Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) for Data Collection in Mobile Sinks

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Abstract—Wireless Sensor Networks (WSN) designed with set of sensor nodes used to collect the information from the network environment and send the data to mobile sink. One of the main tasks of wireless sensor network is collecting the data in mobile sink. Existing works presented for data collection in mobile sink, it supports only single hop transfer of data from sensor nodes. In [13] presented energy-constrained mule traveling salesman problem (EM-TSP) for data gathering, routing and energy consumption of the wireless sensor network. To enhance the efficiency of data collection in WSN, plan to introduce mobile elements endures large data latency but with the use of TSP it can be lessened. So, in this paper, the initiation of a Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) for data collection in mobile sinks. This technique initially constructs an optimal tour path through TSP. The generated Hamiltonian paths are divided into multiple loops by means of BFO algorithm, where the fitness function is calculated considering average delay of each loop. Multiple loops are formed such that total delay is minimized. Further, the process of data gathering is enhanced by combining multiple aggregation tasks together to conserve more energy and increases the life time of the network. Simulation evaluation is conducted to estimate the performance of the proposed BFO based TSP for data collection in WSN in terms of delay, delivery rate and energy consumption. Evaluation report shows that the proposed BFO-TSP consumes 15-20% less in energy for data collection in WSN.

Keywords—WSN, data collection, mobile sink, Bacterial Foraging optimization, Traveling salesman problem, energy consumption

1. INTRODUCTION

Wireless sensor network (WSN) usually comprises of sensor nodes which are proficient in gathering information from the environment and sending the data to the Sink. Usually the sensor node is enclosing the short capacity series and alternatively the sink is classically loaded in energy. Energy is the major significant issue in the WSN since each sensor plants with its non-rechargeable battery. Data compilation is the standard request in the WSN. Wireless Sensor Networks (WSNs) contain numerous possible applications, which comprise ecological monitoring, tracking, healthcare observation, smart homes, etc. Because sensors are set powered, extending the network lifetime of WSNs is vital for the practice of sensors in this broad choice of applications. Communication is one of the chief bases of energy consumption. With restricted broadcast range, sensors classically transport their evaluation to the sink in a multi-hop mode.

In heterogeneous construction, influential sensors with superior energy capability and stronger communication ability are organized to lessen the energy utilization of normal sensors and to augment the data collection rate. Utilizing the set of mobile nodes, data can be communicated from a sensor to the sink by means of less number of hops. The process of data collection in mobile sink in WSN is shown in fig 1.
To forward the collected readings to the sink, the boundary sensors will receive and store the readings and then remain for mobile sink to overtake through their transmission ranges. Though, sensors nearer to the middle of the supervising region would have much less data-relaying workloads than the border line sensors. 

Presume that the sensor nodes are arbitrarily deployed. The mobile sinks group the data from sensor nodes when it gets nearer to them. The entire network region is separated into two divisions. Direct communication area (DCA) among routes and multi-hop communication area (MCA) for distantly sensor nodes. In Direct communication area, the sensor nodes termed as sub-sinks can openly broadcast data to mobile sinks and in multi-hop communication area, the sensor nodes termed as members initially broadcast data to the sub-sinks which then communicates closing data to the mobile sinks. The period (communication time) among every sub-sink and the mobile sink is understood to be fixed. Consequently, the mobile sink system (i.e., the method that uses mobile sinks) can decrease energy consumption and progress the network lifetime.

In this task, there is a plan to devise Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) for data collection in mobile sinks to reduce energy consumption and improve the network lifetime. The organization of paper is done as follows; section-1 presents introduction and section-2 gives description about literature review. The proposed technique is given in section-3 and section-4 details simulation results and section-5 discuss the results obtained from the existing and proposed technique. Section 6 finishes off the paper with conclusion.

