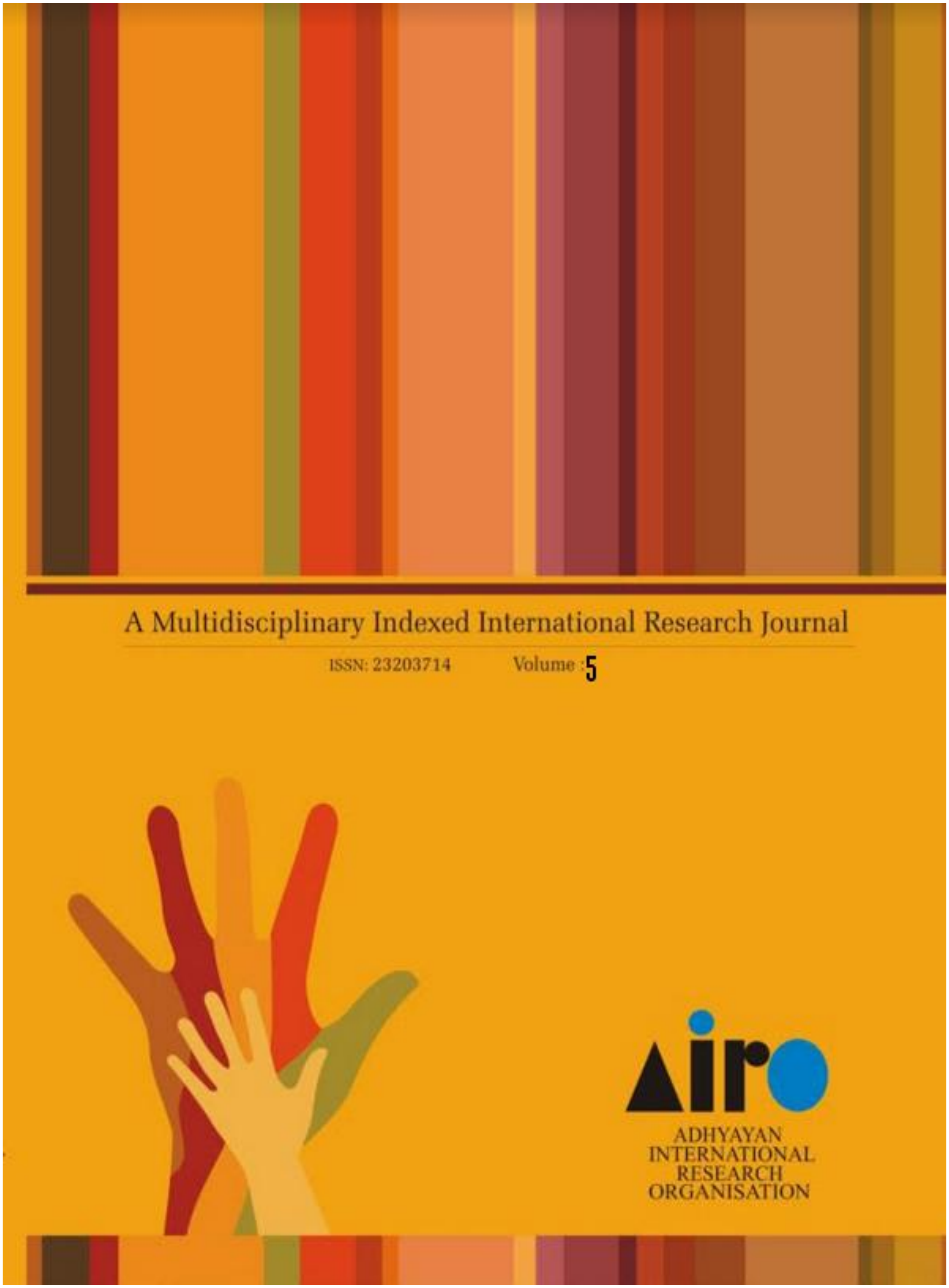

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LEAST ENERGY COST ROUTING TREE WITH DATA AGGREGATION

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Abstract- Data aggregation is one critical issue in network routing of energy-obliged Wireless sensor networks since routing with aggregation can devour less energy than conveying data to base station straightforwardly. The energy consumption is dictated by traffic control and data transmission. Consequently it is important to discover a transmission structure that coordinates with data aggregation so as to limit energy consumption. In such cases, routing tree with data aggregation is a sensible routing scheme.

