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Self-Adaptive Intelligent Routing in Dynamic WSN using Natural Inspired Computing

Self-Adaptive Intelligent Routing in Dynamic WSN using Natural Inspired Computing

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Abstract: Mobile Adhoc Networks are designed dynamically without any infrastructure and each node is accountable for routing information amongst them. In MANET's, the network topology dynamically variations over time to time due to energy preservation or changes in node position. Thus both routing problem turn out to be dynamic optimization problem in MANET's. Hence it is crucial to design solution for the optimization problem is to quickly adopt to changing environment and produce high quality optimization using Modified Particle Swarm Optimization. The Particle Swarm Optimization is effective in determining optimal solutions in fixed locations, but it suffered from poor performance in locating a changing extreme. It was also necessary to impose a maximum value V_{max} to avoiding the particle exploded because of there was no exist a mechanism for controlling the velocity of a particle. PSO searches wide areas effectively, but difficult to search in local precision. Hence, introduced a control parameter called the inertia weight, "w", to damp the velocities over time, allowing the swarm to converge more accurately and efficiently.

Keywords: Constriction Factor, Inertia Weight, MANET's, Mutation Operator, PSO.

1. INTRODUCTION

The particle swarm optimization (PSO), initially hosted by Kennedy and Eberhart[1], is an optimization technique stirred by swarm intelligence and theory in common such as bird flocking, fish schooling and even human social behavior. PSO is a population-based evolutionary algorithm in which the algorithm is initialized with a population of random solutions. However, unlike most of other population-based evolutionary algorithms, PSO is driven by the simulation of social behavior instead of the survival of the fitness.

The PSO algorithm consists of three different steps, they are generating particles positions and velocities, velocity update, and position update [2],[3]. Here, a particle states to a point in the design space that makes variations in its position from one iteration to another based on velocity updates. First, the positions, $\mathbf{x}_k^i$, and velocities, $\mathbf{v}_k^i$, of the primary swarm of particles are arbitrarily generated using higher and lower bounds on the design variables values denoted as

x_{min} and x_{max} , as expressed in Equations .1 and .2. The positions and velocities are given in a vector format with the superscript and subscript denoting the i[th] particle at time k. In Equations (1) and (2), the term 'rand' is a consistently distributed random variable that can yield any value among 0 and 1. This initialization method permits the swarm particles to be arbitrarily distributed across the design space.

$$x_0^i = x_{min} + rand(x_{max} - x_{min}) \tag{1}$$

$$v_0^i = x_{min} \frac{x_{min} + rand(x_{max} - x_{min})}{\Delta t} = \frac{\text{position}}{\text{time}} \tag{2}$$

The second step is to update the velocities of all particles at time *k*+1 using the particles objective or fitness values which are functions of the particles current positions in the design space at time *k*. The fitness value of a particle defines which particle has the best global value in the current swarm as $p_k^g$and also defines the best position of each particle over time as p^i , i.e. in current and all previous changes. The velocity update function uses these two information for each particle in the swarm along with the effect of current motion denoted as v_k^i, to provide a search direction, v_{k+1}^i , for the next iteration. The velocity update function consists of some random parameters, represented by the consistently distributed variables, '*rand*', to ensure good coverage of the design space and avoid entrapment in local optima. The three values that effect the new search direction they are current motion, particle own memory, and swarm influence, are combined through a outline approach as shown in (3) with three weight factors, namely, inertia factor '*w*', self-confidence factor 'c_1 ,and swarm confidence factor 'c_2'[3].

velocity of particle*i* at time *k*+1

$$v_{k+1}^i = w\, v_k^i + c_1 rand \frac{(p^i - x_k^i)}{\Delta t} + c_2 rand \frac{(p_k^g - x_k^i)}{\Delta t} \tag{3}$$

inertia factor self confidence swarm confidence factor

The research presented in this paper found out that setting the three weight factors w, c_1, and c_2 at 0.5, 1.5, and 1.5 respectively provides the best convergence rate for all test problems considered. Other combinations of values usually lead to much slower convergence or sometimes non-convergence at all.

