

## Hybrid packet routing algorithm based on ant colony system and tabu search in wireless sensor network

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### Article Info

#### Article history:

Received May 18, 2023

Revised Jun 10, 2023

Accepted Aug 2, 2023

#### Keywords:

Ant colony system

Local optima

Packet routing

Tabu search

Wireless sensor network

### ABSTRACT

Packet routing in wireless sensor network is one of the most crucial aspects as it controls the way packets move through sensor nodes with various capabilities to reach to the destination node. Inefficient routing process may lead to higher energy consumption, higher failure rate, and lower throughput. Metaheuristic algorithms have been some of the common approaches to solve these problems due to their adaptability with dynamic environment. This paper proposed a hybrid metaheuristics routing algorithm that hybridizes ant colony system and tabu search which focuses on exploitation and exploration mechanism while reducing the local optima. The proposed algorithm uses ant colony system technique to discover the best path for packet transmission by considering the energy level of each sensor node. Additionally, tabu search technique is applied to overcome the local optima problem by temporarily suspending the bad nodes and initiate backward movement with the aim to prevent the search agent from getting trapped in a blind alley. The proposed hybrid routing algorithm was evaluated against single and hybrid routing algorithms in terms of throughput, energy consumption, and energy efficiency. Experimental results showed that the proposed algorithm outperformed the other routing algorithms in terms of throughput, energy consumption, and energy efficiency.

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## 1. INTRODUCTION

Wireless sensor network (WSN) is a group of connected sensor nodes that sense data, execute basic operations, and communicate with each other. Management of sensor nodes is crucial in order to maximize the network lifetime as well as to increase packet delivery rate. There are several important aspects in WSN that must be addressed in order to achieve maximum network lifetime such as load balancing, packet routing, energy efficiency, and fault tolerance. Due to the characteristics of sensor nodes that have limited transmission range, data packets can only be forwarded to the destination node by using multi-hop technique through other nodes that act as an intermediate medium [1].

Packet routing in WSN primarily focusing on reducing the energy consumption and local optima while optimizing the throughput, energy efficiency, load balancing, and success rate [2], [3]. Hotspot may occur when specific group of nodes are overutilized to handle many packets while the other nodes are underutilized. This situation will lead to inefficient use of energy and eventually reduces the network lifetime.

In addition to that, local optima problem may also occur when the search agent is trapped in a blind alley during the path searching process [4]. An effective routing process should consider the distance from the source node to the destination node, capacity and energy level of each sensor node during data packet transmission.

Packet routing is considered as one of the nondeterministic polynomial (NP)-complete problems that is unsolvable by an exact solution in a polynomial period [5], [6]. Metaheuristic algorithms such as cuckoo search [7], [8], ant colony optimization (ACO) [9], [10], genetic algorithm (GA) [11], and fish swarm algorithm (FSA) [12], [13] are some of the alternatives to solve this problem through movement from one solution to another solution in constructing the best solution. In addition to that, the ability to adapt with dynamic changes in the environment is also another key capability of metaheuristic algorithms.

Metaheuristic applies different strategies in exploring the search space [14]. These strategies aim to balance between exploitation of the previous set of search experience (intensification) and exploration of the new search set (diversification). Balancing between intensification and diversification is important to determine a high-quality solution within the areas of the search space in a short time [15]. As illustrated in Figure 1, there are two main categories under metaheuristic which are local search and population-based which consists of evolutionary computing and swarm intelligence [16].

