



# A multi objective Tabu particle swarm optimization for effective cluster head selection in WSN

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## Abstract

The advent of sensors that are light in weight, small-sized, low power and are enabled by wireless network has led to growth of wireless sensor networks (WSNs) in multiple areas of applications. The key problems faced in WSNs are decreased network lifetime and time delay in transmission of data. In many critical applications such as military and monitoring the eco system, disaster management, etc., data routing is very crucial. Multi hop low-energy adaptive clustering hierarchy protocol has been proposed in literature but is proved to be inefficient. Cluster head optimization is a NP hard. This paper deals with selection of optimal path in routing which improves network lifespan, as well as network's energy efficiency. Various meta-heuristic techniques particularly particle swarm optimization (PSO) has been effectively used but with poor local optima problem. The proposed method is on the basis of PSO as well as Tabu search algorithms. Results show the efficiency of the proposed Tabu PSO by enhancing the number of clusters formed, percentage of nodes alive and shows the reduction of average packet loss rate and average end to end delay.

**Keywords** Wireless sensor networks (WSNs) · Cluster head selection · Particle swarm optimization (PSO) · Tabu search (TS)

## 1 Introduction

Wireless sensor networks (WSNs) are conventional wireless ad-hoc network which can collect, integrate and transmit data autonomously. This is a fast growing information acquisition technology which can integrate latest achievements of technology including micro-electronics, network and communications thus making it an essential element in areas including military, environmental monitoring, controlling the industry, and urban transport system. The limitation in the energy nodes, hence their computing, communication and capacity to store [1] are the disadvantages of WSN. Moreover, the routing protocols that are proposed for wireless networks do not hold good for WSN, and certain modifications have to be made, so as to become WSN compatible.

Specific routing protocols have to be developed for WSNs as challenges are complex in WSN compared to other networks. A few are: the number of nodes are large, there is restriction in nodes with effect to energy, processing, storage capabilities, failing nodes is high, etc. So, careful resourceful management is essential and multi-hop routing is supported by routing protocols for WSN.

Clustering is the technique of collecting sensor nodes in a sensor network that is densely deployed. Data aggregation is combining and compressing the data that belongs to a single cluster in an intelligent way is called data aggregation. In WSN, clustering technique faces many issues. Primary problem is the quantity of clusters formed which could optimize certain parameters of performance. Secondly, the number of nodes that should be present in a single cluster [2]. The final and the problem of utmost importance is the process of selection of cluster head (CH) in a cluster.

Introducing heterogeneity in the network is another area of interest for researchers which focus on putting up more powerful nodes that can work as CH with other simpler nodes as cluster members. Reduced communication overheads are offered by the clustering schemes and efficient resource allocation decreases the overall consumption of energy and the interferences among sensor nodes are reduced [3]. There will

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be in congestion in the area with too many small-sized clusters, while a large amount of messages will be transmitted by the cluster members through the CHs.

In networks with static clustering, the network is proactively divided into many clusters, while in dynamic clustering, a cluster is created reactively proximal to the event sensing nodes. CH collects all the data and aggregates it and is sent to the sink. The advantage of dynamic over static node is that in data aggregation, only the necessary nodes will participate where the energy of the other nodes will be preserved. So, data aggregation for dynamic cluster is quite high. There is a CH for each cluster in clustered based approaches which gets selected among cluster node (members).

The role of aggregator is played by the CH which aggregates the data that is received from members of the cluster locally and the result is transferred to BS. In WSN, for cluster formation, sensor networks have to organize systematically to form a cluster, where one of the nodes with CH [4]. Hierarchical structures are allowed through clustering which are built on the nodes and more efficient use of resources is enable, such as spectrum frequency, bandwidth and power. The CH is selected randomly at every round of aggregation so as to ensure workload distribution.

The first protocol based on cluster is low-energy adaptive clustering hierarchy (LEACH); here the CHs work as aggregation nodes and communicates directly with BS or sink node. Based on the residual energy, CHs are selected periodically in hybrid energy-efficient distributed clustering algorithm and as node degree, so that load is balanced among CH in order to extend WSN's lifetime [5].

Through partitioning of network, the consumption of energy was improved and through evolutionary protocols for the selection of optimized CHs, the position information and residual energy are considered by the WSNs. Set of CHs is defined as dominant set. As the basic structure of CH is changing constantly because of the dynamic state of mobile nodes, it is essential to minimize the number of CHs, thus creating a large overhead. Optimization of CH is a NP hard issue. To solve this type of issue, a generalized approximation algorithm which runs in polynomial time should be used. To reach near optimal solution, it is difficult to find such a problem.