Position update is the last step in each iteration. The Position of each particle is updated using its velocity vector as shown in (4) and in Fig. 1[7].

$$x_{k+1}^i = x_k^i + v_{k+1}^i \Delta t \tag{4}$$

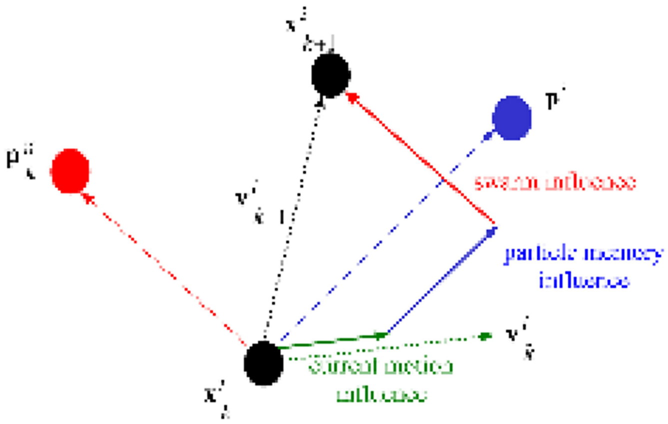

Fig.1 Representation of the velocity and position updates in Particle Swarm Optimization.

2. RELATED WORK

David Gan Chye Ong, represents AntNet, is very slow in terms of end-to-end delay which is a main disadvantage. The performance of AntNet routing detoriates as network size or link density is elevated [4],[5],[6]. It is robust to changes in the topology of network and confluence to a good solution. It performs better than shortest path routing. Information exchange with neighboring nodes is promoted by helping ants of “modified AntNet”, which is extension of AntNet. Gunes M., Sorges, U. & Buouazizi I., presents Ant-Colony-Based Routing Protocol (ARA) [8] is a routing protocol based on AntNet and routes are maintained primarily by data packets as they move through the network. The path to the destination is reinforced by increasing the pheromone value in the routing table as data packets move along instead of using periodic ants. This brings higher benefit as flooding of periodic ants is being reduced. ARA implements a pheromone decay mechanism where its value in the routing table decreases over time. It has no updating mechanism to adapt the changes in a dynamic network such as MANET.

Incheon Park, Jinguk Kim, Ida Pu London, proposed Blocking-ERS [9], third party route reply ,time to live (TTL) based local route repair and n-hop local ring concept to improve the performance of proposed routing protocol in terms of network routing load (NRL), end-to-end delay and packet delivery ratio (PDR). AODV is used for comparison with proposed Optimized-Ant. The important evaluation parameters like PDR, end-to-end delay and NRL have been considered. This proposed Optimized-Ant protocol performs better than AODV for MANET but still it has a routing problem when it turn out to be dynamic optimization problem in MANET’s.

S. Misra, S.K. Dhurandher, M.S. Obaidat, N. Nangia, N. Bhardwaj, P. Goyal, S. Aggarwal[10], have considered the problem of location updating in MANETs. Author has proposed a node stability-based location updating approach. Performance of given approach is compared with conventional location updating algorithm. Different types of results have been obtained by varying different parameters such as the number of nodes and the terrain dimensions.

S.Misra, P.V.Krishna, A.Bhiwal, A.S.Chawla, B.E.Wolfinger, C.Lee[11], have proposed a learning automata-based fault-tolerant routing algorithm (LAFTRA). It performs routing with faulty nodes in MANETs with multipath routing algorithm. The theory of learning automata (LA) has been used for optimizing the selection of paths, reducing the overhead in the network, and for optimizing the selection of paths, reducing the overhead in the network, and for realizing about the faulty nodes present in the available network.

Lin, Tao[12], demonstrated that reactive protocols do not always have low control overhead because the control overhead for reactive protocols is sensitive to the traffic load. The traffic load is considered in terms of the mobility, number of traffic flows, and link connectivity change rates. Thus, reactive protocols effective for network with small traffic loads and lower link-connectivity change rates. It was also demonstrated that it was practical to maintain a full network topology with low control overhead for efficient working of MANET.

B.Nancharaiah and B.C.Mohan [13], proposed the work designate routing problem by hire the Ant Colony Optimization and Fuzzy Logic performances while developing the routing algorithm. The path details by the ants will be given to the FIS (Fuzzy Interference System) to calculate the score values of the path convenient. With use of this score value from the FIS system, the optimal best paths will be choosing. Hence, the routing problem can be answered more effectively and efficiently by achieving a highly successful path transportation rate rather than by the ACO routing algorithms.

