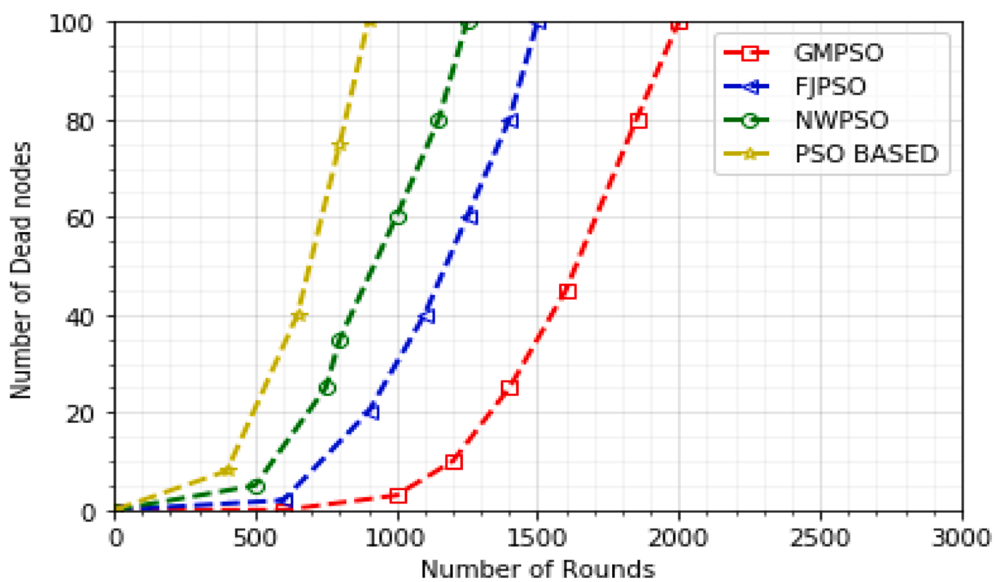

Fig. 13. Number of dead nodes with respect to the Number of Rounds for a Single Sink

a significant impact on fitness value. Fitness value F is calculated using equation 3.10.

$$F = \alpha f_1 + \beta f_2 \ = \alpha \frac{E_{CNtoCS}}{E_{SDCNtoCN}} + \beta \frac{1}{D_{SDCNtoCN} \ + D_{CNtoCS}} \tag{10}$$

Here, $D_{SDCNtoCN}$ describe the average distance within the software-defined common nodes (SDSNs) and the corresponding control nodes. Were D_{CNtoCS} is the average distance between the control nodes and the control server. Furthermore,$E_{SDCNtoCN}$ depict the power dissipated in data communication among the common nodes and the corresponding control nodes. E_{CNtoCS}Represents the power dissipated in data communication within the Control nodes and the control server. To make a balanced tradeoff between distance fitness and energy fitness α, β is set to value 0.5. This modification drastically effects on fitness value of the network. Control nodes selection is done by considering sink distance and clusters are formed [11].

5.2. *Adaptive inertia function*

Inertia weight performs an important role in PSO. Inertia weight W (large inertia weight) facilitates greater global search and small inertia weight is facilitate greater local search therefore we use adaptive inertia. Initially, inertia weight is assigned with the value 0.94 and it decreases according to the tuner given in equation 11.

$$inertia \ = \ inertia \ - - \ \delta \times inertia * Gbest \tag{11}$$

Here δdenotes a seed value (δ =0.02) that can be adjusted on the network configuration.