Node-density-based clustering and mobile collection (NDCMC), was combined with hierarchical routing along with ME data collection in WSNs by Zhang et al. [6]. Simulations showed that presented hybrid NDCMC technique lead to remarkable performance enhancement along with a convenient trade-off between network energy saving as well as data collection latency. For efficient performance of WSN, Shah et al. [7] described concentrating on cluster design strategy. The proposed water-rippling shaped clustering which can cluster large-scale network that looks like the shape of water rippling. An entirely novel protocol was proposed by

Dayananda and Straub [8] that performed both functions of selection and distribution of centralized algorithms of CH. While transmitting, the surplus energy is used so as to conserve energy, and improve the life of network. Cisse et al. [9] put forth a clustering algorithm, energy aware neighbor oriented clustering (EANOC) to improve the lifetime of the network. Results proved that HWCA was outperformed by EANOC and also dynamic load-balancing cluster-based protocol to attain longer network lifetime. For routing in WSNs Javaid et al. [10] proposed an application-aware threshold-based centralized energy efficient clustering (ATCEEC) protocol. Simulation results showed that ATCEEC yielded maximum network lifespan as well as stability period in comparison with the selected protocols. Palan et al. [11] proposed novel concept of self-power analyzing energy efficient protocol using energy model (eM). eM with CH decides in an adaptive manner to initiate the next round on the basis of balanced energy. The results revealed that latest technique proposed would decrease the power consumption of CH and thus improve the network's lifetime. The resultant is fault tolerant network.

A semi-distributed approach with consideration given to hybrid of centralized gridding for upper level head selection as well as for lower level head selection distributed clustering were proposed by Lee and Kao [12]. Al-Aboody and Al-Raweshidy [13] proposed a three-level hybrid clustering routing protocol algorithm (MLHP) based on grey wolf optimizer for WSNs. The evaluation of algorithm was done by examining energy efficiency of network, lifespan along with its stability period. A CH selection process was introduced by Patra and Chouhan [14] as well as cluster formation algorithm through reselection of CHs which is known as improved energy efficient hybrid clustering scheme (IEEHCS). Simulation outcomes proved that IEEHCS reduced the power consumption effectively and the network lifespan was prolonged for the death of the first node up to 45.39 and 11.36% over LEACH-C and EEHCS, correspondingly, for particular network settings. A cluster structured path planning algorithm known as, hybrid advance distributed centralized clustering (HADCC) path planning energy efficient algorithm was presented by Aslam et al. [15]. Referring to the stability and lifespan of the network, HADCC outperformed the existing clustering algorithms. Energy consumption efficiency was improved by distributed cluster algorithm and this was proposed by Gao et al. [16]. A hybrid relative distance dependent clustering scheme is proposed and it considers the relative distance to BS as well as the residual energy level at the stage of CH selection. Simulation outcomes proved that the presented method has the ability to have long network lifespan compared to the familiar protocol LEACH. Xu et al. [17] proposed a hybrid clustering as well as routing protocol which accounts all the CH selection and routing discovery problems. The

proposed design goals are achieved through backing up randomly and as gradient routing techniques with low overhead.

While considering multi-objective optimization (MOO), it is need to handle more number of optimization in which there will no clear solution is defined and there may be no superior position will be there for solution obtained. This is because many objectives are considered.

Fei et al. [18] offered a survey of recent research and development efforts on the issue of MOO. Various dominant methods were elaborated for MOO based on the mathematical programming based scalarization techniques, the heuristics/metaheuristics based optimization techniques, and a diversity of other advanced optimization techniques. Lalwani et al. [19] reviewed on all the applications of multi-objective particle swarm optimization. An introduction to the key concepts in MOO and survey of existing work, systematized by application area with their multiple objectives, variants and more characterized variants. Zou et al. [20] presented an algorithm based on artificial bee colony that speaks on MOO problems (MOPs). Results show that the proposed approach has been highly competitive and considered as a feasible substitute to solve the MOPs.

