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Tour Path Planning for Mobile Data Collectors in IoTusing Modified Archerfish Hunting Optimization (MAHO) Algorithm

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ABSTRACT

In large-scale Internet of Things (IoT) based sensor networks, it is crucial and vital to create an effective path planning strategy for Mobile Data Collectors (MDCs). This paper proposes a tour path planning for MDCs in IoT-WSN using Modified Archerfish Hunting Optimization (MAHO) algorithm. The main objective of this work is to determine the MDC tour paths based on path stability and energy efficiency. The TPP-MAHO algorithm is simulated in NS2. Simulation results have shown that the proposed TPP-MAHO algorithm attains maximum packet delivery ratio and energy efficiency with minimized delay and packet drops.

Keywords: Internet of Things (IoT), Mobile Data Collectors (MDCs), Tour path planning, Modified Archerfish Hunting Optimization (MAHO) algorithm, Path stability

I. INTRODUCTION

IoT has emerged in recent years as a result of substantial advances in computer and communication technology [1]. IoT solutions yield lesser energy costs and resource utilization [1]. IoT has gained the attention of academics because of their fast increase [2]. IoT networks may save a lot of power by using mobile data collecting. When using a MDC, the biggest problem is determining and arranging the MDC's course to gather data from nodes. Static techniques of obtaining mobile data only identify a solution to a problem with predetermined variables [3][4].

IoT networks may save a lot of power by using mobile data collecting. When using a MDC, the biggest problem is determining and arranging the MDC's course to gather data from nodes. Static techniques of obtaining mobile data only identify a solution to a problem with predetermined variables [5].

In large-scale IoT based sensor networks, it is crucial and vital to create an effective path planning strategy for MDCs to reduce the tour travel distance and increase the lifespan [6][7]. The stopping time of MDCs should be enough to gather data from all the nodes from a specific region without increasing the data gathering delay.
Hence the main objective of this work is to determine the MDC tour paths based on path stability and energy efficiency.

II. RELATED WORKS

TheMDCdefined by Kamarei et al [8]uses a learning automaton to migrate to the network's core or to the center of each logical partition. By updating its action probability vector based on logical partition information, the learning automatatechnique chooses the optimal logical separation at each interval.

Deadline-based periodic data collecting technique utilizing the fewest possible MDSs has been presented by Kumar and Dash [9]. For the purpose of gathering data from mobile sensors utilizing MDSs, a heuristics-based approach is given in which MDSs are not necessary for the final data transmission to the base station.

To discover a short path that covers the most sensors, Gao et al. [10] have introduced a travel route planning schemeusing mobile collector (TRP-MC). The number of stopping points is calculated based on the maximum coverage rate. The PSO technique is then used to find the best locations for SPs with the highest coverage rates and the lowest overlapped coverage rates.

III. PROPOSED METHODOLOGY

We apply the modified archerfish hunting optimization (MAHO) algorithm to compute the tour paths of MDC in IoT-sensor networks.

3.1 Fitness function

In this section, a fitness function for tour path selection is derived in terms of link stability and remaining energy.

Link stability (LS) depends on the Expected Transmission Count (ETX) metrics.

ETX metric for a link is given by

$$\text{ETX} = \frac{1}{(\text{Pr}_{tx} * \text{Pr}_{rx})} \qquad (1)$$

where Pr_{tx} and Pr_{rx} are probabilities of successful packet delivery and successful packet reception.

Then LS of the link between two sojourn points SP_i and SP_j is given by

$$\text{LS}_{ij} = \frac{1}{(ETX * PER)} \qquad (2)$$

The energy expended for transmitting a data packet of length k-bits over a distance (i, j) is given by:

$$E_{tx}(i, j) = \begin{cases} (ED + k \times u(i,j)^2 \times \gamma, \text{if} u(i,j) < u_0 \\ ED + l \times u(i,j)^4 \times \gamma, \text{otherwise} \end{cases} \qquad (3)$$

Where ED is the energy dissipation in circuit , k and γ are energy dissipation at amplifier and circuit, and u = k/l.

