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Path Optimization and Object Localization Using Hybrid Particle Swarm and Ant Colony Optimization for Mobile RFID Reader

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Abstract– This paper proposes a hybrid approach of Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) for the mobile Radio Frequency Identification System (RFID) reader to get the shortest path for object localization. In this approach, we have adopted the ACO global pheromone updating information of ants to guide the update velocities and position for PSO based on nearest neighbor constraints. The pheromone information is used efficiently to guide the selection of each particle in a search space of its visits. The best path will be used for mobile RFID reader for objects localization in search space. Simulation results show that the method is effective, minimizing the number of visited nodes for a mobile RFID reader.

Keywords: RFID, Path Optimization, PSO, ACO

1. Introduction

Nowadays, many optimization techniques have become part of important problem solving, such as particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Genetic Algorithm (GA) and so on. These are used to develop applications in engineering, business, and education. These techniques have the same goal: to find the best result among the possible output but in practice sometimes this techniques deliver only marginal performance. Among the key features of this techniques are self-adaptation, population-based collective learning process and robustness. To reach the best results (global optimum), this evolutionary optimization should be imposed with two characteristics, i.e. exploration and exploitation. Exploration is the ability the algorithm to search the whole given area (search space) whereas exploration is the ability to convergence to the best solution. Exploitation is the ability to find the global optimum as efficiently as possible. For all heuristic optimization algorithms, exploitation and exploration should be balance efficiently to ensure the global optimum, but to reach the best point for exploration and exploitation is difficult because strengthening one ability the other will weaken the other [1]. Hybrid optimization algorithms have been built for inducing exploitation/exploration relationships that avoid the premature convergence problem and optimize the final results.

Hybrid optimization algorithm is a one technique to balance the exploration and exploitation relationship during the run where the main objective is to optimize the performance. Many studies have been done in the literature to create a new algorithm for hybrid optimization such as PSO and ACO, PSO and Genetic Algorithm (GA) and PSO and Gravitational Search Algorithm (GSA). Hybrid optimization is becoming popular due to its capabilities in handle problems involving imprecision, complexity, noisy environment, uncertainty, and vagueness [2a].

For certain problems, an optimization algorithm alone may be sufficient to reach an acceptable solution, but according to [3-6], there are certain types of problem in which a direct optimization algorithm may not be good enough to obtain an optimal solution. For a mobile reader, path optimization can be solved by hybrid optimization technique based on particle swarm optimization in association with ant colony optimization.

This paper is organized as follows. In Section II, we detail a hybrid path optimization algorithm using PSO and ACO. We present localization algorithms and heuristics in Section III. We evaluate the proposed algorithm in Section IV using mobile RFID reader simulation, and conclude Section V with extensions and future directions.

2. Related Work

A shortest path problem (SPP) is used to find the shortest path between first node and any of the other nodes in the search space whereas the main goal is to find total cost associated with the path could be minimized. For this purpose, some researchers have applied swarm optimization in their SPP, including path planning in robotic applications (Peyer et al., 2009), communication network for traffic routing ((Fu and Rilett, 1998), transportation systems for vehicle routing (Pallottino and Scutellà, 1998). For optimization approaches, Liang et al. (2013) proposed a neighborhood and parameter optimization for a personalized modelling system. That system integrates a gravitational search inspires algorithm for informative selection features, model parameters, and neighbor optimization. Zhang et al. (2013) proposed multi-objective constrained programming using bioinspired immune optimization. This technique executes in evolution and memory update within a run period of time.

Cheng et al. (2014) solved the stochastic combinatorial problem using branch and bound algorithm by second-order cone programming for SPP. Takaoka et al. (2014) suggests a technique in sharing information for all the pairs SPP using special classes of directed graphs. The objective is to speed up information sharing by n single source of SPPs. For the first phase of this technique, existing time complexity of all pairs SPP is improved upon. In the second phase, a directed graph will bounded with non-negative integer. Pulido et al. (2014) proposed a multi-objective SPPs with lexicographic goal based preferences. Their method depends on possibility of improving search performance whereas portion of the Pareto front can be bounded. This approach has been evaluated as showing a performance improvement up to several orders of magnitude as goals become more restrictive.