2. LITERATURE REVIEW

The concept of TSP is widely used in many areas of applications, such as X-Ray crystallography, computer wiring, drilling of printed circuit boards, overhauling gas turbine engines and mask plotting in PCB production. During data gathering process its efficiency can be enhanced through TSP. [1] Apart from these real time applications, the vehicle routing problem is designed as the problem of TSP. In operational research and computer science, TSP is considered as most exhaustively deliberated problem. TSP can be defined as the problem of finding shortest Hamiltonian cycle, (i.e) it should traverse each vertex only once in an undirected complete graph with specified edge lengths. [2] In this case, the minimum number of vehicles required to serve each user can be found by TSP. Further, it is also used to scheduling problems. [3]

One of the major problem of TSP is it requires polynomial time algorithm for solving the problem [4]. It put forwards more issues when more problems in fields such as science, engineering
and bioinformatics are formulated as TSP’s [5]. Some other issues are also initiated as it necessitates network contention and memory demands [6]. Analysis of crossover operators, analysis of mutation operators, and mechanism of keeping diversity are the issues of TSP in Genetic algorithms. [7]

Data aggregation is the process of collecting information sensed by sensor nodes and transporting them to the central base station generally known as sink, where the data are analyzed and processed further. [8] This process is referred as basic data processing procedure and this can conserve energy and lessen the contention in medium access layer (MAC). [9] In wireless sensor networks (WSNs), using TSP a path with minimum cost can be obtained. Thus, TSP improves QoS. [10] Generally, introducing mobile elements in WSN endures large data latency but with the use of TSP it can be lessened. [11]. WSN applications with stringent energy requirement can utilize TSP to conserve significant amount of energy. [12]

Rafael Falcon et al. [10] have introduced a novel combinatorial optimization problem. They have characterized by the fact that the demand of any delivery customer can be met by a relatively large number of pickup customers to minimize its cost. Six ACO heuristic functions are put forward and a recently proposed exploration strategy is exploited to accelerate convergence in dense networks. Liang He et al [11] have introduced the mobile elements to reduce and balance energy consumption in wireless sensor networks. The combine-skip-substitute (CSS) scheme is presented with optimal tour path through TSP and the generated paths are combined using Welzl’s algorithm.

Zichuan Xu et al [12] have investigated the network lifetime maximization problem in a delay-tolerant wireless sensor network with a mobile sink by exploiting a nontrivial tradeoff between the network lifetime and the data delivery delay. Fang-Jing Wu et al [13] have considered a spatially separated wireless sensor network (SS-WSN). In this network, the authors have addresses the problem of using mobile mules to collect data from these sensor nodes. They have designed this problem as a bi-objective problem, called energy-constrained mule traveling salesman problem (EM-TSP) to minimize the traversal paths of mobile mules by consuming more energy.

Hengchang Liu et al [14] have proposed the problem of lifetime optimization under storage constraint for wireless sensor networks with a mobile sink node. Junyoung Park et al [15] supposed an approach that a mobile sink travels along a fixed path and uses a stop-and-collect protocol since this has previously been shown to be an efficient WSN data collection method. But the problem of selecting an optimal set of stop points is shown to be an NP-hard problem. R. Moazzez-Estanjini et al [16] have considered the problem of routing and scheduling a set of mobile elements (ME). Their key idea is to minimize the data delivery latency. Most of the existing work has focused on designing delay minimizing routes for the mobile nodes by leveraging variants of the Traveling Salesman Problem (TSP). So, they do not focus on data gathering. Delia Ciullo et al [17] have considered transmission energy optimization in WSNs where messages are collected by a mobile receiver (collector). In view of the above fact, they propose an algorithm for choosing both the transmission radii and the mobile collector’s path. In [11] they have formulated the data collection approach to find optimal path for mobile elements in WSN using normal TSP. But this approach consumes more time to setup the optimum paths and also its time efficiency is exponential as the number of nodes increases. Hence the new proposal of a
Bacterial Foraging Optimization based TSP approach to find an optimal path for the mobile element to traverse, collect and deliver the data to the sink.