The energy dissipated for receiving a data packet of k-bits is given as follows:

$$E_{rx} = ED*\gamma \qquad (4)$$

The total energy consumption is given by

$$E_c = E_{tx} + E_{rx} \qquad (5)$$

The remaining energy is given by

$$E_r = E_i - E_c \qquad (6)$$

Then a fitness function is defined as

$$\text{Fit}_{ij}() = w_1 . \text{LS} + w_2 .E_r \qquad (7)$$

Where, w1 and w2 are weight values in the range of (0,1).

3.2 MAHO Algorithm

In this function MAHO algorithm is applied to select the optimum tour path among the sojourn points with maximum fitness function.

The MAHO algorithm is a nature-inspired optimization technique that draws inspiration from the hunting behavior of archerfish, a unique species of fish known for its remarkable ability to shoot down insects above the water's surface using precise water jets. This algorithm is designed to solve optimization problems by simulating the hunting behavior of these fish. The MAHO algorithm operates by iteratively searching for optimal solutions in a problem space, mimicking how archerfish identify and target their prey. We assume a d-dimensional search space with several archerfish. The area of branch I at emphasis t is displayed underneath, and the group size or number of archfish is N.

$$X^{\langle y,t \rangle} = (y_1, y_2, ..., y_s)$$

The following function is used to randomly initialize the location $Z^{\langle u,0 \rangle}$ at iteration r = 0.

$$y^{\langle u,0 \rangle} = \left(\alpha_1 \times \left(y_1^{\max} - y_1^{\min}\right) + y_1^{\min}, ..., \alpha_a \times \left(y_a^{\min} - y_a^{\min}\right) + y_a^{\min}\right) \qquad (2)$$

where α1,...,αs are consistently dispersed irregular numbers from 0 to 1. When the bowfishrecognizes vibrations started by the prey, which denotes as follows.

$$y^{\langle u,r+1 \rangle} = y^{\langle r,r \rangle} + q^{-\left\| z_{prey}^{j,r} - Z^{\langle u,r \rangle} \right\|^2} \left(y_{PREY}^{\langle j,r \rangle} - y^{\langle u,r \rangle} \right) \qquad (3)$$

$$y_{prey}^{\langle j,r \rangle} = y^{\langle j,r \rangle} + \left(0, \dots, \frac{x^2}{2_d} \times \sin 2\theta_0, \dots, 0 \right) + \varepsilon \qquad (4)$$

The record position indicated by term is an irregular number that falls inside a reach. The variable will replace the division for straightforwardness. It specifies an archerfish's rate of attraction to a particular prey.

$$y^{\langle u,r+1 \rangle} = y^{\langle u,r \rangle} + q^{-\left\| y_{preey}^{\langle u,r \rangle} - y^{\langle U,R \rangle} \right\|^2} \left(y_{\text{Prey}}^{\langle u,r \rangle} - y^{\langle u,r \rangle} \right) \qquad (5)$$

$$y_{prey}^{\langle h,t \rangle} = y^{\langle h,t \rangle} + \left(0, \dots, \frac{v^2}{2_d} \times \sin 2\theta_0, \dots, 0 \right) + \varepsilon \qquad (6)$$

It specifies an archerfish's rate of attraction to a particular prey. The benefit of seeing point (θ_0) ensures the trading between the investigation and exploitation stages.

$$\theta_0 = (-1)^v \times \alpha \times \tau \qquad (7)$$

For this situation, the relating archerfish moves to another spot as indicated by a Duty Flight.

$$y^{\langle y,m+1\rangle} = y^{\langle y,t\rangle} + \alpha\left[\frac{y_1}{(\varsigma_1)^{1/\chi}}, \ldots., \frac{u_s}{(\varsigma_s)^{1/\chi}}\right] \tag{8}$$

$$\begin{cases} y_u \approx \Re(0,\partial^2), \partial = \left(\dfrac{\Gamma(1+\chi)\sin\left(\dfrac{\tau\chi}{2}\right)}{\Gamma\left(\dfrac{1+\chi}{2}\right)\times\chi\times 2\dfrac{\chi-1}{2}}\right)^{\frac{1}{\chi}} & ,u\in\{1,\ldots.,s\} \\ \varsigma_i \approx \Re(0,\partial^2) \quad ,\partial = 1, & u\in\{1,..s\} \end{cases} \tag{9}$$

MAHO algorithm is ability to combine exploration and exploitation strategies, much like the archerfish's hunting behavior. It adapts over iterations, refining solutions and converging towards optimal or near-optimal solutions. The working process of cluster formation using MAHO is explained in Algorithm 1.