Keywords: Data aggregation, traffic control, energy consumption etc.

1. INTRODUCTION

In this paper to discover a routing tree with data aggregation to accomplish least energy cost. This issue is a NP-finish issue since it can be reducible to weighted set cover issue in graph theory, which has been appeared to be NP finished. Since taking care of the NP-finish issue requires extraordinary computation cost that is super-polynomial in the input size, it might be sufficient to discover close optimal answer for get a satisfactory outcome in polynomial time rather than a correct arrangement. Heuristic calculations are connected to either give about the optimal answer quick and effectively or give an answer not to all occasions of the issue.

In this paper second section describe the Generic Algorithm. In third section discuss propose a solution for data energy efficient problem. In section four discuss PSO modified by GA for routing with aggregation and followed by conclusion.

2. GENETIC ALGORITHM

Genetic algorithm (GA) is a stochastic search strategy which is motivated by evolution laws of nature. The primary property of the GA is that the algorithm can work specifically on the goal without obliged by derivation or progression of capacity. The procedure of the GA is as per the following:

Step1. Encoding: Because the GA can't process data of solution space specifically, so we express them as genotype string data of genetic space through encoding. By and large, the variable is communicated by binary encoding. Since binary encoding requires change between real numbers, decimal framework is once in a while used to encode normally.

Step2.Population initialization: In the GA a string data is called an individual, and N people create a population. In the first place, framework creates N string data randomly. The emphasis of the GA at that point begins with an initial point which alludes to the N string data.

Step3. Fitness evaluation: Substitute initial population into predefined fitness capacity, and utilize the fitness esteems to decide the benefits of people.

Step4. Selection: As indicated by the fitness values figured by Step 3, select the fittest people as parents to reproduce offspring.

Step5. Reproduction: In this progression, generate new people from the mating pool by crossover and change operations.

a.) Crossover: The crossover operation takes a couple of parents from the mating pool randomly, and gives a couple of off-springs chromosomes by trading sub-strings of the two parent chromosomes. The new off-springs acquire the parents' highlights which speak to a exchange and combination of data. After the crossover operation, we supplant the guardians in the mating pool by their off-springs. The mating pool has hence been modified, yet at the same time keeps up a similar number of components.

b.) Mutation: The mutation is a vital strategy for preserving the diversity of the people by presenting small and arbitrary changes in to them. Keeping in mind the end goal to accomplish that, chromosomes are taken from the mating pool randomly, and the estimation of a quality is adjusted with a given likelihood. The mutation supplies an open door for creating new people in a bigger range.

Step6. Stopping criteria check: If the stopping criteria is fulfilled, the GA closes, generally come back to **Step 3**.

3. PROPOSED SOLUTION TO THE ENERGY-EFFICIENT PROBLEM

This paper proposes a novel routing scheme for data gathering and aggregation. In the routing scheme, source nodes initially discharge control packets and empower them to move arbitrarily from the source nodes to the base station. At the point when the control packets touch base at the base station, the ways go by the packets are then encoded to be people, and beginning population is framed as needs be. By methods for choice, crossover and change among the people, we can locate a close ideal routing tree for data gathering and aggregation.

This plan in view of the swarm intelligence comprises of

- *A*n ACO algorithm which is misused to give candidate solutions,
- A PSO algorithm that goes for discovering a close optimal aggregation tree which limits energy utilization of routing.

4. PSO MODIFIED BY GA FOR ROUTING WITH AGGREGATION

For a directing tree with data aggregation, the current algorithms presented in Section 3.4 and Section 3.5 is deficient to execute enhancement. Exclusively utilizing the ACO algorithm needs a significant number of control packets, and the overhead will increment in like manner. The genetic algorithm can develop into a satisfactory outcome; however it's joining is moderate. Optimization on an aggregation tree identifies with path choice, and way determination has a place with a discrete issue. The standard PSO algorithm is the genuine valued PSO, and it can't work expansion or subtraction straightforwardly on the way. Henceforth, the standard PSO algorithm ought to be reached out to manage the discrete optimization issues which require the ordering or orchestrating of discrete components, for example The routing tree with aggregation issue.