3. PROPOSED METHODOLOGY

A Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) is presented for data collection in mobile sinks. Initially, an optimal tour is constructed using TSP. The generated paths are known as Hamiltonian paths and they are transformed into multiple loops using BFO. Edges of each loop are taken as inputs to the BFO and fitness function is calculated considering average delay of each loop. Multiple loops are formed such that total delay is minimized. At the end of BFO algorithm, multiple loops are produced. Further, the utilization of Welzl’s algorithm to enhance the performance of data aggregation process, where multiple data gathering tasks are combined together to conserve network energy. Thus, the technique conserves more energy and increases the life time of the network. The architecture diagram of the proposed BFOTSP is shown in Fig.1.

From Fig.1, it is being observed that with the TSP, the optimal route path in the sensor node is determined and the BFO is utilized to divide the path into several set of loops. For the obtained loop, determine the fitness function to compute the average delay. By implementing the data aggregation, the data collection in the mobile sink is achieved.

3.1 Average Delay Estimation
Presume that the network contains ‘n’ static nodes that produce data at the rate \( R_i \) (i=1, 2… n). So process the generated data which are aggregated and forwarded to the sink by Mobile Elements (ME’s). Thus, a ME visits nodes periodically to gather sensed information. We presuppose that the speed of ME is a constant and termed as \( S_p \). Let \( \text{avg} \ D \) as the average delay taken to deliver data that is generated at node i. [16]

\[
\text{avg} \ D = \frac{\sum^n_{i=1} \beta_i d_{ei}}{\sum^n_{i=1} \beta_i} \quad \ldots (1)
\]

Here \( \beta_i \) is the delay factor that represents the delay taken while producing data at node \( n_i \) and it is set to \( R_i \), where i=1, 2…n. \( d_{ei} \) is the average delay of node \( n_i \) and it is described as the sum of time that a node waits before transmitting data to the ME and the time taken by the ME to deliver data to the sink. The former is referred as waiting time of a node \( (W_i) \) and the later is carrying time of ME \( (C_{ME}) \). The computation of \( W_i \) and \( C_{ME} \) is given below with the assumption of constant bit rate.

\[
W_i = \frac{|T_L|}{2S_p} \quad \ldots \quad (2)
\]

\[
C_{ME} = \frac{D_{(n_i,S)}}{S_p} \quad \ldots \quad (3)
\]

In equations 1 and 2, \( |T_L| \) is the length of a period, \( D_{(n_i,S)} \) is the distance traveled by ME between node \( n_i \) and the sink (S). Using these equations, \( d_{ei} \) (delay estimation) can be rewritten as,

\[
d_{ei} = \frac{|T_L|}{2S_p} + \frac{D_{(n_i,S)}}{S_p} \quad \ldots \quad (4)
\]

The delay estimation is computed based on the summation of waiting time and carrying time of the sensor nodes in the WSN.

3.2 TSP based Optimal Tour Construction

Initially paths are constructed through Traveling Salesman Problem (TSP). Let T be the solution set which is getting obtained through TSP, it contains suboptimal paths that connect the sink. Then brief
the generated suboptimal paths as Hamiltonian paths. The generated Hamiltonian paths are shown in

![Figure-2](image)

Figure-2.

3.3 Transforming Hamiltonian Paths into Multiple Loops through BFO

3.3.1 Bacterial Foraging Optimization (BFO)

Bacterial Foraging Optimization (BFO) algorithm is first proposed by Passino in 2002. It is inspired by the foraging and chemotactic behaviors of bacteria, especially the Escherichia coli (E. coli). By smooth running and tumbling, The E. coli can move to the nutrient area and escape from poison area in the environment [18]. Since its inception BFO has proved as an effective technique to solve many real world problems and also it is applied greatly in other fields because of its biological motivation and graceful structure. Researchers are trying to hybridize BFOA with different other algorithms in order to explore its local and global search properties separately [19]. The Bacterial Foraging algorithm is a computational intelligence based technique that is not largely affected by the size and nonlinearity of the problem and can converge to the optimal solution in many problems where most analytical methods fail to converge [20].