5.3. *Smallest position value (SPV)*

The PSO results for global best and personal best are in continuous value but for any routing problem, it was hard to work with continuous values it needs to be a vector of discrete value. Therefore a heuristic method is used to solve this problem which is known as the smallest position value developed by Verma et al. [24]. This method converts the

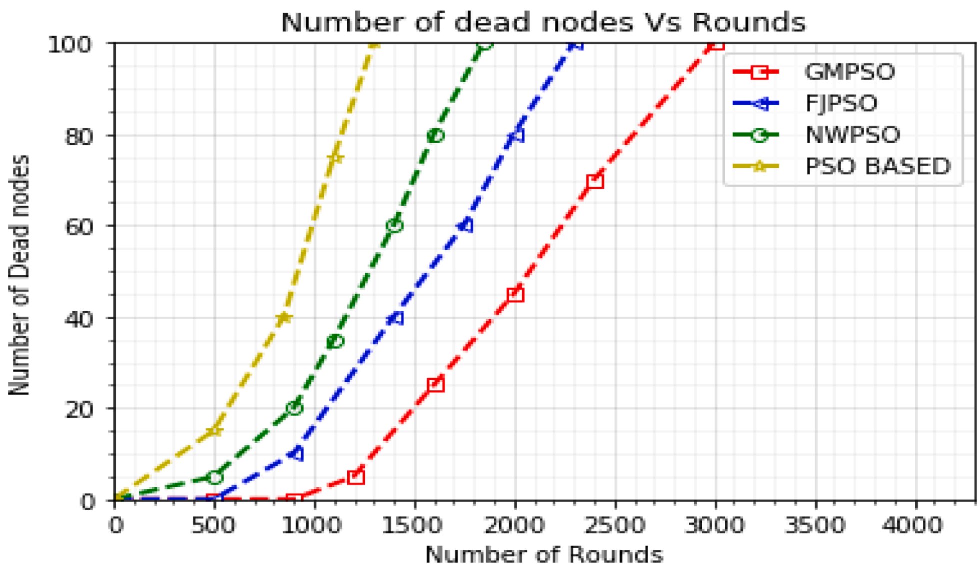

Fig. 14. Number of dead nodes with respect to the Number of Rounds for multiple sinks

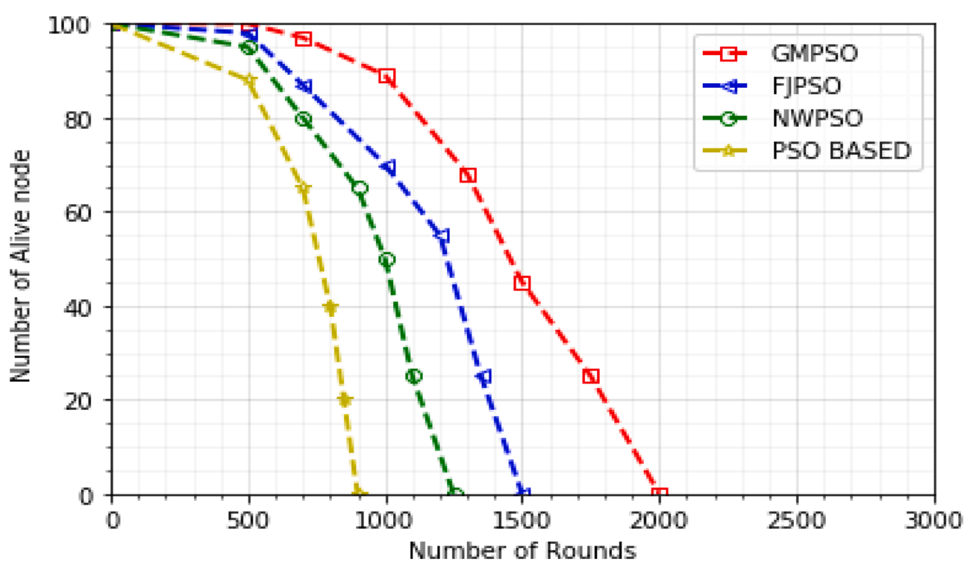

Fig. 15. Number of alive nodes with respect to the Number of Rounds for a single sink

continuous position value vector into a discrete position vector. Further, the first *rvar* sequence is selected as control nodes from this vector. Initially, the continuous values of the position vector are sorted after arranging them in ascending order of their value. Further, this arraignment gets there dimensional indices as SPV vector $S_i(k)$in discrete vector form.