Trevizan et al. proposed stochastic SPPs, in which every state has a nonzero probability of being reached using at most actions based on two approaches used for stochastic SPPs i.e. probabilistically reachable states and a plan for a subset of these reachable states.

SPP can also be solved by using artificial neural network (ANN) as proposed by Araujo et al. (2001) using parallel architecture method. This technique can deliver fast result, but has limitations such as the network increasing dramatically if number of nodes increased. Other technique can be used is genetic Algorithm (GA) to solve the problem SPP which is as one of the evolutionary algorithms (Ahn and Ramakrisna, 2002). GA performance, compared to ANN, is better and also overcomes limitations.

3. A brief overview of the PSO

Particle swarm optimization (PSO) is a population-based stochastic optimization technique that originates from the nature and evolutionary computations developed by Kennedy and Eberhart (10). This method finds an optimal solution within a population called "swarm'. The PSO algorithm flow consist of a population of individuals named "particles". Which is every particle is a potential solution to an *n*-dimensional problem. The group can achieve the solution effectively by using the common information of the group and the information owned by the particle itself. The particles change their state by "flying" around in an *n*-dimensional search space based on the velocity updated until a relatively unchanging state has been encountered, or until computational limitations are exceeded. PSO has two types of learning: cognitive and social learning.

PSO has been successfully applied to solve many optimization problems and it has attracted significant attention such as power system design, data classification, pattern recognition and image processing, robotic applications, decision making for stock market, and simulation and identification of emergent systems. With reference to the original PSO, each particle knows its best value so far (*pbest*), velocity, and position. Additionally, each particle knows the best value in its neighborhood (*gbest*). A particle modifies its position based on its current velocity and position.

For all iteration, any particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far this value is called pbest and the fitness value is also stored. Another "best" value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population, which is called a global best (gbest).

The velocity vector update equation which controls the direction the particle will move in the design space is calculated using

$$\boldsymbol{v}_i^{k+1} = \omega v_i^k + c_1 r_1 \left(pbest_i^k - S_i^k\right) + c_2 r_2 (gbest^k - s_i^k) \quad (1)$$

where v_i^k is the velocity vector, v_i^{k+1} is a modified velocity vector and s_i^k is a positioning vectorof particle *i* at generation k. Whereas for $pbest_i^k$ is the best position found by particle *i* and $gbest^k$ is the best position found by particle's neighbourhood of the entire swarm. c_1 and c_2 are the cognitive and social coefficients which are used to bias the search of a particle toward its individual's own best history (*pbest*) and the best history accumulated by sharing information among all particles of the entire swarm (*gbest*). ω is the inertia weight factor to control the level of contribution from the particles current velocity vector to the new velocity factor. Large values of ω facilitate exploration and searching new areas, while small values of ω navigate the particles to more refined search. The velocity equation includes two different random parameters, represented by a variable r_1 and r_2 to ensure good exploration of the search space and to avoid entrapment in local optima. The direction and velocity of the particle will move is based on its current velocity vector, previous best location (pbest) and global best location (gbest).

In PSO path planning optimization, each particle of particle swarm represents a single possible path that could be taken by the mobile RFID reader. Hence, the particle swarm is trying to find the optimal path for the mobile RFID reader to move from node to another node. This technique randomly generates a population of particles within the given dimension area. Therefore the swarm is trying to find the optimal path that the path will be used for the mobile RFID reader to move in every single node in the given area.