Consider $P(\theta)$ as a minimum value that required to find in the system. A search agent is traverse on the functional surface to track down the global optimal output. A prediction of a chemotactic step may be a tumble followed by a tumble or a tumble followed by a run. The following table(Table1) describes the parametric description used in this work for data collection process.

<table>
<thead>
<tr>
<th>Constraints</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x$</td>
<td>Loop variable of chemotactic step</td>
</tr>
<tr>
<td>$y$</td>
<td>Loop variable of reproduction step</td>
</tr>
<tr>
<td>$z$</td>
<td>Loop variable of elimination dispersal step</td>
</tr>
<tr>
<td>$D$</td>
<td>Search space dimension</td>
</tr>
<tr>
<td>$A$</td>
<td>Total number of bacteria in the population</td>
</tr>
<tr>
<td>C_N</td>
<td>number of chemotactic steps</td>
</tr>
<tr>
<td>-----</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>S_L</td>
<td>swimming length</td>
</tr>
<tr>
<td>Re_S</td>
<td>number of reproduction steps</td>
</tr>
<tr>
<td>E_n</td>
<td>number of elimination dispersal events</td>
</tr>
<tr>
<td>Pr (E_n)</td>
<td>probability of elimination dispersal</td>
</tr>
<tr>
<td>si (i)</td>
<td>size of step which is directed by the tumble in the random direction</td>
</tr>
</tbody>
</table>

**Table 1. Parametric description**

Let \( L(x, y, z) = \{ \theta^i(x, y, z) | i = 1, 2, ..., A \} \) to denote the position of each member at \( x^{th} \) chemotactic step, \( y^{th} \) reproduction step and \( z^{th} \) elimination dispersal event in the population of A bacteria. \( P(x, y, z) \) is the cost function that stands for cost of search agent \( i, \theta^i(x, y, z) \in \mathbb{N}^D \) at a location in \( D \).

The general algorithm of BFO is given below,

**Algorithm-1**

Step 1: Initialize the parameters \( D, A, C_N, S_L, \text{Re}_S, E_n, \text{Pr}(E_n), \text{si}(i), i=1, 2, ..., A, \theta^i \)

Step 2: Elimination dispersal loop \( z = z + 1 \)

Step 3: Reproduction loop \( y = y + 1 \)

// Chemotaxis

Step 4: loop \( x = x + 1 \)

Step 4.1: For \( i = 1, 2, 3, ... A \)

Step 4.2: Fitness function is calculated \( P(i, x, y, z) = J(i, x, y, z) + P_{CC} \sum_{i=1}^{A} (\theta^i, \theta^D(x, y, z)) \)

...... (5)

// the cost function \( P_{CC} \)

Step 4.3: Consider \( P_{\text{final}} = P(i, x, y, z) \) // we save this value for we may get better cost value during iteration

Step 4.4: Tumble- A random number \( \Delta (i) \) is generated with each element where \( (\Delta(i) \in \mathbb{N}^D) \)

\( \Delta_g(i), g = 1, 2, ..., D \)

Step 4.5: Move- (as per equation 1)

Step 4.6: Compute \( P(i, x+1, y, z) = P(i, x, y, z) + P_{CC}((\theta^i(x+1, y, z), D(x+1, y, z))) \) .. (6)

// Swim
Step 4.7: Estimate the optimal path through the following steps
Step 4.7.1: Assume \( g = 0 \) // It is the counter for swim length
Step 4.7.2: While \( g < S_L \)
\[ g = g + 1 \]
Step 4.7.3: If \( (P(i, x+1, y, z) < P_{\text{final}}) \) Then
\[ P_{\text{final}} = P(i, x, y, z) \]
\( \theta^j(x+1, y, z) = \theta^j(x, y, z) + s(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \) \ldots \ldots (7)

