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Maximize The Energy Efficiency of IoT Devices Through Optimization and Localization

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Abstract – Wireless sensor nodes in IoT-based WSN's are increasing congestion between sensor networks. An optimized solution can be created based on a centralized approach or a local approach. Algorithms such as particle swarm optimization (PSO) use a centralized approach to address the limitations of the wireless sensor network. The centralized algorithms depend on the receiver node or base station node in the network. All information about the source and destination nodes, available communication paths and packet forwarding will be monitored by a centralized base station node. Implementing this centralized algorithm on a larger network result in degraded network performance. The limitations that exist in the network communication path, overcome the constraints by using local control approaches such as ant colony optimization. To overcome these limitations of solving optimization problems in larger networks, local controller approaches are used to improve energy efficiency and network performance. In this paper we compare optimization algorithms with different network parameters for different performance metrics.

Index Terms – ACO, PSO, D2D, IoT based WSN

I. INTRODUCTION

Traditional communication architectures and protocols for traditional wireless networks have no impact on the Internet of Things. In fact, IoT communication parameter and limitations must be considered by all important mechanisms that interfere with communication processes, like routing [1].ACO originated as a foremost met heuristic technology for solving combinatorial optimization problems that may be is used to find the shortest path from end to end structure diagram. By modeling the behavior of biological insects, the IoT can develop optimal algorithms to solve various problems of self-grouping and self-sustaining [2]. IoT devices used in Wireless Sensor Networks have unique identities and the benefits of sending data over the network without being affected by end to end devices. Therefore, the human community requires close cooperation based on the real-time cooperation of sensor nodes that are widely used in various applications [3]. Sensor nodes also provide wide-ranging opportunities to monitor, regulate, and decision making a range of observable character of subject in the relevant application environment, rather than data usage processes only adapt the data in the object environment. In the IoT architecture, nodes in a WSN are given limited storage, processing power, battery power, and bandwidth. Existing optimization algorithms have no effect when the network size increases. Particle Swarm Optimization (PSO) is one of nature's most efficient algorithms and can be the best choice because of its ease of execution, high class solution, and the ability to terminate local optimal fast convergence and the ability to move from residual energy to PSO-based Energy efficient approach[4]. Several methods can be used to determine the distance between two nodes, such as organization and the physical uniqueness of the carrier [5]. The WSN's localization method can deviate from previous network positioning and rely on location information from several specific sensors, such as time, and mutual measurements in the network difference between arrivals, arrival angles and links [6]. Conventional sensors for position information are called anchors or references, the position can be obtained through the GPS, or anchors can be installed at points with known coordinates. In fact, the equipment of any sensor with a positioning system or GPS is complicated by the high energy consumption of GPS [7].

II. LITERATURE REVIEW

It provides a common foundation for heterogeneity and communication between IoT devices. Recently, developing a middleware publishing / subscribing system on IoT to provide asynchronous communication between IoT devices. EECBR protocol for IoT that minimizes routing protocol power topology for publishing /subscribing schemes. It's a centrally created virtual structure that delivers events from publishers to interested subscribers in a distributed manner [8]. RSSI ensures ranking accuracy based on the level indicator of the received signal. Robust localization algorithms based on RSSI rank areas, which cause RSSI rank errors with fixed parameters during signal propagation. The model is practically excluded. In the signal propagation model, RSSI values and ranges of distances are compared one-to-one based on the range of the path loss index [9]. WSNs have become an important technology for various smart environments, and different types of devices can be interconnected according to IoT principles. Of the various WSN methods designed to determine the location of unknown nodes, an evaluation method based on the level of the received signal is best suited for localization because it is easy to implement and has less hardware necessities. The authors proposed a distributed localization algorithm with a dynamic circle expansion mechanism that can more accurately determine the geometric relationship between unknown and reference nodes to improve the localization accuracy [10]. The MDS algorithm is used to calculate the shortest path (e.g., the minimum number of hops) between all pairs of nodes. Once the distance connecting two nodes along this path is determined, can calculate the distance between two nodes on the shortest path. Localization of results that can improve the previous step by minimizing the least squares. The basic form of MDS is centralized localization. [11]. The ICDV hop algorithm use collinear diagrams to limit the topological relationships between the nodes. Localization Nodes If localization errors are below the error threshold, they are called new signals to support the remaining unknown nodes especially for iterative collaboration expands the range of locations [12]. An example of a localization algorithm is based on the number of jumps. This algorithm completely avoids spreading through anchors using an average hop size locally at each regular node or at any location. Analysis equations for jumps are obtained for nodes of various distributions. It can be defined locally on any generic node with or without prior knowledge of node distribution. The jump counter can reduce the number of errors associated with jump marks in distance units[13]. It is based on the calculation of number of transitions and estimates the coordinates of unknown nodes using multidimensional scaling analysis.. Then polish the nodes using multiple power transfer methods. Coordinates to get a bigger real number This method is called the depreciation method using the multidimensional (BIA-MMS) method[14].