6. Performance analysis of the proposed method

The simulation of the proposed method called GMPSO is implemented for 3-tire of heterogeneity over the JavaScript framework with the testing parameters given in Table 1 by considering both the single sink and multi-sink model. The GMPSO method is simulated by varying several parameters to fairly understand the performance. The performance of the GMPSO is compared with the existing methods like NWPSO, PSO based, and FJPSO. The GMPSO simulated for $100 \times 100m^2$ the network where 100 randomly generated heterogeneous sensors are deployed with their respective The number of control sink are varied based on the model. In the proposed work, we applied three-tier energy heterogeneity in terms of potential power for the heterogeneous network. This three-tier characterization divides the network into normal, intermediate, and advanced nodes. This division of nodes has a different proportion of energy that varies based on network requirements. We have dedicated 70 % of total nodes are normal nodes, 20 % of total nodes are intermediate nodes and the remaining 10 % as advanced nodes. The energies of 3-tire of heterogeneity nodes are 1.0 J, 1.50 J, 2.0 J, respectively. The deployed location of the control sink for a single sink model and multi sink model is given in Table 1.

Here C1, C2 are the control parameters in the PSO algorithm these parameters are having a high impact on the convergence of the particles towards the global best solution. The exploration of the particle is controlled using C1, C2 parameters. On experimentation over the various values of C1 and C2, it was found that a balanced exploration of the particle is at the point of value 2 [21]. The proposed model is simulated several times and their collective average is considered as the result. The performance of the GMPSO is carried out by considering the stability period, fitness value for a packet sent to CS, dead nodes, alive node, residual energy, control nodes per round and inertia function for heterogeneous networks.

Fig. 5 and 6 represent the clustering in GMPSO for a single sink and

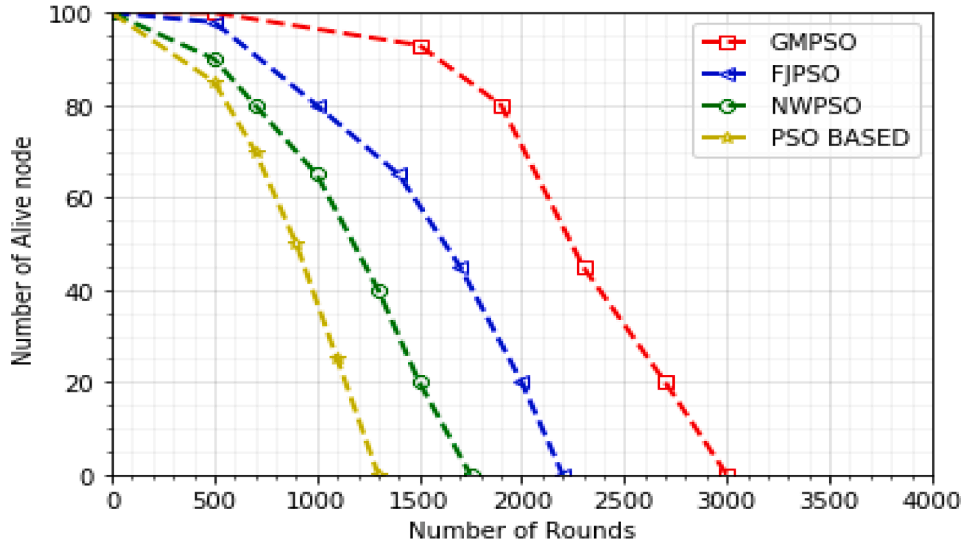

Fig. 16. Number of alive nodes with respect to the Number of Rounds for multiple sinks