A prominent solution is to keep the velocity update equation unaltered, yet the genuine new position parts are changes to be 1 or 0 with likelihood. Another strategy sees the position vectors of the particles as probabilities and utilizing roulette wheel determination for discretisation. The two strategies both stretch out the real valued PSO to its binary version, specifically Binary PSO (BPSO), by a straightforward discretisation of the estimations of speeds or places of particles. A more general discrete PSO is proposed in to tackle the traveling sales representative issue. The strategy rethinks the six fundamental mathematical objects and operations in the discrete space.

Since the standard PSO can't lead optimization straightforwardly on the discrete issue, it needs a comparable frame for velocity and dislodging equation. In velocity equation, subtraction between the optimal position and the present position exemplifies the pattern that particles near the optimal position. In such cases, the subtraction, which can be comprehended as the procedure of information trade, is like the crossover operator of the GA. multiplication between inactivity weight and velocity can be translated as broadening seek range, and it is like the mutation operator of the GA. As a result, we consider proposing a PSO algorithm which is altered by the GA in order to address the discrete nature of our optimization issue.

Through the study of the dispersed properties of the ACO algorithm, we abuse a generally modest number of control packets to create some candidate ways, gather and forward the data about the network to the base station. In the base station an arrangement of routing trees are encoded as the people, and utilize the PSO algorithm to discover the close optimal transmission structure. The base station at that point sends the decided routing data to each source hub, and empowers the source nodes and transfer nodes to refresh their routing tables.

In the accompanying segments, we characterize our particle portrayal, indicate the initial population, and depict the fitness capacity and selection, and the methodologies for crossover and mutation.

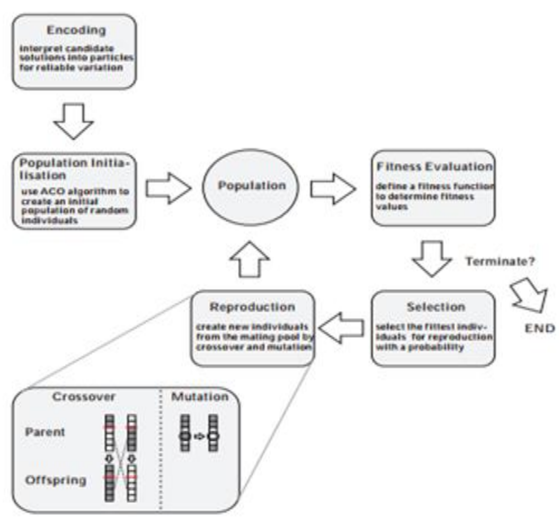


Figure 1: Discrete PSO algorithm conceptual flow

4.1 ENCODING

Encoding includes coding paths serial into a feasible arrangement (or a position) in the pursuit space. On account of encoding, distinctive schemes which are connected to comparing issues will influence the design of selection, crossover or mutation straightforwardly, in this manner impacting the convergence and unpredictability of the PSO algorithm. Generally Pr üfer number is utilized for tree encoding; however this way has complex encoding-decoding procedure and terrible area that small varieties in the portrayal may cause enormous changes in the network structure. Likewise it has poor heritability and if the graph is inadequate then this strategy speaks to infeasible solutions. Gen et al. uses priority-based encoding scheme, yet this scheme has to know neighbor nodes' priority ahead of time and is non-pertinent for solving our problem. Ahn and Ramakrishna makes utilization of variable-length encoding plan which can limit seek space. Notwithstanding, this design will expand multifaceted nature of crossover or selection as aftereffect of variable-length of string information. Encoding approach proposed by Munetomo et al. Is like the encoding technique for the TSP which depends on way, yet it is hard to do crossover. Thusly, we receive fixed-length position encoding to see routing tree straightforwardly.