The PSO algorithm as shown below which is the equation is sigmoid function for the updating velocity

$$sig = \frac{\mathbf{1}}{\mathbf{1} + e^{-V_i^{k+1}}}$$

The modified position vector is obtained using

$$\boldsymbol{S}_i^{k+1} = \begin{cases} 1 & if\ r_3 < sig(\boldsymbol{V}_i^{k+1}) \\ 0 & \text{otherwise} \end{cases}$$

4. A brief overview of the ACO

The ant colony optimization (ACO) is metaheuristic for combinatorial optimization problems. A concept of metaheuristic is framework that can be imposed to other optimization cases with some modification. For this research, we examine ant colony system (ACS) as a representative of ACO technique. The ACS has three main components. The first component is state transition rule provides a direct way to balance between exploration of new edges and exploitation of a priori and accumulate knowledge about the problem. The second component is global updating is applied only to edges which belong to the best ant tour and last component the ants develop and applied solution for local pheromone updating rules.

Initially using ACS process, the m ants are putting on randomlyin n nodes chosen according to some initialization rule. Each ant develop a path by repeatedly applying the state transition rule. During path development, the ant make changes the amount of pheromone on the visited edges by applying the local updating rule. Once all ants have finished their path, the amount of pheromone on the edges is modified again by applying the global updating rule. For the path with a high amount of pheromone, this path will be chosen by ants as a shorter path.

a. State transition rule

The ACS transition rule, also referred to as *pseudo-random-proportional* rule, was developed to explicitly balance the exploration and exploitation abilities of the algorithm. In ACS, the probability for an ant to move from node r to node s depends on a random variable q and q_0, as shown below:

$$p_k(r,s)_{\text{ACS}} = \begin{cases} \arg\max_{u \in J_k(r)} \left\{ [\tau(r,u)] \cdot [\eta(r,u)]^{\beta} \right\} & if\ q \le q_0, \\ S & \text{otherwise,} \end{cases}$$

Where q is a uniformly distributed random variable [0,1], q_0 is between 0 and 1, and S is the variable selected according to the probability distribution.

$J_k(r)$ is the set of feasible components; that is, edges (r, s)where r is current node and s is a next node which is not yet visited by the *kth*ant. (r, u) is the other edges, where u is all nodes not yet visited by the *kth* ant. The parameter β ($\beta \geq 0$)controls the relative importance of the pheromone versus the heuristic information $\eta(r, s)$, which is given by:

$$\eta(r,s) = \frac{1}{d_{rs}},$$

Where in mobile RFID reader, d_{rs} is the distance between nodes r and s, and $\tau(r, s)$ is the pheromone trails, which refer to desirability of visiting node s directly after r. For implementation purposes, the pheromone trails are collected into a pheromone matrix with elements $\tau(r, s)$.

b. Global updating rule

The global pheromone update is applied at the end of each iteration to one ant, which can be either the *iteration-best* ant or the *best-so-far* ant.The pheromone updating rules are designed to give more pheromone to edges which should be visited by ants.

c. Local pheromone updating rule

The local pheromone update is performed by all ants after each construction step using

$$\tau(r,s)_{t+1} = (1-\zeta) \cdot \tau(r,s)_t + \tau_0$$

Where $\zeta \in [0, 1]$ is the pheromone decay coefficient, and $\tau_0$is the initial value of the pheromone.

The main goal of the local update is to diversify the search by decreasing the pheromone concentration on the traversed edges. Thus, the ant would choose other route to produce different solutions. This would prevent several ants to produce identical solutions during iteration.

5. A brief overview of RFID

Radio Frequency Identification (RFID) is wireless and uses electromagnetic fields to communicate and transfer data.The main purposes of using RFID technology is automatically identifying and tracking tags attached to objects. The tags contain electronically stored information powered by electromagnetic induction produced by near reader. The tags do not need to be positioned precisely relative to the reader, which is the main significant advantage compared to barcodes.