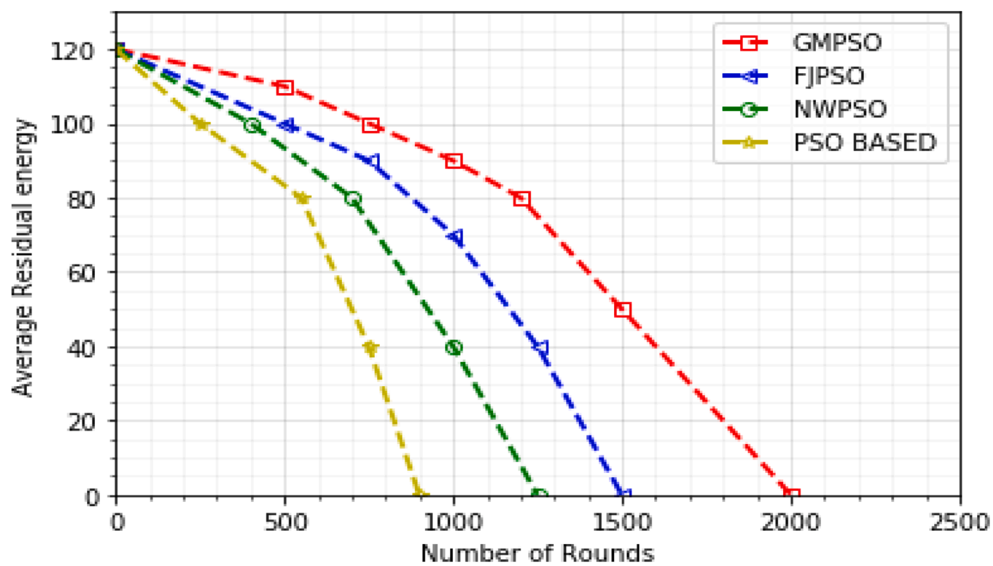

Fig. 17. Residual Energy with respect to the Number of Rounds for a single sink

multiple sink model respectively. Several simulations have carried out and it has been observed that the proposed GMPSO method has succeded to cover over 80-90% deployment area using a fewer number of control nodes. The proposed model shows a mutation of the genetic algorithm and particle swarm optimization leads to the optimal selection of control nodes. Because of this, GMPSO can have better convergence over the whole network and overall results of these clustering have shown fair effectiveness over other states of arts.

Stability Period: The GMPSO has shown excessive network stability on execution which can be observed from Fig. 7 and 8 for a single sink and multiple sinks, respectively. In the multiple sink model proposed method GMPSO experimentation is done by deploying four sinks over the various position in the network. As obvious, the multiple sinks model having more number of sinks which results in maximization on the scale for the performance matrix. The impact of the number of the sink on a network can be seen from the proceeding results. Generally, the stability period of a network is considered as a number of rounds after which the first node dies or drains it's all energy. By studying the simulation result shown in Fig. 7 and 8 it can be observed that GMPSO has enhanced the stability period by 50 to 60 % with comparison to NWPSO and PSO based algorithm and 20 to 25% over FJPSO for single sink model. The results are quite improved in the multiple sink model. The GMPSO has shown 65 to 70% of improvement in the stability period against PSO based and NWPSO method whereas it has shown a 30 to 35% increment for FJPSO. The stability period can be affected by various factors such as an inadequate number of control nodes. This can lead to a high load on the particular node and result in faster drainage of energy. The GMPSO has effectively addressed this issue by proposing a dynamic selection of control nodes. The control node selection in GMPSO is dynamic it means the number of control nodes is not fixed. It can be selected haphazardly in every iteration. The dynamic selection of control nodes helps the network to administer itself in real-time.

Fitness Value: Fig. 9 and 10 illustrate the simulation results of fitness value for a single sink and multiple sink model. The selection of the control node is based on the merit of fitness value. In the proposed method fitness value of every particle is calculated. The fitness value calculation is based on the formulation of energy and distance parameters. Also, to preserve the survival of fittest and to inherit the property of the fittest particle proposed method uses a two-step mutation. For a single sink model fitness value of GMPSO has increased by 65.4 to