Algorithm 1 Tour path planning using MAHO

```
Input   : Search space, objective function, swapping angle and attractiveness rate
Output : Node cluster formation

for i ← 1 to N do
    Generate a random location $Z^{\langle r,r\rangle}$ using Equation 1;
end
for t ← 1 to Itermax do
    for i ← 1 to N do
$\theta_0$ ← generate a random perceiving angle
if $\theta_0 = (-1)^v \times \alpha \times \tau$ then
        Compute $Z^{\langle r,r\rangle}$ prey using Equation 3;
        for K ← 1 to M do
        if $[x_1^{min}, x_1^{max}],\ldots., [x_d^{min}, x_d^{max}]$ then
        Update the location $Z^{\langle r,r\rangle}$
        end
         else
         If the location $Z^{\langle r,r\rangle}$ has not changed for given iterations
        Generate a new location for $Z^{\langle r,r\rangle}$
         end
         end
      end
else
      Compute $Z_{prey}^{\langle j,r\rangle}$
 If
Update the location $Z^{\langle r,r\rangle}$
end
  else
   If the location $Z^{\langle r,r\rangle}$ has not changed for number of iterations.
   Generate a new location for $Z^{\langle r,r\rangle}$
               end
            end
        end
end
```

IV. EXPERIMENTAL RESULTS

4.1 Experimental Parameters

The TPP-MAHOalgorithm is simulated in NS2.The experimental parameters are presented in Table 1.

Parameters	Values
Network size	50-250
Network size	50×50 m^2
MAC protocol	IEEE 802.15.4
Initial energy	50 Joules
Traffic model	Constant bit rate (CBR) and Exponential
Transmission power	0.5819 J
Receiving power	0.049 J
Propagation model	Two way Ground
Traffic rate	50Kbps
Simulation time	100 sec

Table 1 Simulation parameters

4.2 Comparison Results

The performance of TPP-MAHO algorithm is compared withTRP-MCscheme [10] by varying the nodes from 50-250.

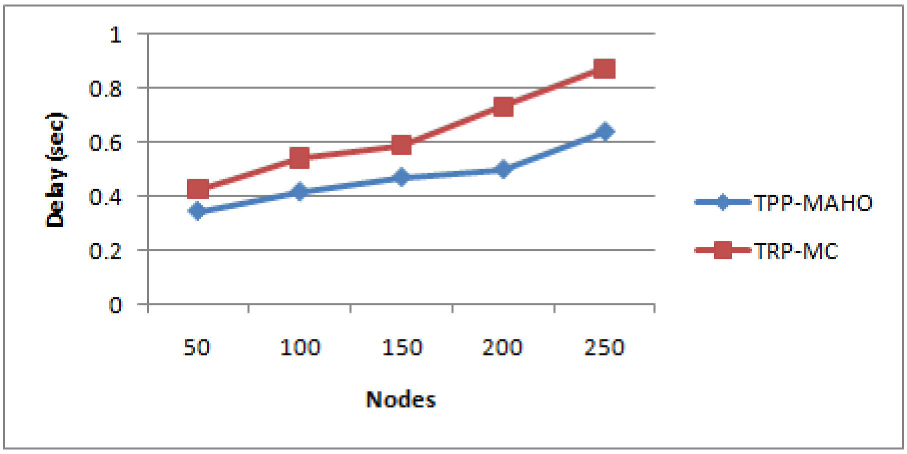

Figure 1 Results of End-to-End Delay

The end-to-end delay results for varying nodes are presented in Figure 1. From the figure it can be see that the delay of TPP-MAHO is 24% lesser than TRP-MC.