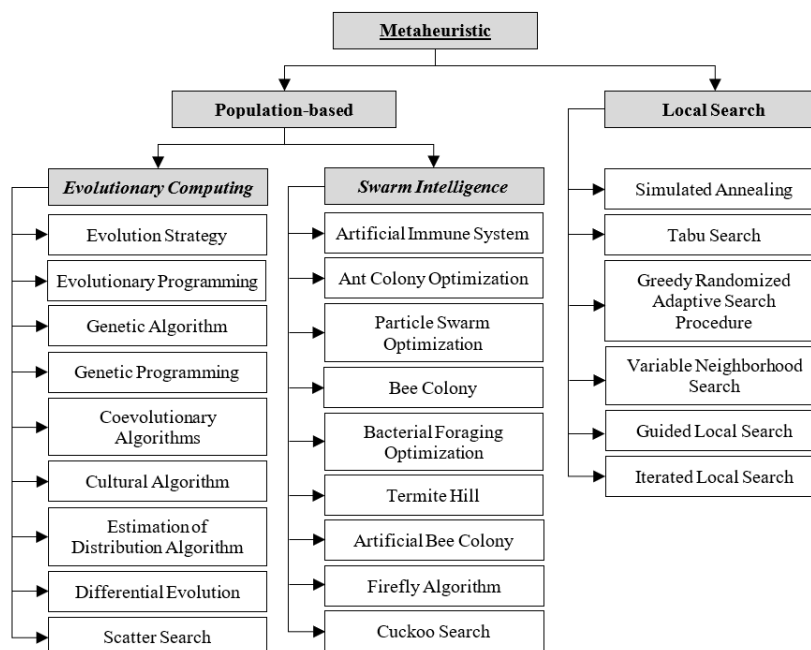


Figure 1. Metaheuristics algorithms

Many metaheuristic approaches are often used to solve specific NP-complete problem. This includes the use of single algorithm or hybridization of multiple algorithms to solve more complex problems. When a specific objective is not achievable by using a single algorithm, hybridization of two or more algorithms are applied to improve it [17]. Algorithms can be combined fully or partially with the objective to obtain the best features from each algorithm in solving the problem more effectively.

ACO algorithm is one of the population-based metaheuristics that was inspired by the ants' behavior in constructing the path from the nest to food sources. Ants use pheromone which is an evaporative chemical substance to mark the traversed path. The more frequent the ants traverse along a particular path, the higher the pheromone level. The path with high pheromone value attracts more ants because it is likely shorter or less obstacle than the path with lower pheromone value [18]. Pheromone evaporation process plays an important role in realizing this behavior as it continues to lower the pheromone level of unutilized paths and eventually segregates between optimal and non optimal paths.

Due to ACO characteristics that is flexible on static, dynamic and mobile WSN environment, many algorithm variants such as energy-efficient ant based routing (EEABR), energy efficient ant colony system, and improved energy efficient ant-based routing have been applied to optimize the WSN packet routing. There are also hybrid ACO algorithms such as fish swarm ant colony optimization (FSACO) [19] and hybrid ant colony and cuckoo search [20]. Hybridization of two or more algorithms aims to improve specific performance

metrics that are not attainable using single algorithm and the good aspects of each algorithm can be taken to form a better hybrid algorithm.

Li *et al.* [19] proposed a FSACO routing algorithm that hybridizes FSA and ACO to enhance the packet routing in WSN. Global pheromone update and state transition rule from ACO are applied for route discovery process. In both formulas, the sensor nodes energy level and path length are considered in finding the optimal path for packet transmission. To overcome the weakness of ACO approach specifically on the hotspot problem, the crowd factor from FSA is applied as a congestion degree within sensor nodes radius. This approach reduces the local optima problem while reducing the stagnation during packet transmission. Experimental results proved that FSACO outperformed the other ACO-based routing algorithms in terms of energy consumption, energy standard deviation, route setup time, throughput, convergence time and network lifetime.

Ant lion optimizer and tabu search (ALO-TS) algorithm was proposed by Deghbouch and Debbat [21] to maximize the network coverage. This hybrid algorithm is inspired by the hunting behavior of antlion and heuristic search algorithm of tabu search (TS). ALO-TS uses three operators which are the swap operator to exchange the value of two elements, reversion operator to choose and invert selected subset between two elements, and insertion operator to move one random element from the sequence to a random new position. These operators are applied in choosing the optimal position of sensor nodes by establishing the exploration and exploitation concept in maximizing the network coverage. Experimental results showed that ALO-TS surpassed the traditional ALO in terms of coverage and convergence. However, ALO-TS only considered the position of sensor nodes but disregarded the nodes remaining energy.

Elite hybrid metaheuristic optimization (EHMO) routing algorithm proposed by Wang *et al.* [22] combines the concept of global search by particle swarm optimization (PSO) and pheromone value of ACO to avoid local search. EHMO aims to find an optimal path to the sink node while controlling the energy consumption among sensor nodes to retain the diversity of the population. Experiments were done to evaluate the performance of EHMO algorithm in two situations. In the first situation, the base station is located at the side of the region while in the second situation, the base station is located at the center of the region. Experimental results showed that EHMO outperformed the other metaheuristics routing algorithms such as PSO, ACO, differential evolution (DE), and simulated annealing in terms of maximum survival time of network, link quality, and impact of data fusion on maximum survival time in both situations. However, one drawback of EHMO is difficulty to search for feasible solution in large infeasible regions which will lead to missing the optimal next path of sink node.