It is ensured through the optimization that every network link is symmetrical as well as energy efficient. Most network attributes are additive in behavior as the optimization is NP hard. Literature show many meta-heuristic methods along with genetic algorithm(GA). On the basis of nature-inspired concepts, many optimization algorithms have been developed. Two categories of nature inspired algorithms include evolutionary algorithms (EAs) as well as swarm optimization algorithms. The phenomenon of natural evolution is simulated through EA. Every species keep searching for beneficial adaptations in the ever changing environment in natural evolution [21].

Examples of EA are GAs as well as differential evolution algorithms. PSO, ACO, and BCO are included in swarm optimization. This paper deals with PSO with TS in avoiding local minima problem. PSO is a population-based search procedure where the position of particles changes with time.

Section 2 talks about the hybrid technique of Tabu PSO technique so as to select the CH which minimizes consumption of energy in the cluster. The performance of the presented protocol as well as outcomes are discussed in Sect. 3 and at the end Sect. 4 discusses results.

## 2 Methodology

In this section, PSO as well as Tabu search (TS) for CH selection process which is used in the proposed work is explained. PSO was selected due to its good local search and global search capability.

### 2.1 Multi-hop LEACH

General issue of WSN is power. When network is large challenges posed on power due to limited level. According to the eM, when an energy consumption increases exponentially based on the communication distance then it is better to choose a multi-hop communication. This is because it is advanced in gathering data for energy saving.

In wireless network protocol, LEACH is the primary network protocol employs hierarchical routing for network lifetime expansion. All network nodes arrange themselves as local clusters, among one node performing as the CH. Each non-CH nodes send out their information towards the CH, whereas the CH node obtain data from every cluster members, act data signal processing functions (e.g., data aggregation), and send information towards the distant base station. LEACH integrates randomized rotation of the high-energy CH position in order to rotate amid the sensors in order that battery draining for at least unit network sensor is reduced. Here, the energy load related with being a CH is uniformly shared between the nodes.

Distance among the CH and base station is enhanced extremely once the network diameter is far across a particular stage. This condition is not appropriate for LEACH routing protocol for the base station is at single-hop to CH. Here, CH energy dissipation is not reasonable. In order that this issue is dealt, multi-hop LEACH is introduced. Multi-hop LEACH is an additional expansion of LEACH routing protocol in order to enhance WSN energy efficiency [22].

Multihop-LEACH, a cluster based routing algorithm self chosen as CHs gather data from each sensor node of its cluster, combined the obtained data by data fusing techniques then broadcast the data in an optimum path among the CH and the BS using rest of the intermediate CHs followed by employing such CHs to be a relay station so that information are broadcasted via them.

The multihop-LEACH function is partitioned to two phases: the set-up phase along with the steady-state data transfer phase. The first phase involves systematizing the clusters followed by choosing the CHs. Throughout this phase, depending on the presented probability percentage of the network clustering, CHs are chosen as well as the node number of times the node was chosen as CH so far. This choice was prepared by every node  $n$  selecting a number randomly among 0 as well as 1. In case, number remains lesser compared to the threshold  $T(n)$ , the node turns a CH for the existing round and it is formulated as in Eq.(1) [23]:

$$T(n) = \begin{cases} \frac{P}{1 - P(r \bmod 1/p)} & \text{if } n \in G, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

In which  $P$  forms the required CH probability,  $r$  is the number of the current round then  $G$  is the set of nodes which did not remain as CHs in the last  $1/P$  rounds.

Multi-hop LEACH permits two communication process which are inter-cluster communication as well as intra-cluster communication. In multi-hop inter-cluster communication. If the entire network is partitioned as many clusters, then every cluster contain a CH which is in charge to communicate between nodes of a cluster. These CHs obtain information from every nodes at single-hop then combine it and send out in a straight line towards sink else to intermediate CH. For multi-hop inter-cluster communication, in case huge distance is among the CH as well as BS, the CH employ an intermediate CH so that communication to the BS is performed.

## 2.2 Particle swarm optimization (PSO)

The PSO algorithm, initially established depending on social as well as cognitive nature by Kennedy and Eberhart [24], resolves problems of several areas, particularly engineering as well as computer science. The entities, known as particles hereafter, are fly using the multi dimension search space with every particle signifying a probable resolution to the multi-dimension optimization issue. Each solution's fitness depend on the performance function relayed to the optimization issue being resolved [25].