III. SYSTEM MODEL

When transmitting data packets from one sensor node to another sensor node, various steps are involved. First, the data acquired by the sensor node is transmit to the server via the gateway. In order to send the data recorded by the sensor node to the server via Gateway, the connection between the gateway and the server must be established. In such a case, the choice of protocol is very important. The protocol is efficient when it comes to bandwidth usage. In IoT devices, devices exchange information with other devices, which generates a large amount of data and traffic. Device-to-device communication data can be transferred between devices autonomously, using licensed spectrum and unlicensed spectrum, which consumes a lot of energy. To overcome Energy Constraint problems, optimization algorithms were introduced in the IoT. In this paper we implement the system for which we apply an ant colony optimization algorithm and a practical swarm optimization algorithm. These algorithms improve energy efficiency and network performance.

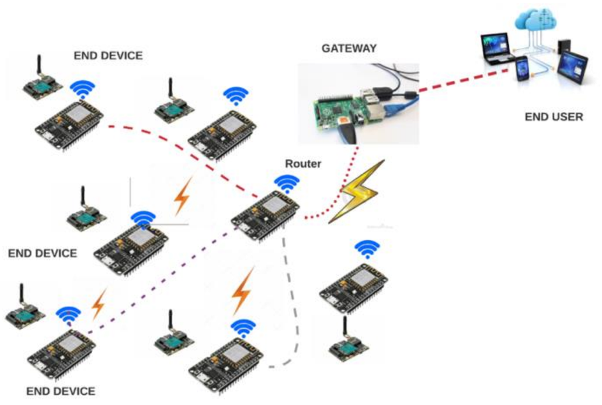

Fig.1. Data Transfer between the IOT devices

Problem Statement

The ant colony optimization algorithm uses heuristics to search for contiguous spaces. This expansion is performed by probabilistic sampling or possible discretization of the explored space. A continuation problem is some of the problems of getting values from current and previous values.

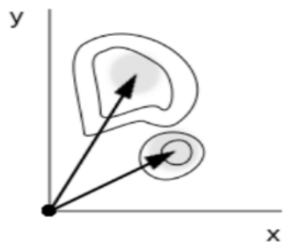

Fig.2. Continuous ACO search evaluation

The motion probability PrψK distribution describes the probability of zero for every move. The Probability distribution is not valid; otherwise, it is calculated using the equation (1), α and β are denoted as distinct factors (0≤α, β≤1).

$$p_{l\Psi}^{k} = \begin{cases} \frac{\tau_{l\Psi}^{\alpha} + \eta_{l\Psi}^{\beta}}{\sum_{(l\zeta)\notin tabu_k}}, & if\ (l\Psi) \notin tabu_k \\ 0, & otherwise \end{cases} \qquad (1)$$

In this equation (1), tabuk is represented by a tabu list of ant k, and the parameters α and β indicate the effects of traces and attractiveness, respectively. Whenever, the algorithm is repeated, if the ant as a whole completes the solution, the formula is updated using the equation (2)

$$\tau_{l\Psi}(\tau) = \rho\tau_{l\Psi}(\tau - 1) + \Delta\tau_{l\Psi} \qquad (2)$$

The $\Delta\tau_{l\varphi}$ denotes sum of the contribution of the entire ants which used move $(l\varphi)$ to form their solution. ρ, 0≤ ρ≤ 1, represents user-defined parameters, evaporation coefficients. The involvement of the ants corresponds to the quality of the solution achieved. In other words, it is best to participate in the traces contained in the movements used by the ants. For example, the Travelling solution problems, move on the arc of the graph. The state "t" can match the path outline of node "i" and the state matches the end of the path, but an arc (ij) at the end is connected, and the move can be a bypass of the arc (ij). The ant k solution can be the length Lk of the trip determined by the ant and equation (2) and the following equation will be obtained.

$$\tau_{ij}(t) = \rho\tau_{ij}(t - 1) + \Delta\tau_{ij}$$
$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij} \qquad (3)$$

M denotes the number of ants, and τ_{ij}^{k} is denoted by the number of trails lying along the edge (ij) using ant k, which can be calculated as follows.