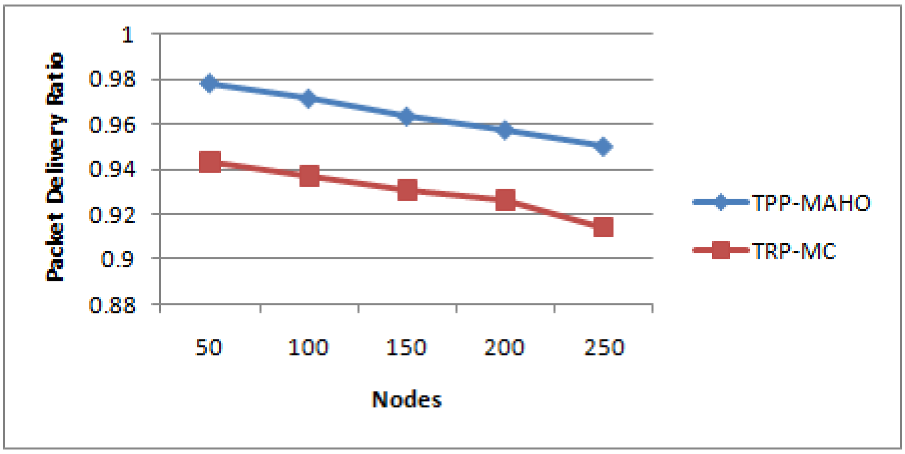

Figure 2 Results of Packet Delivery Ratio

The results of packet delivery ratio for varying nodes are presented in Figure 2. It can be seen that packet delivery ratio of TPP-MAHO is 3.5% higher than TRP-MC.

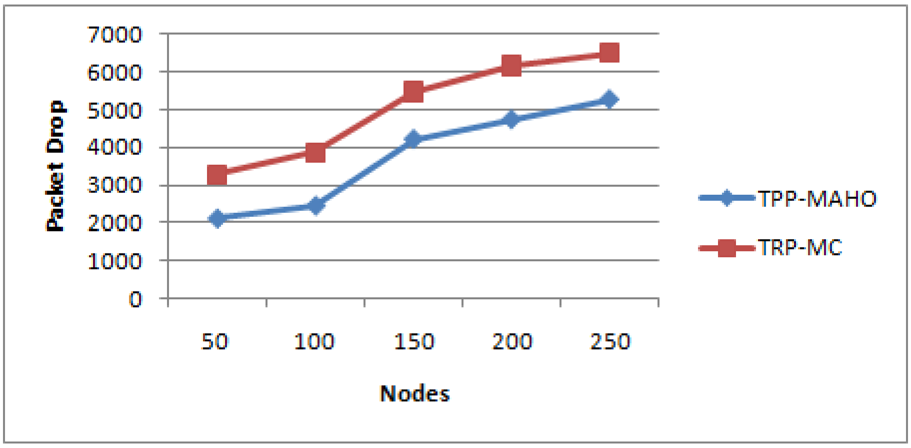

Figure 3 Results of Packet Drop

The results of packet drop for varying nodes are presented in Figure 3. It can be seen that TPP-MAHO has 27% lowerpacket dropthan TRP-MC.