The particle motion is manipulated using two aspects through information from iteration-to-iteration and particle-to-particle. Consequently iteration-to-iteration information, the particle accumulates in its memory the optimal solution stayed until now, known as  $p_{best}$ , then practices an appeal towards the solution since it negotiates via the solution search area. In consequence to the particle-to-particle communication, the particle accumulates in its memory the optimal solution attained with the help of other particle, thus practices an attraction nears this solution, known as  $g_{best}$ , too.

The initial as well as second aspects are termed cognitive and social elements, correspondingly. Following iteration, the  $p_{best}$  and  $g_{best}$  are revised for every particle when an enhanced or much dominative resolution is originated. This procedure persists, iterates, in anticipation of either the needed consequence is congregated over, else it is found that an appropriate solution couldn't be determined under computational limits.

Optimal solution can be found through iteration after PSO is set to a set of particles randomly. Through the decision of fitness function, all particles need to be optimized, speed should be determined for each particle through the direction of their flight as well as distance, then the best particle in the solution is searched for the following best location. For each iteration, by tracking the two extremes, the best particles update themselves. The first one remains the particle itself in finding the optimum solution  $P_{id}$ ; the another end is the much

optimum result of the present population  $P_{gd}$ . The updating formulae are shown in Eq. (2) [26]:

$$\begin{aligned} v_{id}(t+1) &= wv_{id} - c_1r_1(p_{id} - x_{id}(t)) \\ &\quad - c_2r_2(p_{gd} - x_{id}(t)), \\ x_{id}(t+1) &= x_{id}(t) + v_{id}(t+1). \end{aligned} \quad (2)$$

In Eq. (2),  $t$  denotes the number of iterations,  $v_{id}$  is the particle's speed,  $x_{id}$  is the location of particle  $i$ ,  $r_1$  and  $r_2$  are one random number within 0 and 1,  $c_1$  and  $c_2$  are accelerating factors,  $w$  is weighting coefficient.

## 2.3 Tabu search (TS)

TS forms a search procedure which is metaheuristic in nature that can analyse the solution space apart from local optimality. Using the adaptive memory is the main component of TS where a more flexible search behavior is created. The hallmark of TS approaches are memory-based strategies which are found on a quest for the integration of principles where other forms of memory are combined in an appropriate manner having effective techniques to exploit them. These principles are sometimes portent sufficiently in yielding effective solution for problems in their own accord without relying on memory. Strategic memory usage could create variations dramatically in its capability in solving problems in spite of wide range of problem settings.

Five steps must be carried out to acclimatize TS heuristics to resolve a certain issue [26]:

- (1) Devise an algorithm that come backs an original solution,
- (2) Describe shifts that find the neighborhood  $n_{\text{osp}}$  of a solution  $s$ ,
- (3) Find out the content as well as size of Tabu lists,
- (4) Describe the aspiration criterion,
- (5) Devise intensification along with diversification systems.

The algorithm terminates if any of the subsequent three circumstances happens:

- (1) Every probable shifts are for bided by the Tabu lists;
- (2) The maximum iterations permitted is attained;
- (3) The maximum iterations, in which the optimal solution is not improved consecutively, have been attained.

The procedure where solutions obtain a Tabu position has some aspects, intended to encourage a sensibly aggressive assessment of novel points. An essential method of analyzing and performing this method is to visualize of reinstating novel assessments of solutions by Tabu assessments, for penalty introduction to deject Tabu solutions choice considerably.

Moreover Tabu assessments also at times comprise incentives to support the option of other solution varieties, as a consequence of objective levels and long term influences.

### 2.4 Multi objective Tabu particle swarm optimization

In vector optimization or MOO, vector of objectives are optimized instead of single objective. To solve various MOPs, MOOs are quite helpful where multiple objectives are treated at the same time with effect to set of constraints. However, multiple objectives cannot attain their respective optima in the similar period [25]. New records have been set up through pure and hybrid TS approach so as find better solution to issues in production planning, and scheduling, resource allocation, network design, routing, etc. The TS scheme has become the technique chose to design solution schemes in hard combinatorial optimization issues in a rapid manner.

PSO hold many benefits such as greater convergence, resolving optimization efficiently, minimized population diversity and directing an early converging towards a local optima. TS is a potent stochastic optimization method that could hypothetically congregate asymptotically to a global optimum solution, however it acquires more timespan to attain the near-global minima [27]. The integration of TS to PSO as a local development process allows the algorithm to sustain the population diversity thus avoid directing to misguiding local optimum (Fig. 1).