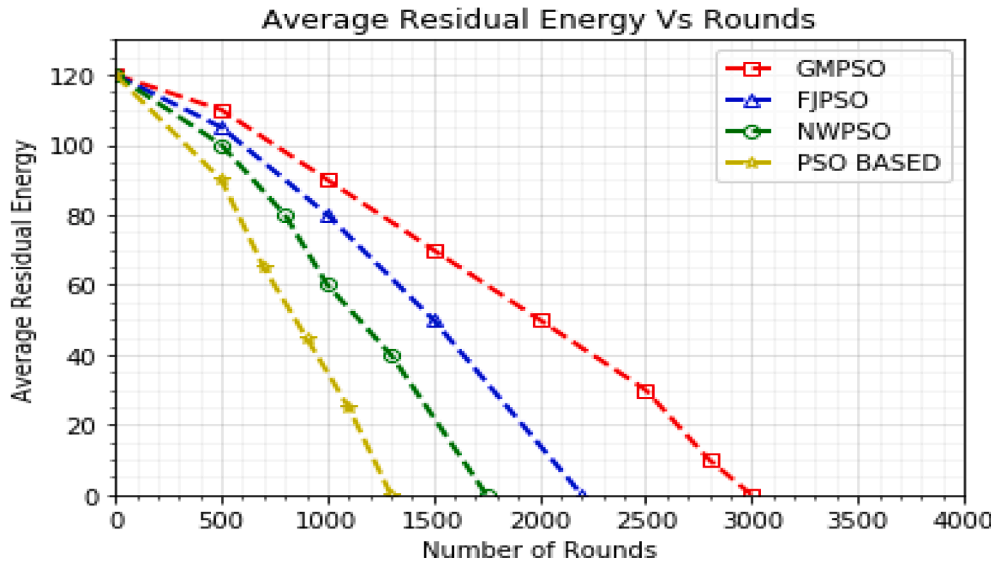

Fig. 18. Residual energy with respect to the number of Rounds for multiple sinks

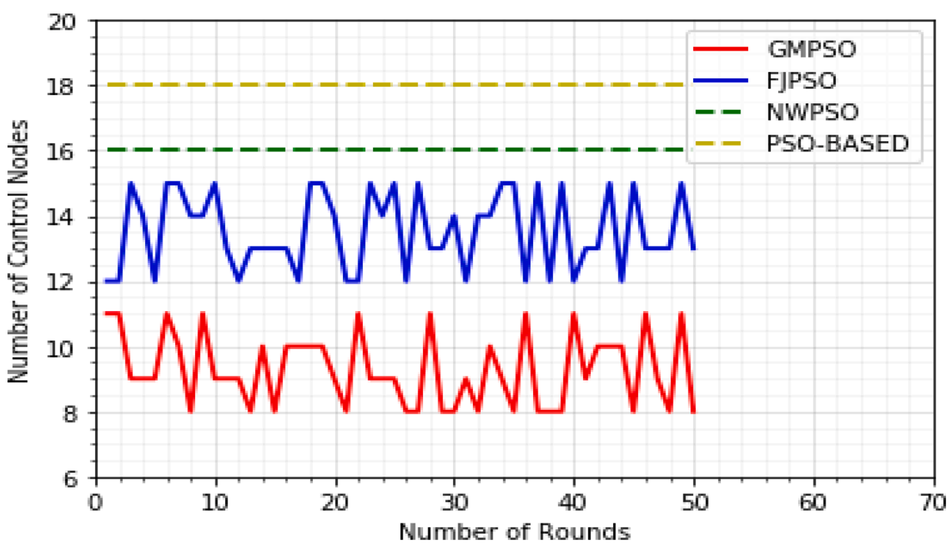

Fig. 19. Comparative analysis of Control Nodes with respect to the Number of Rounds

72.56% concerning PSO based and NWPSO. While comparing with FJPSO it has noted about 30.41 to 36.84% increment as shown in Fig. 9. Observing the results for the multiple sink model from Fig. 10 it can understood that GMPSO has shown around 70.4 to 75.3% increment for PSO based and NWPSO while for FJPSO it is 35.74 to 40.23%. the GMPSO has shown this improvement because it has weighted the distance between control nodes and common nodes as a key parameter in fitness value calculation.