We speak to the person, for a particular aggregation tree, as a string of node numbers. The length of every individual is constantly equal to the quantity of relay nodes. A steering plan for a network with 7 relay nodes, and one base station, is indicated motel Fig.2(a) and the relating molecule is appeared in Fig.2(b). In this case, the value of the gene in position 1 is 3, showing that node 1 transmits to node 3. Additionally, the value in position 3 is 8, demonstrating that node 3 transmits to node 8 (the base station).

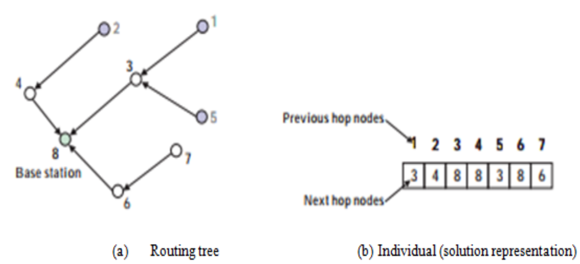


Figure 2: Encoding a routing tree as an individual.

For (b), the number serial at the upper string shows the past hop nodes while the number serial at the lower string speaks to the following hop nodes.

4.2 POPULATION INITIALIZATION

By and large, there are two approaches to create the initial population, heuristic initialization and random initialization. For most extensive scale issues, for example, network communication design, random initialization has better impact on global optimal arrangements. The ACO calculation said in Section 3.8.1 is utilized to create initial population that comprises of random trees. The ACO calculation is an algorithm that discovers ways for associated graphs. It begins from source nodes and chooses next hop nodes as per pheromone. On the off chance that pheromone is refreshed by transition probability works, the following hop nodes are randomly chosen to shape the ways with the ACO calculation. As an outcome, we have an initial population with random trees. Note that every single initial particle are substantial and no repair work is required.

We enhance the execution of particle swarm seek by deciding an appropriate initial population. The principle thought of our work is that the correspondence of nodes conduct through nearby optimization (versus worldwide optimization) is more prominent than the correspondence of nodes conduct in random initialization. The SPT algorithm and the MST algorithm have great outcomes in initial population, when connection coefficient is equivalent to 0 and 1 individually. For example, at the point when correlation coefficient approaches 0, if in the SPT algorithm, node v_i connects to v_j, then in the global optimum the probability for v_i to connect to v_j is greater than the probability of v_i to associate with another node. Subsequently the likelihood of comparability between corresponding components of the local optimum and the global optimum is more prominent than corresponding components of random vector and global optimum.

We can state that the probability of mapping the estimations of enhanced nodes (by The SPT algorithm or the MST algorithm) to estimations of nodes in the worldwide optimum is more noteworthy than the probability of mapping the estimations of random usage to the worldwide optimum. By utilizing this thought, the execution of the PSO algorithm is enhanced when the search space increments.

4.3 FITNESS FUNCTION

Subsequent to producing each new individual, we have to assess its fitness esteem. We characterize the fitness esteem as the energy utilization of the network. We figure the total transmit energy ,$E_{Tx}(k_{tij}, d_{ij})$, dissipated in a round by each relay node i, $1 \leq i \leq n$, to transmit k_{tij} bits data to another node (either a relay node or the base station) j,$1 \leq i \leq n + 1$, utilizing the accompanying first order radio model

$$E_{Tx}(k_{t_{ij}}, d_{ij}) = \begin{cases} k_{t_{ij}} E_{elec} + k_{t_{ij}} \epsilon_{fs} d^2, & d < d_0; \\ k_{t_{ij}} E_{elec} + k_{t_{ij}} \epsilon_{tg} d^4, & d \geq d_0; \end{cases}$$

(4.1)

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{tg}}}$$

(4.2)

where d_{ij} is the euclidian distance between node i and j, E_{elec} is the per bit energy dissipation for running the transceiver circuitry, ϵ_{fs} and ϵ_{tg} are both parameters but for different propagation model, d_0 is the cross-over distance. Similarly, the receive energy, $E_{Rx}(k_{ri})$, scattered in a round by each relay node i, $1 \leq i \leq n$, is defined as i

$$E_{Rx}(k_{r_{hi}}) = k_{r_{hi}} E_{elec}$$

(4.3)