\( \theta^j(x+1, y, z) \) is used to generate new \( P(i, x+1, y, z) \)
Step 4.7.4: Else,
Take \( g = S_L \)
End if
End while
Step 4.8: If \( i \neq A \) then \( i = i + 1 \)
Step 5: If \( x < C_N \)
Go to step 4

// Reproduction
Step 6: Identify the bacterium
Step 6.1: Health of the bacterium is estimated with \( y, z \)
Step 6.1.1: For each \( (i = 1, 2 \ldots S) \)
\[ P_{\text{health}}^i = \sum_{x=1}^{c_{x+1}} P(i, x, y, z) \] \ldots \ldots (8)
Step 6.1.2: Sort bacteria and \( T(i) \) in the ascending order of cost function
Step 6.1.3: the bacterium with highest heath value dies and bacteria with best values are divided
Step 6.1.4: End For
Step 7: If \( y < R_e S \)
Go to step (3) // Iteration is needed to reach the specific number of reproduction steps.

// Elimination Dispersal
Step 8: For every \( i \ (i = 1, 2 \ldots A) \) the elimination dispersal steps are performed with the probability \( P_r(E_n) \)
Step 8.1: If \( z < E_n \) Then
Goto Step (2)
End if
Step 9: End For
Step 10: End

Bacteria Foraging Optimization Algorithm (BFOA) encompass four important steps as follows, Chemotaxis, Swarming, Reproduction, Elimination and Dispersal

Chemotaxis
In this process, movement of each search agent is triggered either by swimming or tumbling. These two are the operations of a search agent throughout its life time. For \( i \)th search agent \( \theta^i(x, y, z) \), \( si(i) \) is the size of the step in random direction, which is taken as mentioned by the tumble, then the chemotaxis (i.e) the movement of bacterium can be computed as,

\[
\theta^i(x, y, z) = \theta^i(x, y, z) + si(i) \frac{\Delta i}{\sqrt{\Delta^2(i)\Delta(i)}} (9)
\]

In the equation 9, \( \Delta \) is the vector in random direction and it takes value between [-1, 1].

**Swarming**

It is observed more commonly in bacteria that after searching optimal path for food, each bacterium attempts to signal others so that the anticipated place can be reached more quickly. This cell-to-cell signaling is achieved through the process of swarming.

**Reproduction**

Through this step the number of search agents remains constant for minimum healthy bacterium (search agent) dies and healthier bacterium are divided into two other bacteria and placed in the same location.

**Elimination and Dispersal**

In this step, some search agents are eliminated randomly with small probability and some search agents are added randomly and initialized in the work space.

### 3.3.2 BFO Based Transformation of Hamiltonian Paths to Multiple Loops

The generated Hamiltonian paths are transformed into multiple paths by means of Bacteria foraging optimization technique. BFO algorithm is applied to the Hamiltonian path set ‘T’ to attain multiple loops.
Initially, BFO commences its procedure with shortest Hamiltonian cycle. Identify \( L_i \) as the set of loops, where \( i=1, 2, \ldots, n \). \( L_i \) is taken as input for BFO. The algorithm computes \( \text{avg } D \) for each \( L_i \) using equation (1) and then splits the loop into two such that total delay is minimal. This process is repeated until the following condition is satisfied,

\[
\text{avg } D_{L_1} > \text{avg } D_{L_2} + \text{avg } D_{L_3} \quad \ldots \quad (10)
\]

The equation (10) is taken as fitness function for BFO. Thus, at the end of BFO algorithm, multiple loops are obtained.