RFID technology are used in many industries such as manufacturing, automotive, services, social retailing, pharmaceuticals, livestock, and so on. In other words, this technology will influence societies and lifestyles. With the ubiquity of RFID deployment, there is a need to ensure that any object can be traced easily when it is tagged. This can be done with RFID together with a wide variety of objects. Generally, RFID should be able to tag, trace, and check an object. RFID tags are attached to objects which a tag has information about the object such as unique ID number, manufactured date and product composition. By organization, we refer to finding the shortest path possible to provide full coverage in the given area. Based on the path obtained, we use a mobile RFID reader to trace the tags (objects) in a given space.

In this paper, we propose a hybrid PSO-ACO techniques incorporating the nearest neighbor for the movement of RFID mobile reader. The optimum path (i.e., shortest path) information obtained is used to compute the location of objects within a given area using the triangulation technique.

In this experiment, initially we intend to find the best way to place the RFID reader (nodes) in a given area that will guarantee 100% coverage with minimum number of reader usage. Then, the first phase will discuss on developing a prototype of the software simulation to determine how many RFID fixed readers are required to cover a given area based on hexagonal packing as shown in figure 1 for every single hexagon equivalent to one RFID reader [2]. Coverage can be computed by taking the union of individual coverage areas of all sensors (readers) in the network. We assume the mobile readers at different nodes locations have the same sensing and transmission range.

In the second stage, the location of RFID reader that we calculate before will be used as reference point for mobile reader to visit in periodical of time. We proposed to use the mobile RFID reader in objects localization due to reducing cost of hardware (reader) and eliminate readers' interference. The mobile reader will be moved from one point (node) to another point based on the shortest path which we calculated using a hybrid PSO-ACO technique for the given dimension area. The tag reading by mobile RFID reader process is repeated from where the circle stop at the last node and it will immediately move to the first start node. Then, the process will repeat continuously.

In the third stage, we start the algorithm with an initialization process to determine the number of tags to be used in the given area. Process continues by putting tag at random in the same area. Later, the process will continue which tags detecting by mobile RFID reader 3 times at different location or point in the given dimension area. We continue the process by detecting a reader and it is done until all three readers are detected the tags. The optimum path i.e. shortest path we get from the application is used to calculate objects in that area using triangulation technique.

Then, we continue with the calculation to determine the position of tags by using the equations discussed in section 3. The equation is based on the data of the received signal strength indication (RSSI) that are obtained during the detection process.

The system can be used to eliminate redundant sensors or readers without affecting network coverage, so that the mobile RFID reader less node to visit. Second will be an introduction of an algorithm for the RFID mobile reader for path optimization using hybrid PSO-ACO techniques incorporating the nearest neighbour. Thirdly, the system will be determined the location of object/tags in that area covered by mobile RFID readers. Finally, the design of a system that can fit with any design of area whether it is asymmetrical or symmetrical. In addition, the system will enable us to define the position/location of the obstacles based on a real working environment.

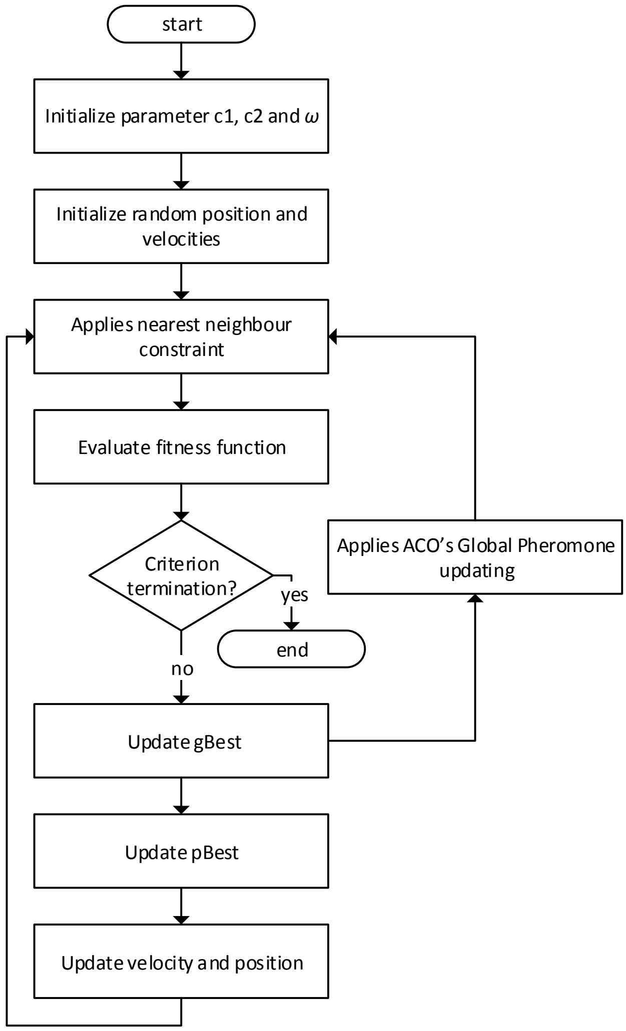
The main contribution of this paper is our proposed hybrid algorithm using ACO-PSO technique to find the shortest path for mobile RFID reader to navigate from one node to another node to cater coverage of given area.