Packet Sent to CS: The number of packets transferred to CS determines the capacity to transfer the collected data in the network lifespan. Fig. 11 shows that the number of packets sent to the control sink is higher as the network lifetime has been increased. In early rounds, the packet transmission is increased linearly. The experimental result is shown in Fig. 11 and 12 conclude that GMPSO has increased the rate of packet transfer by 50.5 to 55.67% in comparison with PSO based and NWPSO for a single sink while 67.43 to 67.96% in multiple sinks respectively.

GMPSO in comparison with FJPSO has shown the rate of packets sent to CS is increased by 30.74 to 32.65% for a single sink and 40.87 to 45.12% for a multiple sink model as presented in Fig. 11 and 12 respectively. As the number of rounds increased lifespan of the network is also increased. Now there are more nodes that remain alive for a longer time due to which the capacity of packet transfer also increased. By analyzing Fig. 12 for multiple sinks it can be seen that packet transmission has increased exponentially.

Dead Nodes: The total number of rounds after the first node dies is considered a stability period of the network. Fig. 13 and 14 show the relationship between the dead node and the number of rounds. After studying the graph, it can be observed that the FND (First Node Dies) takes approximately 750 to 810 rounds for GMPSO in a single sink model whereas in the multiple sink model it has raised to 950 to 1050 rounds. The comparative analysis shows that due to optimization in the control node selection it takes less energy for packet transfer to CS. Therefore, the rate of the number of dead nodes in subsequent rounds decreases for GMPSO. Observing the result of Fig. 13 for the GMPSO single sink model in contrast with PSO based, NWPSO, and FJPSO rate of the dead node is decreased by 59.12%, 54.44%, and 37.98%, respectively. Whereas Fig. 14 depicts the result for GMPSO multiple sink model were it can be observed that GMPSO has succeeded in decreasing the rate of dead node per round by 51.12%, 46.44%, 31.98% for PSO based,

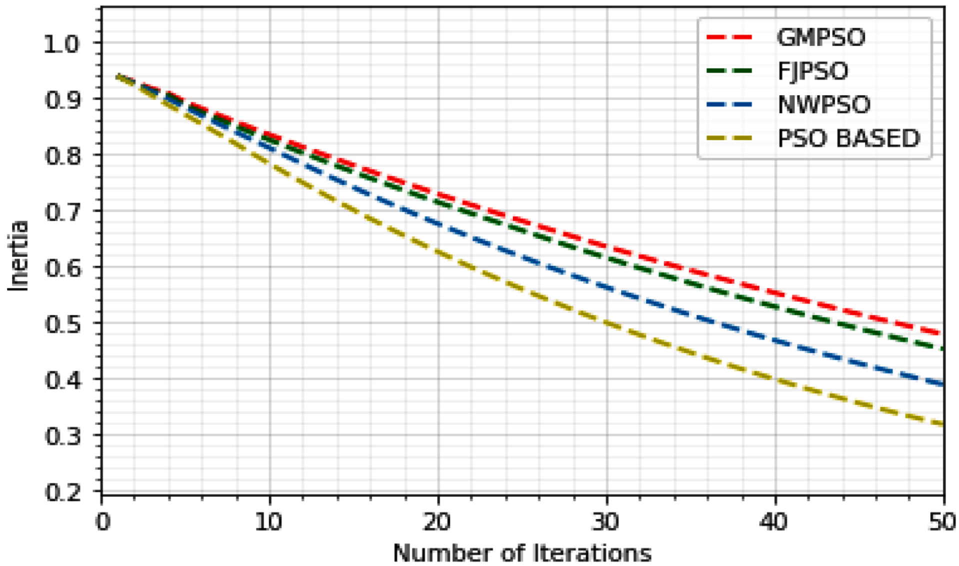

Fig. 20. Comparative analysis of Inertia with respect to the Number of Rounds

NWPSO, and FJPSO respectively.