Average energy consumption is high in TS in comparison with PSO and less calculation time is utilized in TS than PSO. By combining both the algorithms, a tradeoff between the two is avoided. Simple PSO and generalized TS are used for hybrid approach. The proposed algorithm is developed and implemented using the following steps.

- *Step 1: initialization* location as well as energy of nodes and the location of BS are initialized.
- *Step 2: formation of clusters* formation of clusters take place through calculating the distance of the nodes corresponding to the base station as well as the energy level of the nodes.
- *Step 3: determine the local best position* through by using PSO, the local best position is found.
- *Step 4: determine the best global position* the global best is calculated by initializing the Tabu list with PSO solution and Tabu memory entries to zero. There is a swapping of routes and an entry is created in the Tabu memory. The constraints are checked.
- *Step 5: determine the next position* in case the fitness value is existing in the list, which is called Tabu and that

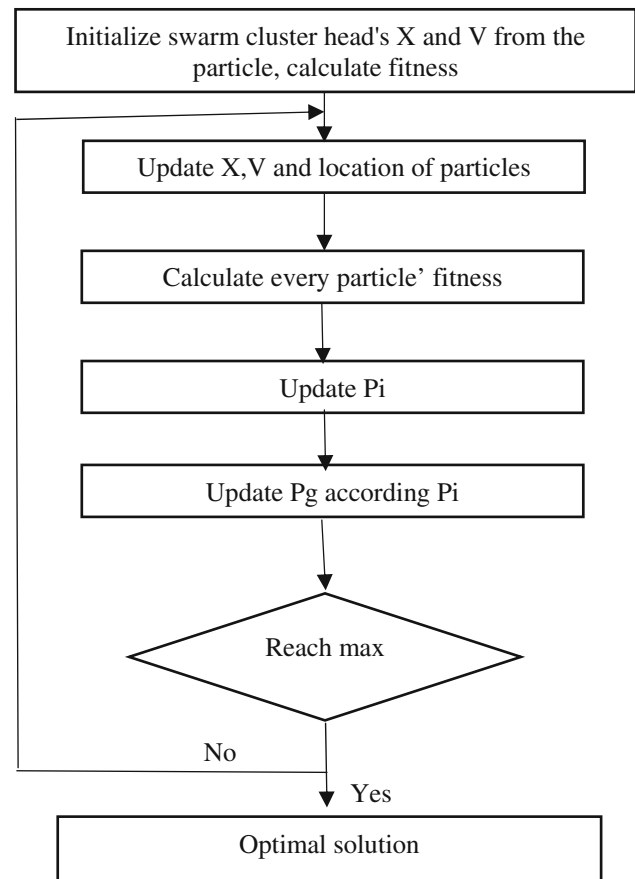


Fig. 1 Algorithm flow for selecting the cluster-heads

fitness value is noted in the list. The best solution from the Tabu list, with minimum hop routing is taken out.

The mapping is achieved by representing the nodes as binary values with selected nodes for CH being represented by ‘1’ as shown below.

	N1	N2	N3	...	...	NL
P1	1	0	1	...	...	0
P2	0	0	1	...	...	1
P3	1	1	0	...	...	1

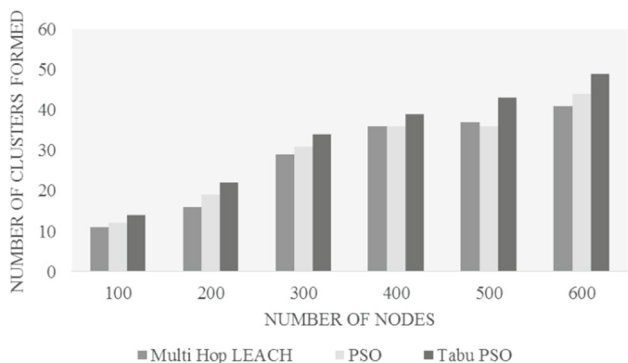
### 3 Results and discussion

The experiments conducted for the multihop LEACH, PSO and proposed hybrid Tabu PSO. Table 1 shows the parameter setting of PSO and TS. Figures 2, 3, 4 and 5 represents the number of clusters created, mean end-to-end delay, average packet loss rate as well as percentage of nodes alive correspondingly.