**Algorithm-2**

1. Let \( L_1, L_2, \ldots, L_n \) be the set of loops in the network
2. Edges of the loops are taken as inputs for BFO
3. \( \text{avg } D_{L_1} \) is computed as per the equation given in equation (1)
4. Node with high delay is eliminated from the loop
5. Loop is divided into two different loops
6. Step 3, 4 and 5 are repeated until

   \[
   \text{Step 6.1 } \text{avg } D_{L_1} > \text{avg } D_{L_2} + \text{avg } D_{L_3}
   \]

7. Break

Figure-1 indicates Hamiltonian path generation. From which, multiple paths are generated namely \( P_1, \ P_2, \ P_3, \ P_4, \ P_5 \) and \( P_6 \) as a result of BFO algorithm. The generated multiple paths are shown in Figure-2.

### 3.4 Discovering Efficient Paths for Data Aggregation

To bring about our data aggregation technique more efficient, the utilization of the Welzl’s algorithm given in [11]. This algorithm combines one or more data aggregation tasks together considering nodes geographical closeness such that ME can perform the aggregation process at a single place. This scheme reduces energy consumption and improves system performance. The output of BFO is considered in Welzl’s algorithm to enhance the efficiency of data aggregation. Let \( r_i \) be the transmission range between node \( i \) and ME. This algorithm reduces the number of collection sites by the side of multiple loops of Hamiltonian paths.

In this technique, Welzl’s algorithm is used to join multiple sensor locations that suits within the radius of transmission range \( r_i \). For a specified set of sensor nodes, the algorithm returns the smallest encompassing disk. Sensor nodes with transmission range in accord with ME are taken as inputs. If radius is lesser than \( r_i \), then it returns radius and center value. Otherwise, it displays error message. This process is repeated until the algorithm reaches the last sensor node.

Subsequently, the algorithm checks feasibility for combining all possible sensors to be within the radius of transmission range \( r \). By performing this operation, the ME can aggregate data only by visiting the center of encompassing disk and not all nodes. Algorithm is given in Algorithm-3.

**Algorithm-3**
1. Multiple loops are considered in Welzl’s algorithm
2. Input: Set of nodes, radius of their transmission range \( r_i \)
3. Algorithm performs comparison
   Step 3.1: If (radius is lesser than \( r_i \))
   then
   Step 3.1.1: algorithm returns radius and center value
   Step 3.2: Else
   Step 3.2.1: It displays error message.
4. End if
5. Process is repeated until the algorithm reaches the last sensor node
6. It checks feasibility for combining all possible sensor nodes within the transmission range
7. Returns small encompassing disk with center and radius
8. ME collect data by visiting center of the smallest disk

4. SIMULATION RESULTS

The proposed Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) (BFOTSP) is evaluated through NS2 simulation. To declare a random network of sensor nodes deployed in an area of 500 X 500m. The number of nodes is varied as 20,40,60,80 and 100. The sink nodes are assumed to be situated 100 meters away from the above specified area. The simulated traffic is CBR with UDP. The transmission rate is varied from 50 to 250kb. The simulation parameters are described in Table 2.

Table 2. Summarization of the simulation parameters

<table>
<thead>
<tr>
<th>No. of Nodes</th>
<th>20,40,60,80 and 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area Size</td>
<td>500 X 500</td>
</tr>
<tr>
<td>Mac</td>
<td>802.11</td>
</tr>
<tr>
<td>Routing protocol</td>
<td>BFOTSP</td>
</tr>
<tr>
<td>Simulation Time</td>
<td>50 sec</td>
</tr>
<tr>
<td>Traffic Source</td>
<td>CBR</td>
</tr>
<tr>
<td>Packet Size</td>
<td>512 bytes</td>
</tr>
<tr>
<td>Rate</td>
<td>50,100,150,200 and 250 kb.</td>
</tr>
</tbody>
</table>
Transmission Range: 250m
Transmit Power: 0.395 W
Receiving Power: 0.660 W
Idle Power: 0.035 W
Initial Energy: 15.1 Joules

4.1 Performance Metrics
The performance of BFOTSP is compared with the EMTSP [13] scheme. The performance is evaluated mainly, according to the following metrics.