Alive Node: Fig. 15 and 16 represent the simulation result for alive nodes for a single sink and multiple sinks respectively. The nodes which are propagating the packets until its drain its all energy are called alive nodes. The simulation result shows that the number of alive nodes per round is much higher in GMPSO because in proposed GMPSO nodes are taking less amount of energy for packet transfer as compared to other methods. The proposed method GMPSO able to transmit the packet till 1950 to 2100 rounds for a single sink model as illustrated in Fig. 15. The result of the multiple sink model shows that in the proposed method alive nodes propagate the packet till 2990 to 3120 rounds as illustrated in Fig. 16.

Residual Energy: The GMPSO simulation behavior is measured to analyze the performance of energy consumption in the form of average residual energy. The comparative analysis per round for single sink heterogeneous network and multiple sink heterogeneous network is shown in Fig. 17 and 18, respectively. The initial energy consumption starts when control nodes send an advertisement packet to CS and its common node for alerting them about the status of control nodes. It is observed that GMPSO consumes quite less amount of energy per round in comparison with other given methods. This improvement is due to better localization of control node using genetic mutation and particle swarm optimization. Here, energy consumption depends on so many factors such as the distance of control nodes to common nodes, the distance of control nodes to sink, the number of control nodes, load balancing, etc. The comparative analysis shown in Fig. 17 illustrates that PSO based and NWPSO have soaring power consumption over other methods this is because this method does not consider genetic mutation for selecting fittest control nodes. Here the GMPSO has considerably able to save up to 48.49 to 51-34% of energy in comparison with PSO based and NWPSO while they save nearly 25.34 to 30.87% in comparison with FJPSO for the single sink model. It is observed that GMPSO able to save up to 60 to 65% energy in comparison with PSO based and NWPSO by complying Fig. 18 for multiple sink model while it can save 30.34 to 35.43% in comparison with FJPSO.

Control Nodes per Round: The GMPSO used dynamic clustering in each round. It will choose the number of control nodes after every iteration dynamically same as FJPSO while in NWPSO and PSO based the number of control nodes in each round is fixed. The GMPSO performs better with the comparably fewer number of control nodes for the same network scenario control nodes in comparison with FJPSO, NWPSO, and PSO based as shown in Fig. 19.

Inertia function for heterogeneous networks: Inertia weight performs an important role in PSO. The Inertia weight ω facilitates greater global search and small inertia weight is facilitate greater local search therefore we use adaptive inertia. Initially, inertia weight is assigned with the value 0.94 and it decreases according to the tuner. The result illustrated in Fig. 20 that the proposed inertia tuner performs synchronically better in comparison with the existing inertia tuner. This is because the proposed inertia tuner uses a feed-forward model in which previous knowledge of inertia along with using gbest and pbest.

7. Conclusion

In the proposed algorithm two-level optimization using GMO is proposed which enable the PSO to work dynamically for control node selection. The proposed algorithm is tested over different parameter in various network arrangement. Firstly, GMPSO simulated by considering the heterogeneous IoT-based SDN network. The results show the proposed algorithm outperforms from various state of art of previous algorithms. The energy and distance tradeoff, inertia tuner, effective fitness function and GA model significantly improves the performance of the proposed algorithm. The multi-sink model shown a major improvement over a single sink model in terms of energy consumption, network lifetime and another performance matrix. This model is flexible and extensively modifiable for different scenario observing the results this model can be seen as the most promising in term of improving lifespan, energy consumption for the trading reconfigurable IoT based SDWSN.

The proposed method is tested for homogeneous and heterogeneous network accompanied with single and multiple sinks respectively. The results show that the proposed method has shown better improvement for fix the type of sink node. Thus, in future, this method can be implemented over various version and scenario of the network having a mobile sink node.

Author statement

Rohit Ramteke: Methodology, Software, Writing- Original draft preparation

Samayveer Singh: Conceptualization, Methodology, Investigation, Writing- Reviewing and Editing, Validation

Aruna Malik: Conceptualization, Methodology, Writing- Reviewing and Editing, Validation

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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