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_k} & if\ ant\ k\ uses\ arc(ij)\ in\ its\ tour \\ 0 & \text{Otherwise} \end{cases} \qquad (4)$$

The main loop is repeated on the ant system, and the ant "m" generates a parallel solution and then the trace level is updated. The operation of the algorithm is based on fine tuning the various parameters: the relative importance of α, β, track and attractiveness, track stability, ij (0), m, Q and ant. These various parameters are used to describe a better solution with low cost.

Global Particle Swarm Optimization (PSO)

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In this type of optimization, each particle has a velocity and position vectors are denoted by xi (k) and vi (k). Where k is the iteration. In each iteration particle can remember the individual best position, denoted by pibest (k), and the global best position, denoted by gibest (k) is updated based on the equation (5)

$$p_i^{best}\ (k+1) = \begin{cases} p_i^{best}\ (k)\ if\ \ f\big(x_i(k+1)\big) < f\left(p_i^{best}(k)\right) \\ x_i(k+1)\ if\ \ f(x_i(k+1)) > f(p_i^{best}(k)) \end{cases}$$
(5)

$$g^{best}(k) = \arg max\ f\left(p_i^{best}(k)\right)\ \ or\ \ g^{best}(k) = \arg max\ f(x_i(k)) \qquad (6)$$

In the time of search process, every particle updates its velocity depends on the global best position and individual best position. For each particle the velocity update equation is shown below.

$$v_i(k+1) = v_i(k) + c_1 r_1(k)\left(\ p_i^{best}(k) - x_i(k)\right) + c_2 r_2(k)\left(\ g^{best}(k) -\ x_i(k)\right) \qquad (7)$$

The equation (1.7) applied in the standard version of PSO. The standard version forms the mechanism to limit the velocity, which discovers the exploitation and exploration abilities of the algorithm. The new concept "Inertia weight (w)" is introduced by Shi and Eberhart to overcome this problem. The velocity update equation is altered as below in order to involve the inertia weight.

$$v_i(k+1) = wv_i(k) + c_1 r_1(k)\left(\ p_i^{best}(k) - x_i(k)\right) + c_2 r_2(k)\left(\ g^{best}(k) - x_i(k)\right) \qquad (8)$$

c1 and c2 represents as trust parameters or acceleration coefficients, r1(k) and r2(k) are arbitrary numbers, which received from uniform distribution among [0,1] at iteration k. The entire particles flying through the search space by modifying their positions, which based on their velocities. At iteratin k+1, the each particle position is computed based on the formula (9).

$$x_i(k+1) = x_i(k) + v_i(k+1) \qquad (9)$$

During optimization process, the formulas (8) and (9) are used to update the particle positions and particle velocities. The each particle initialization is given by the formula (10)

$$x_i(0) = x_i^{min} + r_i(x_i^{max} - x_i^{min}) \qquad (10)$$

ximax and ximin denoted as maximum and minimum ranges of the search space, ri is represents the arbitrary number acquired from uniform distribution among [0,1]. Initial personal better positions are equal to the initial positions as shown in formula (11)

$$p_i^{best}(0) = x_i(0) \qquad (11)$$

Performance Evaluation

The nodes are placed on an area of 2000 square meters and the entire network is implemented using Wi-Fi standards. PSO algorithms need more swarm information to get more efficient results in IoT. The PSO algorithm is suitable for cluster-based networks and small IoT. If the number of routing nodes is set to a constant value, the throughput of the PSO algorithm increases.

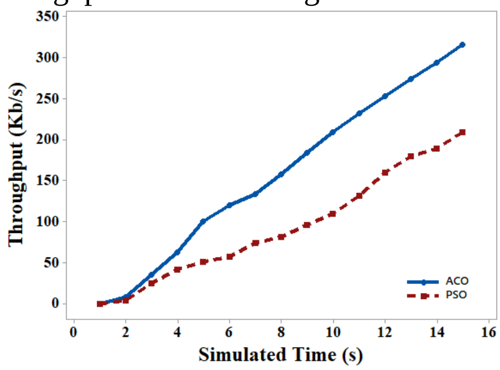

Fig.4.1. Throughput

The maximum delivery rate of 57% is achieved with the ACO algorithm and 55% is achieved with the PSO algorithm.