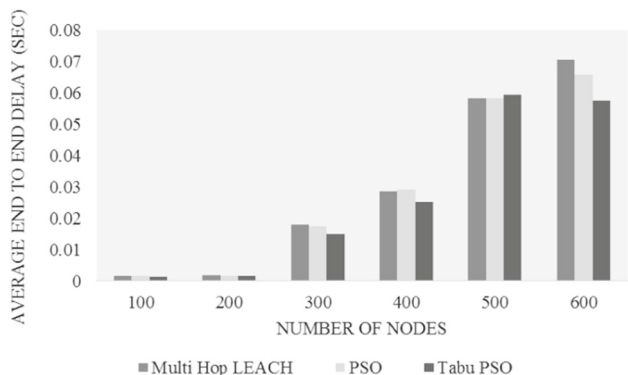
Observing the Fig. 2, it could be said that the proposed Tabu PSO technique enhanced the number of clusters formed

**Table 1** Simulation parameters of PSO and Tabu search

Swarm size in PSO	20
Maximum number of generations	500
C <sub>1</sub> , C <sub>2</sub>	1, 1
Fitness value for termination	$1.5 \times 10^{-3}$
Tabu list size	25
Neighborhood size	25
Move method	Swap



**Fig. 2** Number of clusters formed



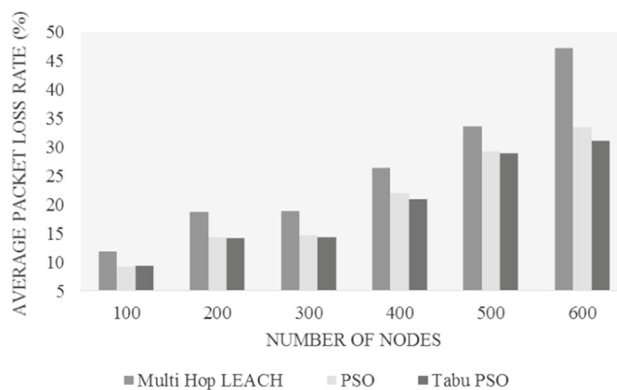
**Fig. 3** Average end to end delay (s)

averagely by 17.71 and 12.14% when compared with multi-hop LEACH and PSO, respectively with various number of nodes.

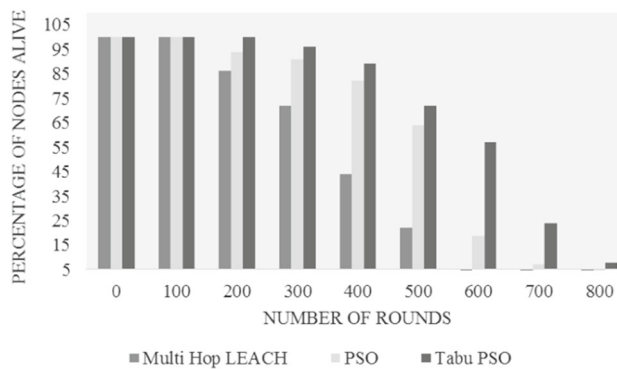
Observing the Fig. 3, it can be noted that the presented Tabu PSO technique mitigated the mean end to end delay averagely by 11.31 and 8.26% when compared with multi-hop LEACH and PSO, respectively with various number of nodes.

It can be observed from the Fig. 4, the proposed Tabu PSO method reduced the average packet loss rate averagely by 27.32 and 3.42% when compared with multihop LEACH and PSO, respectively with various number of nodes.

It can be observed from the Fig. 5, the proposed Tabu PSO method improved the percentage of nodes alive averagely by



**Fig. 4** Average packet loss rate (%)



**Fig. 5** Percentage of nodes alive

40.82 and 14.79% when compared with multihop LEACH and PSO, respectively with various number of nodes.

### 4 Conclusion

For operating WSNs reliably and efficiently, energy is saving is the major prerequisite, and for important aspects of technical issues and resource management, more and more attention is being given to energy consumption. The main purpose of this work is to enhance the CH selection in WSN by using hybrid heuristic approach. So, an algorithm based on PSO and TS is proposed for optimizing the routing in WSN and CH selection. The presented technique is energy efficient as well as in response with the network. The presented scheme chooses effective CHs, optimizing the routing as well as increment the lifespan of network. The proposed system selects efficient CHs, optimization of routing and increase the network lifetime. The proposed Tabu-PSO method reduced the average packet loss rate in an average of 27.32% in comparison with multihop LEACH with many number of nodes. In future, the existing results may be enhanced by hybridizing the firefly techniques with TS.

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