6. Proposed Algorithm

The optimization algorithm has a rapid development in recent years, that algorithm is used to solve complex control problems such as travelling salesman problem (TPS). The main contribution of this paper is hybridization mechanisms of PSO and ACO algorithm which can perform better convergence. Through the acceleration parameters, the velocities and position of the particle swarm is integrated with ACO's global pheromone updating. The search space can be elaborated by local search exploration (pbest) tours and the best global search (gbest) solution which are advantageous to improve the convergence performance of PSO. The element to achieve best performance of PSO algorithm is to combine the search space exploration with the best solutions exploitation in PSO.

In this section we developed simulation program using hybrid PSO-ACO technique to optimized path of RFID mobile reader which is a technique incorporated with nearest neighbor.

The flow chart for this problem is as follows



The pseudo code of the hybrid PSO-ACO as follows

The pseudo code of the hybrid PSO-ACO algorithm can be summarised as follows:

Step 1: Initialize parameters c1, c2 and ω for the particles

Step 2: Initialize random positions for all dimension each particle and their associated velocities. For example, suppose we have 8 nodes and number of particles is 5 as shown in table 1.

Table 1

Dimension		2	3	4	5	6	7	8
Particle 1		5	4	3	2	1	3	6
Particle 2		7	8	7	1	1	1	7
Particle 3		1	2	2	4	7	7	8
Particle 4		7	2	7	2	2	3	3
Particle 5		5	5	4	7	8	5	4

Step 3: Apply nearest neighbour constrain in which the nodes can only malimove to the adjacent nodes with all nodes have the same distance of values in adjacent nodes.

Step 3: Evaluate the fitness function for each valid particle.

Step 4: Check criterion termination based on number of iteration.

Step 5: Update velocities and position based on nearest neighbour constraints.

Step 6: Update local best (pbest), which compares the current value of fitness function with the previous best value of the particles.

Step 7: Update global best (gbest), which determines the current global minimum fitness value among the current positions of the particles. In this stage also we apply global pheromone updating, and the best value between ACO and PSO techniques will be chosen.

Step 8: Apply state transition based on nearest neighbour constrain and the process will continue until the end conditions when the maximum number of iterations is reached.

Similar to the PSO model, time constraints apply to the nearest neighbour, and node selection is based on the largest part of the pheromone matrix.

7. SIMULATION AND RESULTS

A lot of research activities have been proposedfor localization and positioning applications of RFID reader and tags [22]. In general, one of the fundamental issues in wireless sensor network is reader coverage. That means every point of selected area must remain within the sensing range of at least one sensor network. In literature, this problem has been proposed in many different ways, for example using Mobile Reader. The coverage of a wireless sensor network may be approximated by a disk of a prescribed radius (sensing range). Coverage can be computed by taking the union of individual coverage areas of all sensors (readers) in the network. This may be done by assuming that each circle is a hexagon which attaches with the others, as shown in Figure 1.