Punithavathi *et al.* [23] proposed a hybrid cluster-based routing algorithm called BWO-IACO, which combines black widow optimization (BWO) and improved ant colony optimization (IACO) to improve energy efficiency and network lifetime. BWO is responsible to find an optimal set of cluster head by considering the residual energy, intra-cluster distance, inter-cluster distance, node centrality and node degree. On the other hand, route selection is done by IACO in inter-cluster communication by utilizing the energy factor of sensor nodes. BWO-IACO was validated against multi-objective particle swarm optimization (MOPSO), GWO, FUCHAR, and improved artificial bee colony (IABC) in terms of average residual energy, average delay, packet loss rate, and network lifetime. Experimental results showed that BWO-IACO produced better results in all performance metrics than the other algorithms. However, BWO-IACO did not consider the throughput value during packet transmission.

A hybrid routing algorithm called MSO-Tabu was proposed by Suganthi *et al.* [24] which combines multi swarm optimization (MSO) and TS techniques. MSO is effective in achieving convergence by decreasing the population diversity which is effective to verify the optimal local position of cluster head. However, this leads to premature convergence as fast convergence does not lead to optimal solution. To overcome this behavior, TS technique is incorporated to introduce more timespan for achieving near-global minima at the same time can maintain the diversity of population and avoid directing towards misleading local optimum. MSO-Tabu algorithm was compared with TS, DE, GA, and MSO-based clustering algorithm and it resulted to better energy utilization and lesser calculation time.

Based on the previous research works discussed above, it can be concluded that hybrid ACO approaches are effective in overcoming the packet routing problem in WSN. However, local optima problem that affects the routing process is not widely considered. Nevertheless, more explorations are essential to further optimize the ant-based algorithms in the application domain specially to avoid the local optima. This research proposed an enhanced ant colony system and tabu search (EACS(TS)) algorithm with the objective to optimize the throughput, energy efficiency, and energy consumption of packet routing in WSN. Section 2 presents the method of the proposed hybrid routing algorithm. Section 3 covers detailed analysis on the experimental results and followed by the conclusion in section 4.

**2. METHOD**

EACS(TS) which is a low-level hybridization algorithm combines techniques from ant colony system (ACS) and TS in constructing the optimal path to transfer packets while incorporating the avoidance of local optima. Systematic process in TS is suitable to be combined with the ACS to improve the exploration steps [25]. In the proposed approach, the inner procedures of both algorithms are coupled where ACS acts as the base algorithm and TS as the sub-algorithm. The ACS state transition rule for ant  $i$  movement from node  $x$  to node  $y$  ( $P^i_{(x,y)}$ ) is defined using the (1):

$$P^i_{(x,y)} = \begin{cases} \text{argmax} \left\{ [\tau_{(x,y)}] \left[ \frac{1}{E_r} \right]^\beta \right\} & \text{if } q \leq q_0 \text{ (exploitation)} \\ R & \text{otherwise (exploration)} \end{cases} \tag{1}$$

where  $\tau_{(x,y)}$  is the pheromone left on the edge between node  $x$  and node  $y$ , while remaining energy of node  $y$  is presented by  $E_r$ . Heuristic value which is  $\frac{1}{E_r}$  is controlled by the parameter  $\beta$ . On the other hand,  $q_0$  ( $0 \leq q_0 \leq 1$ ) controls the possibility of exploitation and exploration.

In order to reduce the pheromone intensity, the forward ant applies the local pheromone update on each visited node to discourage the following ants from exploiting the same path. The (2) defines the proposed local pheromone update:

$$\tau_{(x,y)} = (1 - \rho) * (\tau_{(x,y)}) + \rho(E_i - E_r) \tag{2}$$

where the pheromone value is bounded by the coefficient value  $\rho$  ( $0 \leq \rho \leq 1$ ) while  $E_i$  and  $E_r$  refers to the sensor nodes initial energy and remaining energy respectively.

During the packet routing process, the ACS is responsible to explore the path while TS is responsible to capture the bad nodes identified during the ACS routing process into the tabu list and initiate backward movement so that the exploration process can continue without the search agent trapped in a blind alley. Thereby, the energy needed to spawn another search agent can be saved as the current ant can continue to explore other potential path instead of getting into local optima, and reference to the next ants to avoid identified bad nodes. The list of bad solutions captured by TS is stored in an array of size  $i$  ( $1 \leq i \leq n$ ) where  $n$  is the total number of nodes.

$$\text{Tabu list} = \text{array}(tl_1, tl_2, tl_3, tl_{\dots}, tl_i) \tag{3}$$

The insertion into the array is done using first-in-first-out method as illustrated in Figure 2 where the array elements will be shifted to the right upon new element insertion and the last element will be purged from the array. This method ensures that the known bad nodes have another chance to be released and recovered from failure instead of permanently classified as bad nodes. On the other hand, the size of tabu list array must be properly defined so that it will not be exceedingly large or inadequate based on the total number of nodes. Bigger array size could lead to bad nodes being retained for longer period time or permanently while smaller array size would not provide significant improvement to the routing process.