Where k_{rhi} is the number of bits got by relay node i from node h in a round. Henceforth, we figure E_o, the total energy dissipated by each relay node i for one round of data gathering as

$$E_o = \sum_{h \in R_i} E_{Rx}(k_{r_{hi}}) + E_{da} \sum_{h \in R_i} k_{r_{hi}} + \sum_{j \in T_i} E_{Tx}(k_{t_{ij}}, d_{ij})$$

Where R_i is the set made up of the nodes that transmit k_{rhi} bits message to node i in a round. T_i is the set made up of the nodes that receive k_{tij} bit message from node i in the same round. E_{da} is the per bit energy dispersal for totaling information which are from various sources. Clearly, our metric for energy scattering mulls over including the transmit energy, the get energy and aggregation energy. In this manner, the fitness work is characterized as E_o.

4.4 SELECTION

The capacity of selection operator is to choose people which have relative extensive fitness values with relative huge probabilities from their parent age. The PSO algorithm at that point puts the picked person in the posterity age and waits for promote advancement executed by crossover and mutation. There are various selection schemes, for example, the roulette wheel selection, the liner ranking selection, and the tournament selection. The guideline of these selection schemes is predictable, which is to choose people "randomly" from an old population to produce a novel population.

Truth be told, the "random" selection isn't totally random. It duplicates an old individual and includes it into new population with a specific likelihood which is corresponding to the proportion of its fitness value to the whole of all people's fitness.

Among different selection schemes, the roulette wheel selection is the most every now and again utilized, however this selection may have issues when the fitness esteems vary in particular. So as to circumvent the issues of fitness proportionate selection strategies, we embrace the ranking selection as a piece of execution of the changed PSO algorithm in this thesis.

In the ranking selection, the probability of an individual to be selected is assigned according to its rank which is based on the objective function values in the sorted list of all individuals in the population. Using the rank smoothes out larger differences of the fitness values and emphasizes small ones. Nevertheless, because the ranking selection is also based on probability to come into effect, on the one hand, the virtue of this method is that individuals with low fitness value are In the ranking determination, the probability of a man to be picked is allotted as demonstrated by its rank which relies upon the target work values in the organized list surprisingly in the people. Using the rank smoothes out greater differences of the fitness values and underscores minimal ones. Regardless, in light of the way that the ranking choice is in like manner in perspective of likelihood to end up plainly viable, from one viewpoint, the virtue of this system is that individuals with low fitness value are

Step1. Rank individuals as per the fitness values and decide their positions in the population. For example, the ranking of the minimum fit individual is the first, and the ranking of the fittest individual is the n th.

Step2. Calculate the probability p_i to be selected for the *i* th individual as: *i*

$$p_i = \frac{i}{\sum_{j=1}^{n} j}$$

(4.5)

Step3. For the *i* th individual, calculate the accumulative probability g_i from the I th to the *i* th individual:

$$g_i = \sum_{j=1}^{i} p_j$$

(4.6)

Step4. Generate a random number *r* which is uniformly distributed in [0, 1]. On the off chance that the condition fulfills $g_{i-1} < r \leq g_i$, the *i* th individual is selected.

Step5. Repeat **Step 4** until the point when the amount of produced people is equivalent to the size of population.

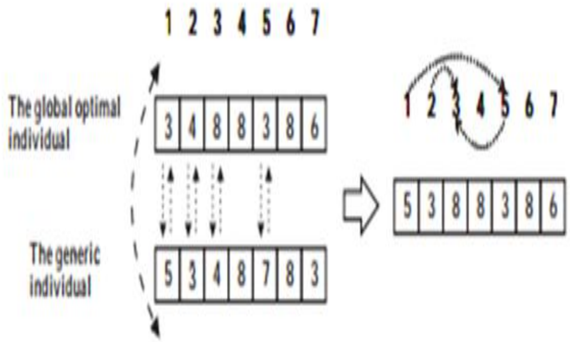
4.5 CROSSOVER

The posterity age acquired by crossover needs to speak to routing trees from source nodes to the base station, else they are illegal solutions. Subsequently, we propose the accompanying crossover technique for the above characterized people.