In this experiment, the number of nodes will depend on dimension of area and interrogation range that we set for the mobile RFID reader. If the dimension of the area is big, then the number of nodes that mobile RFID reader will be visited will increase. Also interrogation range will influence number of nodes that mobile RFID will be visited if small range then number of nodes will increase. We need consider that all tags in certain covered area must be detected at least three times at different nodes (places) to measure the location of the RFID tags.

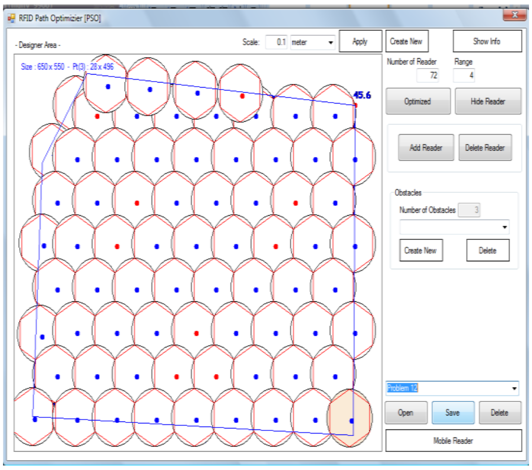


Figure 1: A typical 76 nodes (number of nodes that mobile RFID reader visits) with an interrogation range of 4 meters, which is fit for the given area.

The size of a hexagon is based on the equivalent to an interrogation of a reader. To address this problem, the software simulation as developed can define the read range of RFID reader and obstacles inside the area covered based on user requirement. In Figure 1, RFID mobile reader will skip the red point (node) because of the obstacle appearing at that point.The system we have developed will determine the coordinates of each reader in an area in order to optimize reader usage and coverage.

In this experiment, we begin the algorithm with an initialization process to determine the number of readers to be used in a given areaand the system will optimize number of readers based on the area. Using PSO and ACO techniques, the RFID mobile reader will scan every single node inside the area above. PSO and ACO will find a path to complete a circle, in which the minimum path (distance) is chosen as the best path for the RFID mobile reader. We ran every algorithm successively for 100 and 500 iterations under the same initialization conditions, then recorded the minimum and maximum path for PSO and ACO. The mobile RFID reader can start at any node at random.

RESULT AND DISCUSSION

We used the following configuration the PSO and ACO algorithm. For PSO, the number of particles is 10, cognition factor c_1 and social factor c_2 are 1.4, and inertia weight w is 0.4 to 0.9. Whereas for ACOnumber of population (ants) is 10,ρ and $\zeta$is 0.1, β is 2 and q_0 is 0.9.. All algorithms were run 100 and 500 times as shown in table 2, 3, 4 and 5. Each running contains 100 and 500 iterations.

Result shown the minimum path for hybrid technique and ACO technique is same as shown in table 2 and 3. The standard deviation for the hybrid technique is better than ACO and PSO technique at 120.30 for 500 running and 500 iterations. Also, the average path for hybrid is better than ACO and PSO technique which is 4921.55 for 500 running and 500 iterations. Another significant finding of this research for hybrid ACO-PSO was that 81% of running completed for 500 running and 500 iteration whereas 19% were uncompleted. The best standard deviation is 9.99% at 500 running and 100 iterations.