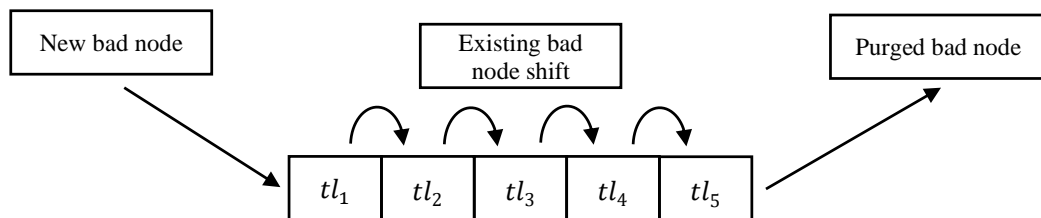


Figure 2. Insertion of new bad node into tabu list array

A good solution is established once the ant successfully constructed the path to the destination node and followed by backward movement with global pheromone update applied to every visited node until the source node. The proposed global pheromone update is defined by using (4):

$$\tau_{(x,y)} = (1 - \alpha) * \tau_{(x,y)} + \alpha(\Delta\tau_{(x,y)}) \tag{4}$$

where evaporation rate value is defined by  $\alpha$  ( $0 < \alpha < 1$ ) and  $\Delta\tau_{(x,y)}$  is defined by (5):

$$\Delta\tau_{(x,y)} = \frac{1}{N_x} \tag{5}$$

where  $N_x$  is the count of visited nodes from source node  $x$  to the destination node  $y$ . The main intention of global pheromone update is to increase the pheromone intensity on the nodes along the good solution path so that they become more attractive for exploitation by the next ants.

### 3. RESULTS AND DISCUSSION

The experiments were conducted using MATLAB based simulator (Prowler) which is integrated with routing modelling application simulation environment (RMASE). The performance metrics used in these experiments are described as follows: i) throughput: the number of successful packets arrived at the destination node per second, ii) energy consumption: the entire energy consumed by all sensor nodes during the experiments and iii) energy efficiency: the total number of packets arrived per total energy used by all sensor nodes.

Several experiments were conducted using the same simulation parameters for each routing algorithm as shown in Table 1. The average results of 10 executions for each algorithm were captured for analysis. Figure 3 shows the result for throughput value of ant-based routing algorithms. Both hybrid-based ant routing algorithms (EACS(TS) and FSACO) achieved higher throughput value compared to single ant-based routing algorithm (EEABR). Throughout this experiment, it can be seen that higher throughput value can be achieved by avoiding local optima where packets can be transported more quickly with minimal possibility of packet loss.

Table 1. Simulation parameter

Parameters	Values
Routing algorithm	EACS(TS), EEABR, FSACO
Number of nodes	100
Node energy	1000 J
Simulation time	300 seconds
Performance metric	Throughput, energy consumption, and energy efficiency

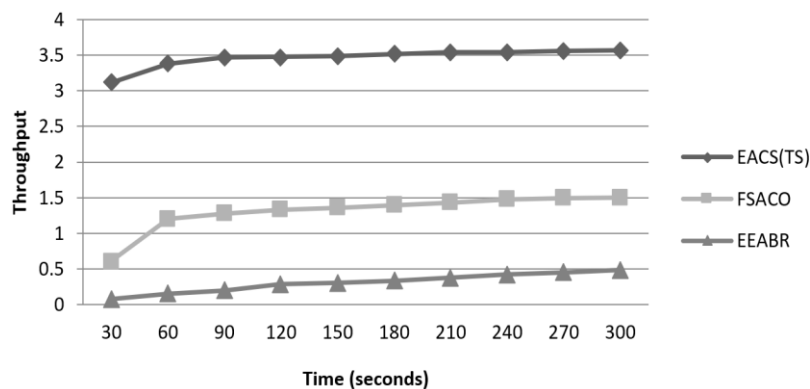


Figure 3. Throughput of ACO-based routing algorithms in WSN

In order to determine the effectiveness of EACS(TS) in terms of throughput, statistical test is used to calculate the mean and standard deviation. The lower the standard deviation, the more consistent the throughput value to the mean. As presented in Table 2, EACS(TS) has the highest mean throughput while both EACS(TS) and EEABR have almost identical standard deviation. This can be concluded that EACS(TS) is consistent and stable during routing process as compared to FSACO which has the second highest throughput but the highest standard deviation.