B. Chen, K. Jamieson, H. Balakrishnan, and R. Morris[14],presents SPAN protocol for maximizing the lifetime of an Ad-hoc network by powering off the nodes for as long as possible called Span. A power-save protocol should be able to send packets between any pair of nodes in the network with minimum delay compared to every awaked node, as well as having nearly as much of the total capacity as the original network. Span is able to make decisions locally and produces a network without considerable detoration in capacity or rise in latency.

3. Proposed System

Introduced a control parameter called the inertia weight denoted as ‘w’, to damp the velocities over time, allowing the swarm to converge more accurately and efficiently as shown in (5).

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \qquad (.5)$$

Where, w_{max} : Initial weight,

w_{min} : Final weight,

$iter_{max}$: Maximum iteration number,

$iter$: Current iteration number.

Equation (5) represents a dynamically adjusting formulation for velocity resultant in has improved fine tuning ability. Looking at (5) reveals that the huge inertia weight eases a global search while the small value eases a local search. Thus, a dynamically adjustable design for inertia weight should be appropriate for attaining a balance between global and local eases and thus faster search result. By presenting linearly decreasing inertia weight into the unique version of PSO, the performance of PSO has been significantly improved through parameter study of inertia weight.

Use of a constriction factor as ‘χ‘, has included that advances PSO’s ability to make and control velocities in the original PSO, effectively eliminating the tendency of some particles to spiral into ever increasing velocity oscillations. The formulation of χ is expressed as in (6).

$$\text{¡} = \begin{cases} \dfrac{2\text{©}}{\text{¨} - 2 + \sqrt{\text{¨}^2 - 4\text{¨}}} & \text{for } \text{¨} > 4 \\ else\ \sqrt{\text{©}} \end{cases} \tag{6}$$

Where ¨Z=C_1 +C_2>4, then the Kennedy and Eberhart’s original PSO for velocity updating becomes

$$\mathrm{v}_{k+1}^{i} = \chi\ [w\ \mathrm{v}_{k}^{i} + \mathrm{c}_1 rand\ \frac{(\mathrm{p}^{i} - \mathrm{x}_{k}^{i})}{\Delta t} + \mathrm{c}_2 rand\ \frac{(\mathrm{p}_{k}^{g} - \mathrm{x}_{k}^{i})}{\Delta t}] \tag{7}$$

Clearly, the constriction factor χ in (7) can be seen as a damping factor that controls the magnitude of the flying velocity of a particle. From the experiments in the literature, the PSO has a potential ability to avoid particles being trapped into local optima effectively while possessing a fast convergence capability and was shown to have superior performance than the standard and modified PSOs. As shown in (6), the value of ¨, defined as the sum of the cognitive and social learning rates, is highly affect the constriction factor χ, and thus is the very important parameter for achieving a good PSO with high performance. In general, when Clerc’s constriction PSO is used, the common value for k=1, ¨ is set to 4.1 and the constriction factor χ is approximately 0.729. This is equivalent to the Shi and Eberhart’s modified PSO.

4. SELECTION OF PARAMETERS FOR MODIFIED PSO

The main parameters of the Modified PSO model are ω, C_1, C_2, V_{max} and the swarm size ‘S’. The settings of these parameters control how it improves the search-space. For example, one can apply a general setting that gives workable results on most problems. Since the same parameter settings not at all guarantee success in different problems, we must have knowledge of the effects of the different settings, such that we can pick a suitable setting from problem to problem.

1. The Inertia Weight (ω)

The inertia weight ω controls the momentum of the particle: If ω << 1, only little thrust is preserved from the previous time-step; thus quick changes of direction are possible with this setting. The concept of velocity is completely lost if ω = 0 and the particle then moves in each step without knowledge of the previous velocity. Setting ω >> 1 must be done with care, since velocities are auxiliary biased for an exponential growth. This setting is infrequently seen in PSO implementation and always together with V_{max}. In short, high settings near 1 facilitate global search, and lower settings in the range [0.2, 0.5] facilitate rapid local search.