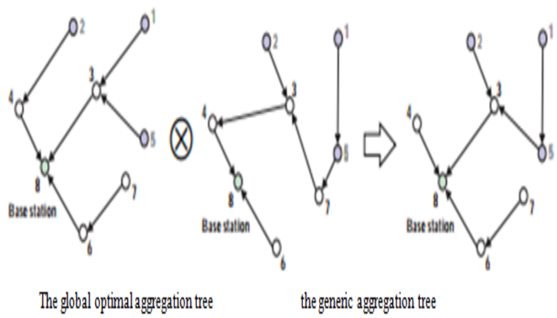
In the velocity formula of the PSO algorithm, the opeartor $\otimes$ in (4.1) demonstrates data exchange which is like the operation of crossing in the GA. In the GA, the crossover replaces the relating position of conventional genes with a section of the optimal genes. So we utilize the hybrid as the proportionate type of the $\otimes$ operation .

The term $p_{gbest}^{k} \otimes x_{id}^{k}$ demonstrates that a particle keeps an eye on the global optimum, so it is equal to the crossover administrator of managing the generic people and the gbest. In view of the prerequisite of encoding, source nodes are known at the phase of crossover. To start with, we randomly select a gene in the locus of a similar source node between the global optimal individual and a generic individual and place it into a similar locus of the offspring. We at that point make a similar choice at the locus of the hand-off node which is demonstrated by the past picked gene. This procedure is rehashed until the point when the base station is found. For the rest nodes which are not utilized, genes from a similar locus between the global optimal individual and a generic individual are chosen haphazardly. Fig. 6.6 is a case for crossover between the global optimal aggregation tree and a generic aggregation tree and comparing elucidation in aggregation tree structure.

The term $p_{gbest}^{k} \otimes x_{id}^{k}$ shows that a particle watches out for the local optimum, so it is proportional to the crossover administrator between the generic aggregation trees and the ibest. , Fig. 3 is a case for crossover between the local optimal aggregation tree and a generic aggregation tree and comparing elucidation in network structure.



(a) Crossover operation



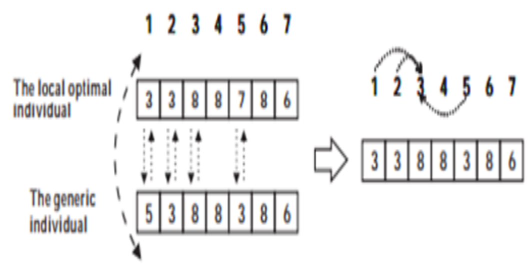
(b) Routing tree structure adjustment

Figure 3: Crossover between the global optimal individual and the generic individual and corresponding interpretation.

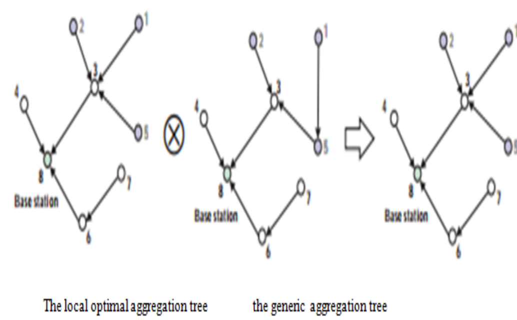
For (a), the number serial at the upper string shows the past hop nodes while the number serial at the lower string speaks to the following hop nodes.

4.6 MUTATION

In the velocity formula of the PSO algorithm, multiplying ω by v_{id}^{k} shows that a molecule seeks toward another space. This moving propensity is like the operation of mutation in the GA. In the GA, the mutation administrator influences customary genes to have substantial alterable scales and pursuit toward more extensive space, so we utilize the mutation as the proportionate type of the multiplying items $\omega\, v_{id}^{k}$. The mutation operator likewise has many structures for comparing encoding schemes. The design of the mutation is to avert



(a) Crossover operation



(a) Routing tree structure adjustment

Figure 4: Crossover between the local optimal individual and the generic individual and corresponding interpretation.

For (a), the number serial at the upper string shows the past hop nodes while the number serial at the lower string speaks to the following hop nodes.

Algorithm from falling into the local optimal solution. It can influence the populace to have a tendency to enhance and certification that there are better people in the offspring era.