- **Packet Drop**: The number of packets dropped during the data transmission.
- **Energy**: It is the average energy consumed for the data transmission.
- **Delay**: It is the average time taken by the packets to reach the destination.
- **Average Packet Delivery Ratio**: It is the ratio of the number of packets received successfully and the total number of packets transmitted.

5. RESULTS AND DISCUSSION
In this section (section 5) describes the performance of the proposed Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) against EMTSP approach. With the experimental evaluation, the results are discussed with the appropriate performance metrics to estimate the performance of the proposed Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP). The following graph describes the evaluation report of both the techniques.

A. Based on Nodes
In first set of experiment, the number of nodes is specified as 20, 40, 60, 80 and 100.

![Fig 5.1: Nodes Vs Delay](image)

Fig 5.1 describes the delay occurred while collecting the data in mobile sink based on the number of sensor nodes in the WSN. Delay is measured in terms of seconds. Compared to the existing EMTSP, the proposed BFOTSP technique achieves minimum delay in delivering the data to the destination. Because, BFOTSP provides optimal route path for routing the data in sensor networks by means of Traveling Salesman Problem. With the obtained path, BFO is applied to form a multiple loops to minimize the delay. But the existing EMTSP focused on only minimizing the traversal path rather than choosing the optimal path. So, the variance in delay is 4-7% less in the proposed BFOTSP.
Fig 5.2: Nodes Vs Delivery Ratio

Fig 5.2 measures the delivery rate of the data from source to destination in the sensor network based on the number of nodes. Delivery ratio is measured in terms of ratio among the number of packets received and total number of packets transmitted. Compared to the existing EMTSP protocol, the proposed BFOTSP offers high rate in delivery ratio. Because, the BFOTSP divides the optimal path into several set of loops by determining the fitness function simultaneously. Depend upon the fitness value, the path has been selected to route the packet. But the existing EMTSP protocol sets a threshold value for delivering the packets but there is a chance of missing the threshold value. So, the variance in the delivery ratio is 3-6% high in the proposed BFOTSP technique.

Fig 5.3: Nodes Vs Energy

Fig 5.3 describes the utilization of energy while collecting the data in mobile sink based on the number of sensor nodes in the WSN. Energy utilization is measured in terms of Joules. Compared to the existing EMTSP, the proposed BFOTSP technique achieves minimum energy utilization in delivering the data to the destination. Because, BFOTSP provides optimal route path for routing the data and formed the multiple loops using BFO in sensor networks by means of Traveling Salesman Problem. So, the utilization of energy is less. But the existing EMTSP focused on only minimizing the traversal path rather than choosing the optimal path. So, the variance in delay is 4-7% less in the proposed BFOTSP.
Fig 5.4: Nodes Vs Overhead

Fig 5.4 describes the overhead arises while collecting the data in mobile sink based on the number of sensor nodes in the WSN. Overhead is measured based on the excess use of energy utilization to reach the destination. Compared to the existing EMTSP, the proposed BFOTSP technique has less overhead in delivering the data to the destination, because BFOTSP consumes less energy against the existing EMTSP. So, the variance in delay is 4-7% less in the proposed BFOTSP.

![Graph showing Nodes Vs Overhead](image)

Fig 5.5: Nodes Vs Drop

Fig 5.5 describes the packet drop arises while collecting the data in mobile sink based on the number of sensor nodes in the WSN. Packet drop is measured based on the number of packets dropped while performing transmission. Compared to the existing EMTSP, the proposed BFOTSP technique has less packet drop in delivering the data to the destination, because BFOTSP provides multiple paths for a packet from source to destination. So, the packet drop rate becomes automatically less.

B. Based on Transmission Rate

In the second experiment, the transmission rate is identified with varying values 50,100,150,200 and 250 which are measured as kb.