2. The Constriction Factor (χ)

An adaptive Modified PSO model that uses a new parameter '*χ*' called the constriction factor. The model also excluded the inertia weight *ω* and the maximum velocity parameter V_{max}. Constriction coefficient results in the quick conjunction of the particles over time. That is the amplitude of a particle's oscillations decreases as it focuses on the local and neighborhood previous best points. Though the particle converges to a point over time, the constriction coefficient also prevents collapse if the right social conditions are in place. If the previous best position and the neighborhood best position are far apart from each other, the particle will perform a more experimental search i.e global search. During the search, the neighborhood best position and previous best position will change and the particle will shift from local search back to global search. The constriction coefficient method therefore balances the need for local and global search depending on what social conditions are in place.

5. SYSTEM MODELOF MODIFIED PSO

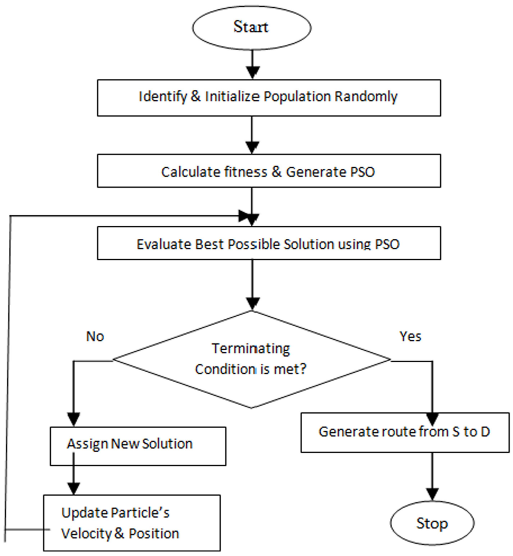

Fig. 2 Design Flow of Modified PSO

As in Fig. 2, each node evaluates the dependence factor of its adjacent nodes. Adjacent nodes are recognized in the search list and initialize population randomly. After initialized the population it will calculate the fitness value and particles are generated accordingly. The PSO algorithm is used to find the best achievable solution. If knowledge condition is fulfilled, then optimal route is generated between Source(S) and Destination (D) else, a new search list is generated with a new particle solution set and evaluation process is repeated until termination condition is met. Therefore, proposed PSO algorithm uses value of particles to generate optimal solution which consists of swarm particles or population nodes between Sources to Destination.

6. RESULTS AND DISCUSSION

Function Name: Generalized Rastringin's Function
Nature of problem: Multimodal characteristics
fun=20+x1.^2+x2.^2-10*(cos(2*pi*x1)+cos(2*pi*x2)) (8)

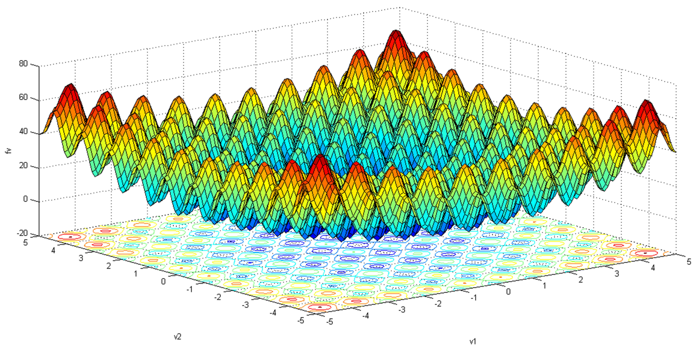

Fig. 3 Multimodal Plot

As in Fig.3, to make the problem very difficult, nature of multimodal which has number of local solution everywhere has applied which was crafted by above defined (8). Here two parameters have taken to define the visual understanding about how problem is difficult to solve. Horizontal two axis represent the independent parameters x1 and x2 while vertical axis is the value of function for different value of x1 and x2. Purpose of solution is to find the minimum vale over this hilly landscape which is nearly impossible for deterministic approach.