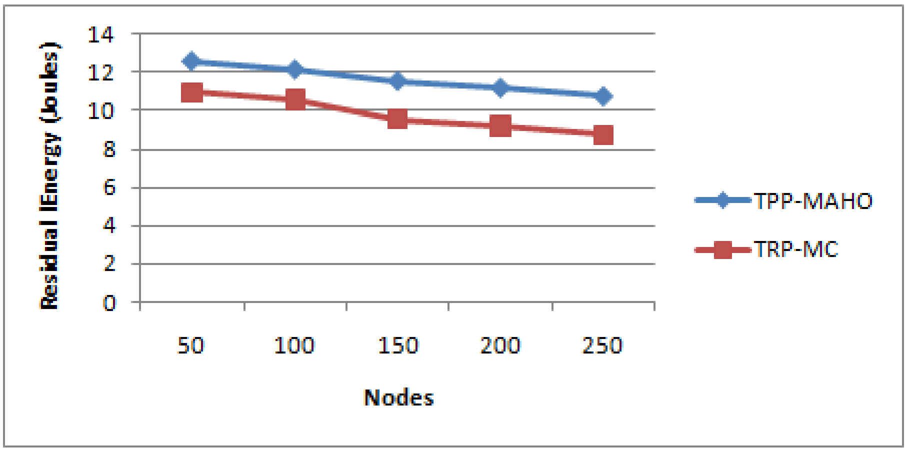

Figure 4 Results of Residual Energy

The average residual energy for varying nodesare presented in Figure 4. It can be seen that TPP-MAHO has 15% higher residual energy, when compared to TRP-MC

V. CONCLUSION

This study has designed a tour path planning for MDCs in IoT-WSN using MAHO algorithm. The main objective of this work is to determine the MDC tour paths based on path stability and energy efficiency. The TPP-MAHO algorithm is simulated in NS2. The performance of TPP-MAHO algorithm is compared withTRP-MC scheme. Simulation results show that TPP-MAHO algorithm attains maximum packet delivery ratio and energy efficiency with minimized delay and packet drops.

REFERENCES

[1]. Andreas P. Plageras, Kostas E. Psannis, Christos Stergiou, Haoxiang Wang and B.B. Gupta, "Efficient IoT-based sensor BIG Data collection-processing and analysis in Smart Buildings", Future Generation Computer System, 2017.

[2]. Walid Osamy, Ahmed M. Khedr, Ahmed A. El-Sawy , Ahmed Salim and Dilna Vijayan, "IPDCA: Intelligent Proficient Data Collection Approach for IoT-Enabled Wireless Sensor Networks in Smart Environments", MDPI, Electronics, 2021.

[3]. Xuemei Xiang, Wei Liu, Tian Wang, Mande Xie, Xiong Li, Houbing Song, Anfeng Liu and Guoping Zhang, "Delay and energy-efficient data collection scheme-based matrix filling theory for dynamic traffic IoT", EURASIP Journal on Wireless Communications and Networking, 2019.

[4]. Cosmas Ifeanyi Nwakanma, Fabliha Bushra Islam, Mareska Pratiwi Maharani, Dong-Seong Kim and Jae-Min Lee, "IoT-Based Vibration Sensor Data Collection and Emergency Detection Classification using Long Short Term Memory (LSTM)", IEEE, ICAIIC, 2021.

[5]. Sana Benhamaid, Hicham Lakhlef, Abdelmadjid Bouabdallah, "Towards Energy Efficient Mobile Data Collection In Cluster-based IoT Networks",IEEE, 2021.

[6]. Fasolo, E., Rossi, M., Widmer, J. and Zorzi, M., 2007. In-network aggregation techniques for wireless sensor networks: a survey. IEEE Wireless Communications, 14(2), pp.70-87.

[7]. Sangolgi, N.B. and Zakir, S.K.A., 2013. Energy aware data aggregation technique in WSN. International Journal of Scientific and Research Publications, 3(10).

[8]. Kamarei, M., Patooghy, A., Shahsavari, Z., JavadSalehi, M., Lifetime Expansion in WSNs Using Mobile Data Collector: A Learning Automata Approach, Journal of King Saud University - Computer and Information Sciences (2018).

[9]. Naweeen Kumar and Dinesh Dash, “Mobile data sink-based time-constrained data collection from mobile sensors: a heuristic approach”, IET Wirel. Sens. Syst., 2018, Vol. 8 Iss. 3, pp. 129-135.

[10]. Yu Gao, Jin Wang, Wenbing Wu, Arun Kumar Sangaiah and Se-Jung Lim, “Travel Route Planning with Optimal Coverage in Difficult Wireless Sensor Network Environment”, Sensors 2019, 19, 1838.