Table 2. Statistical test for the throughput values of the experiment

Parameters	EACS(TS)	FSACO	EEABR
Mean	3.464	1.308	0.310
Standard deviation	0.134	0.264	0.133

As shown in Figure 4, the energy consumption for each algorithm shows a linear growth following the increase of simulation time. However, both hybrid algorithms (EACS(TS) and FSACO) have better energy consumption as compared to the EEABR. This result suggests that an effective load balancing by using global and local pheromone update techniques can directly improve the energy consumption as nodes are fairly utilized to preserve their energy to direct packets successfully.

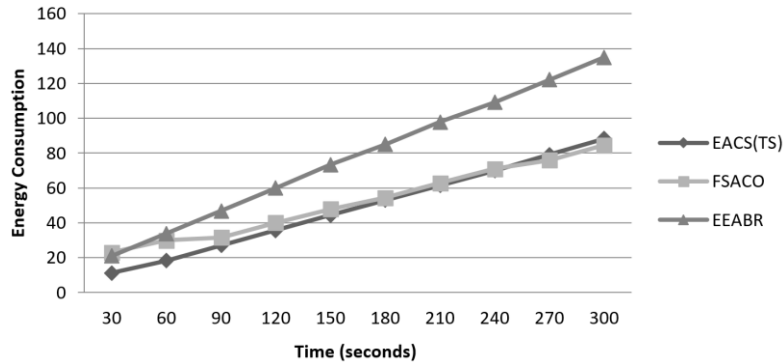


Figure 4. Energy consumption of ACO-based routing algorithms in WSN

Figure 5 shows the performance of energy efficiency which is measured by dividing the number of packets arrived with total energy consumed by all sensor nodes. Even though EACS(TS) and FSACO achieved almost similar energy consumption as in Figure 4, EACS(TS) performed significantly better than FSACO in terms of energy efficiency. This result is influenced by the low energy consumption and high throughput value. The combination of ACS and TS also contributes to EACS(TS) having better mechanism to avoid the local optima by applying backward movement when the ant is unable to further move forward during the exploration process. Most importantly, the known bad path is not considered during the routing process and eventually leads to less energy consumed because minimal number of data packets or ants are dropped during the routing process.

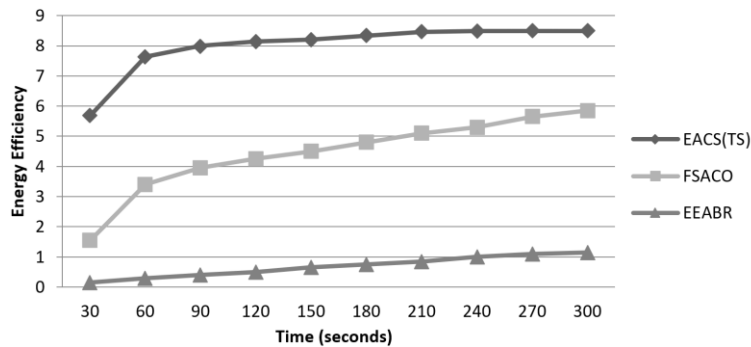


Figure 5. Energy efficiency of ACO-based routing algorithms in WSN

Throughout all the experiments, EACS(TS) outperformed the other algorithms in terms of throughput and energy efficiency. Out of all performance metrics, energy efficiency is the main concern since it directly affects the amount of energy used by sensor nodes, throughput, and network lifetime. It can also be noted that the increase of time would also lead to a linear increment of each performance metric.

#### 4. CONCLUSION

The proposed EACS(TS) algorithm combines effective techniques from ACS and TS in improving the searching process for packet submission while reducing the local optima. The local and global pheromone update in ACS play important roles in exploration of new path and exploitation of known optimal path respectively. This is complemented with technique from TS that captures bad nodes identified by ACS and initiates backward movement to prevent the search agent from getting trapped in a blind alley. Without this preventive step, the search agent will be terminated prematurely and the exploration process will require more time. Overall, EACS(TS) achieved the best performance as compared to FSACO and EEABR in terms of throughput and energy efficiency. For future work, the proposed EACS(TS) algorithm can consider the packet priority aspect during the routing process in WSN. This is essential to represent real WSN implementation in which different types of sensor nodes exist within a single WSN environment.


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