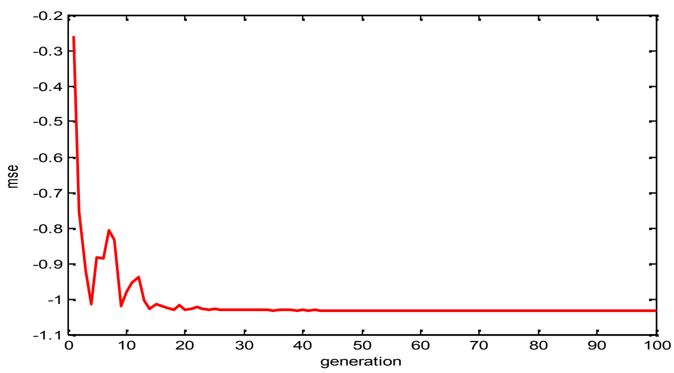

Fig. 4 Minimization of Objective Function

As in Fig. 4, solution fitness with iteration for best solution has shown in figure.it is clear that at the beginning there is low fitness (high value of function) because of random solution assignment. As the time progress there is improvement in solution and started to improve the fitness value (lower function value).After 25^{th} iteration value of function is very close to 0 which is optimal value of solution.

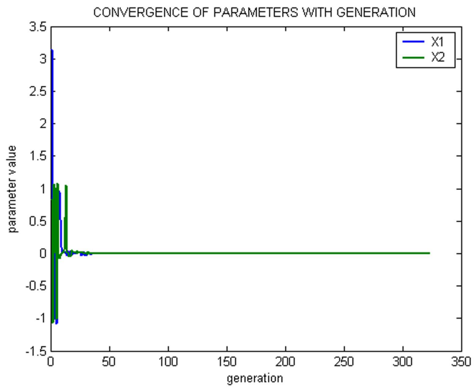

Fig. 5 Convergence of Parameter with Generation

Journey of parameters in search of optimal value for both parameters have shown in Fig. 5.At the beginning both parameters are very away from optimal value and started to converge towards the exact value with time. Some random fluctuation appeared because of mutation operation.

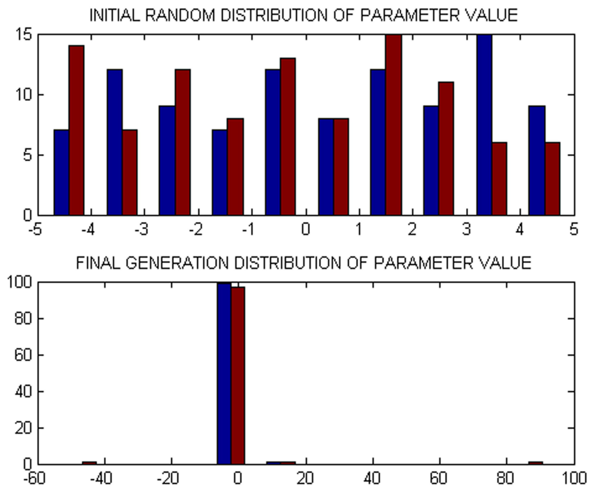

Fig. 6 Histogram of Initial & Final Distribution of Parameter Value

To understand how population is converging toward the optimal graph at the 1^{st} generation and last generation have shown in terms of histogram which distributes the members according to their value. It is clear from graph that there is uniformly the members have placed in the search range of [-5 to 5] which is because of uniform random number applied at the beginning to define the population solution. But in the final generation where all solutions except few of them, have been converge to the optimal value or nearby hence total number of member near the value of 0 is very large. This indicate not only one solution get improvement instead whole population started to improve with the time and this is the required characteristics of evolutionary computation as shown in Table 1.

Table 1. Improved Population Solution

Parameter	Evolved Obtained Value	Optimal Value
X1	0.4778e-6	0
X2	-0.0139e-6	0
Objective Function	2.2524e-12	0

CONCLUSION

To obtain intelligent routing, we have implemented adaptive genetic algorithms like, Modified Particle Swarm Optimization. It is used for the optimization problems for Local minima and Global by using various constraints like Constriction Factor, Inertia Weight and Constriction coefficient. In future it can implement by following Genetic Algorithms like Redefined Population with Time [RGA], Perturbation with Time [PGA], Sharing Knowledge with Time [KGA].These algorithms provide better connectivity in dynamic environments of wireless sensor networks. The dynamic environments obtain when the sensors are moved from place to another place with the help of animals, robotics and human beings. The adaptive genetic algorithms provide better solutions when the sensors in dynamic environment.

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