In view of the necessity of encoding, source nodes are known at the phase of mutation. On the off chance that someone in particular is chosen to conduct mutation, the routing tree spoke to by the individual will be adjusted. We select a node I to substitute for node j from set Ω where the node I has the same past hop node and next hop node as node j. Subsequently, we can utilize node I to supplant node j, in this way creating another routing tree. , This procedure is shown by Fig.6.

4.7 ADDITION

The addition operation shows the whole of a few handling steps. Through efficient executing the equivalent sub-items in the PSO algorithm, we can acquire the impact of addition. In the equivalence of the addition, the outputs of past advances are the

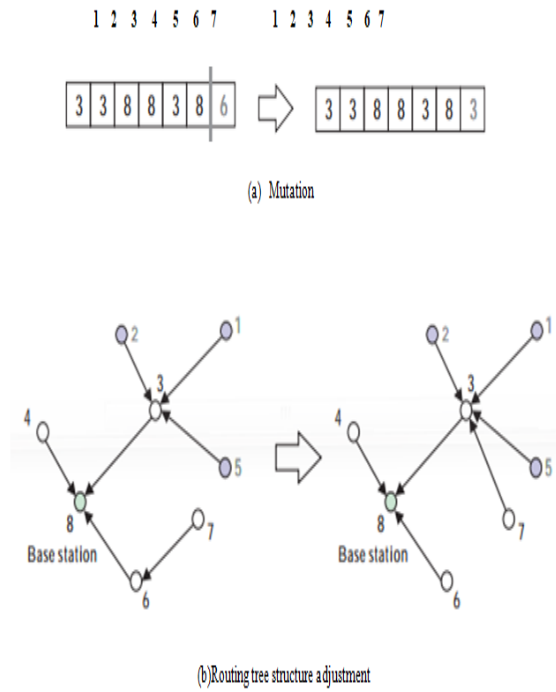


Figure 5: Examples of the mutation operation.

For (a), the number serial at the upper string shows the past hop nodes while the number serial at the lower string speaks to the following hop nodes. The gray number after the bar is chosen to execute the mutation.

Input of last steps. As per (3.15) and (3.16), we can derive that

$$\begin{aligned} x_{id}^{k+1} &= x_{id}^{k} + v_{id}^{k+1} \\ &= x_{id}^{k} \oplus \omega v_{id}^{k} \oplus (p_{ibest}^{k} \otimes x_{id}^{k}) \oplus (p_{gbest}^{k} \otimes x_{id}^{k}) \end{aligned}$$

(4.7)

By means for the equivalence of the crossover, mutation and addition, the PSO algorithm can be utilized to fathom the routing tree with information aggregation issue. In addition, keeping in mind the end goal to save data of the optimal arrangement, the optimal individual in a specific iteration isn't updated. After this iteration, if the impact of another individual is better than the optimal individual, the person who has better impact will turn into the optimal person. The past optimal particle is viewed as a generic particle and will be refreshed in the following iteration.

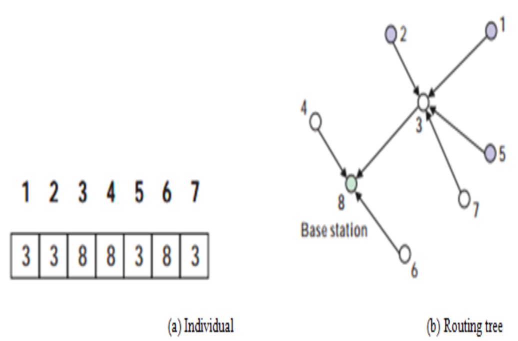


Figure 6: Decoding of result output by PSO algorithm.

For (a), the number serial at the upper string shows the past hop nodes while the number serial at the lower string speaks to the following hop nodes.

5. CONCLUSION

In this paper we present basics of Generic Algorithm and Particle Swarm Optimization. At the time of Data aggregation, consideration of sensor node energy is important. Sometimes nodes are die due to energy loss. So energy efficient is important. In this paper we present data aggregation with low energy cost by using Routing Tree. In this paper discussed a transmission structure that coordinates with data aggregation with limit energy consumption.

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