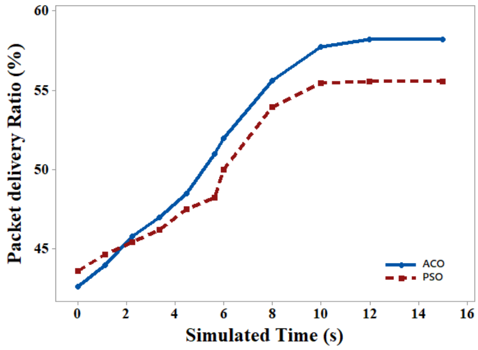

Fig.4.2. Packet Forwarding Rate

The ACO algorithm overcomes losses on the way to IoT and deploys an Ant system that selects the best path with high energy resources. This condition reduces the packet loss rate due to the loss of the network path. the maximum packet loss of about 0.11% is achieved by the ACO algorithm and 0.13% by the PSO algorithm.

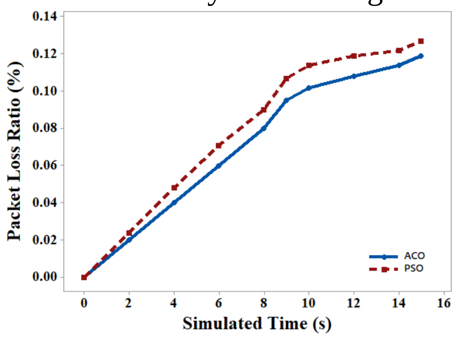

Fig.4.3. Packet Loss Ratio

If the packet size is larger than 200 bits, the end-to-end delay increases. Using the ACO algorithm creates a maximum delay of 2 ms and the PSO algorithm creates 2.5 ms delay.

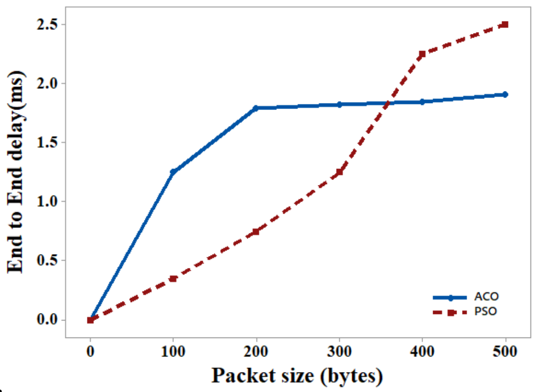

Fig.4.4. End to End Delay

Residual energy is a degree of power consumed by the network for a fixed period. the energy of about 0.55 joules consumed by the ACO algorithm and 0.75joules consumed by PSO algorithm.

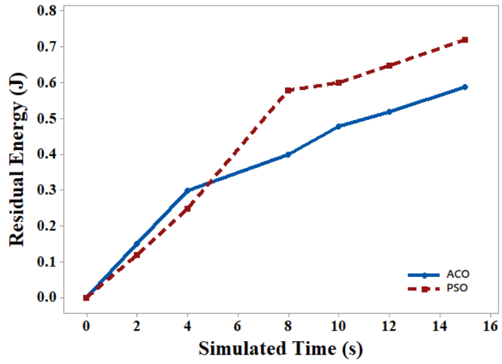

Fig.4.5. Residual Energy

The maximum packet size of 300 bytes generates a normalized overhead of approx. 1.35 with the ACO algorithm and 1.2 with the PSO algorithm.

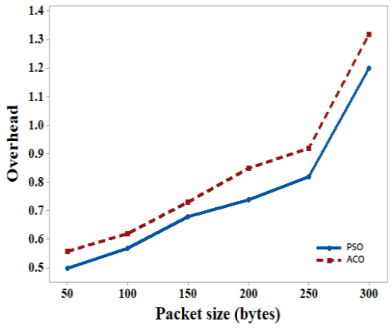

Fig.4.6. Normalized Overhead

IV. CONCLUSION

The centralized algorithms depend on the receiver node or base station node in the network. All information about the source and destination nodes, available communication paths and packet forwarding will be monitored by a centralized base station node. Implementing this centralized algorithm on a larger network result in degraded network performance. The limitations that exist in the network communication path, overcome the constraints by using local control approaches such as ant colony optimization. To overcome these limitations of solving optimization problems in larger networks, local controller approaches are used to improve energy efficiency and network performance.

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