![Graph showing Rate Vs Delay](image)

Fig 5.6: Rate Vs Delay

Fig 5.6 describes the occurrence of packet delay based on the transmission rate of packet data in the WSN. Delay is measured in terms of seconds. Compared to the existing EMTSP, the proposed BFOTSP technique achieves minimum delay in delivering the data to the destination. Because, BFOTSP provides optimal path for data delivery by means of Traveling Salesman Problem. With the obtained path, BFO is applied to form a multiple loops to minimize the delay. But the existing EMTSP focused on only minimizing the traversal path rather than choosing the optimal path. So, the variance in delay is 4-9% less in the proposed BFOTSP.
Fig 5.7: Rate Vs Delivery Ratio

Fig 5.7 measures the delivery rate in the sensor network based on the transmission rate of packet data in the WSN. Delivery ratio is measured in terms of ratio among the number of packets received and total number of packets transmitted. Compared to the existing EMTSP protocol, the proposed BFOTSP offers high rate in delivery ratio. Because, the BFOTSP divides the optimal path into several set of loops by determining the fitness function simultaneously. Depend upon the fitness value, the path has been selected to route the packet. But the existing EMTSP protocol sets a threshold value for delivering the packets but there is a chance of missing the threshold value. So, the variance in the delivery ratio is 3% high in the proposed BFOTSP technique.

Fig 5.8: Rate Vs Energy

Fig 5.8 describes the utilization of energy needed to transmit the data in the WSN. Energy utilization is measured in terms of Joules. Compared to the existing EMTSP, the proposed BFOTSP technique achieves minimum energy utilization in delivering the data to the destination. Because, BFOTSP provides optimal route path for routing the data and formed the multiple loops using BFO in sensor networks by means of Traveling Salesman Problem. So, the utilization of energy is less. But the existing EMTSP focused on only minimizing the traversal path rather than choosing the optimal path. So, the variance in delay is 4-7% less in the proposed BFOTSP.

Fig 5.9: Rate Vs Overhead

Fig 5.9 describes the overhead arises while collecting the data in mobile sink based on the transmission rate of data packet in the WSN. Overhead is measured based on the excess use of energy utilization to reach the destination. Compared to the existing EMTSP, the proposed BFOTSP
technique has less overhead in delivering the data to the destination, because if data traffic occurs, the packet data will route to some other optimal path to reach the destination. So, the variance in delay is less in the proposed BFOTSP.

![Fig 5.10: Rate Vs Drop](image)

Fig 5.10 describes the packet drop arises while collecting the data in mobile sink based on the transmission rate of data packet in the WSN. Packet drop is measured based on the number of packets dropped while performing transmission. Compared to the existing EMTSP, the proposed BFOTSP technique has less packet drop in delivering the data to the destination, because BFOTSP provides numerous optimal paths for a packet to reach the destination. So, the packet drop rate becomes automatically less. Finally, it is being observed that the BFOTSP technique efficiently provides an optimal route path for directing the packet data from source to destination. Multiple paths are available for the given packet data to reach the destination if data traffic occurs. So, through the BFOTSP, the energy utilization for packet transmission become less and increase the network lifetime.

6. CONCLUSION

In this paper, a Bacterial Foraging Optimization (BFO) based Traveling Salesman Problem (TSP) is presented for data collection in mobile sinks. This technique initially constructed an optimal tour path through TSP. Then the generated Hamiltonian paths are divided into multiple loops by means of BFO algorithm, where fitness function is calculated considering average delay of each loop. Multiple loops are formed such that total delay is minimized. Further, the enriching process of data gathering by combining multiple aggregation tasks together. The technique BFOTSP conserves more energy and increases the life time of the network. Experimental evaluation is done to estimate the performance and simulation reports showed that the proposed BFOTSP technique is better in performance in terms of packet drop, delay, delivery ratio and achieves 17% less in energy consumption of nodes in the network.

References