Table 2: The result of optimization path using hybrid PSO-ACO for 150 nodes

	Hybrid PSO-ACO			
No of Iteration	100	500	100	500
No of Running	100	100	500	500
Max Path	5893.32	5466.31	5478.09	5321.88
Min Path	4611.82	4611.82	4661.82	4661.82
Average Path	5223.54	5176.44	5001.44	4921.55
Standard Deviation	189.29	153.31	149.38	120.39

Table 3: The result of optimization path using ACO and PSO techniques for 150 nodes

	ACO				PSO			
No of Iteration	100	100	500	500	100	500	100	500
No of Running	100	500	100	500	100	100	500	500
Max Path	6999.93	6966.88	6509.91	6313.98	7938.29	7956.39	7533.10	7513.57
Min Path	4611.82	4611.82	4661.82	4661.82	4721.24	4611.82	4700.21	4661.82
Average Path	5613.05	5543.36	5424.99	5221.39	5721.76	5843.36	5224.99	5521.39
Standard Deviation	318.23	311.12	268.80	219.46	312.28	310.77	277.88	229.58

Table 4: Results for hybrid PSO-ACO

Method		PSO-ACO							
# Running		**100**		**500**		**100**		**500**	
# Iteration		**100**		**100**		**500**		**500**	
			%		**%**		**%**		**%**
Uncompleted		2090	20.90%	15029	30.06%	14783	29.57%	47832	19.13%
Completed	FALSE	1928	19.28%	8092	16.18%	7982	15.96%	23892	9.56%
	TRUE	5982	59.82%	26879	53.76%	27235	54.47%	178276	71.31%
Total		10000	100.00%	50000	100.00%	50000	100.00%	250000	100.00%
Max Conv at #		100	100%	100	100%	500	100%	500	100%
Min Conv at #		45	45%	46	46%	44	9%	43	9%
Avg Conv		66.55	66.55%	50.37	50.37%	150.89	30.18%	144.28	28.86%
Std Dev Conv		19.23		9.99		114.21		23.43	

Table 5: Results for PSO and ACO techniques

Method		PSO								ACO							
# Running		**100**		**500**		**100**		**500**		**100**		**500**		**100**		**500**	
# Iteration		**100**		**100**		**500**		**500**		**100**		**100**		**500**		**500**	
			%		**%**		**%**		**%**		**%**		**%**		**%**		**%**
Uncompleted		5552	55.52%	26781	53.56%	26131	52.26%	120023	48.01%	4712	47.12%	22039	44.08%	21234	42.47%	102932	41.17%
Completed	FALSE	2401	24.01%	12921	25.84%	13393	26.79%	60283	24.11%	2375	23.75%	13281	26.56%	12793	25.59%	63283	25.31%
	TRUE	2047	20.47%	10298	20.60%	10476	20.95%	69694	27.88%	2913	29.13%	14680	29.36%	15973	31.95%	83785	33.51%
Total		10000	100.00%	50000	100.00%	50000	100.00%	250000	100.00%	10000	100.00%	50000	100.00%	50000	100.00%	250000	100.00%
Max Conv at #		100	100%	100	100%	489	98%	491	98%	100	100%	100	100%	489	98%	491	98%
Min Conv at #		60	60%	60	60%	125	25%	147	29%	58	58%	56	56%	102	20%	90	18%
Avg Conv		90.21	90.21%	82.32	82.32%	345.32	69.06%	320.26	64.05%	86.43	86.43%	82.32	82.32%	250.3	50.06%	232.01	46.40%
Std Dev Conv		15.41		15.34		250.77		250.45		15.15		13.44		231.11		213.44	

The experimental results are presented in table 2, 3, 4 and 5. The results of the algorithms show that the hybrid technique is significantly better than the PSO and ACO algorithm. The analysis of the results indicates the superiority of the hybrid PSO-ACO technique approach over those using PSO and ACO techniques. The sweet point for hybrid ACO-PSO is500 running and 500 iteration.

8. Conclusion

In this paper, a new hybrid approach for RFID mobile reader to optimize the path to cover the given area using PSO-ACO has been presented. The technique is incorporated with nearest neighbor to get better result. The feasibility and effectiveness of hybrid PSO-ACO is validated and illustrated by the experiment. The performance results show that the hybrid PSO-ACO technique has competitive potential for solving discrete optimization problems like shortest path optimization compare to PSO and ACO techniques based on previous experiments.

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