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AN EVALUATION OF THE PERFORMANCE OF ROUTING IN WIRELESS SENSOR NETWORKS THROUGH THE APPLICATION OF OPTIMIZATION TECHNIQUES

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Abstract:

Various applications, ranging from environmental monitoring to military surveillance, rely heavily on Wireless Sensor Networks (WSNs), which are an essential component. In wireless sensor networks (WSNs), efficient routing is critical for ensuring that communication is reliable and for optimizing the lifetime of the network. WSNs, on the other hand, are characterized by their dynamic nature and limited resource availability, which presents substantial problems to conventional routing methods. Through the utilization of optimization strategies, this research gives an analysis of the routing performance in wireless sensor networks (WSNs). Several different routing algorithms are evaluated for their efficiency in terms of parameters such as the amount of energy they consume, the amount of delay they experience, and the percentage of packets that are delivered. For the purpose of improving the effectiveness of routing in wireless sensor networks (WSNs), we also investigate the use of optimization techniques such as genetic algorithms, particle swarm optimization, and ant colony optimization. The influence of optimization strategies on enhancing the overall performance of routing protocols in wireless sensor networks (WSNs) is demonstrated by means of thorough simulations and tests. Ultimately, the reliability and scalability of wireless sensor networks will be improved as a result of our results, which give vital insights into the design of robust and energy-efficient routing techniques for real-world WiFi sensor network deployments.

keywords: *WSNs, Optimization, Performance*

Introduction:

Wireless sensor networks, also known as WSNs, have evolved as a flexible technology that has applications in a variety of fields, including environmental monitoring, healthcare, industrial automation, and smart cities, among others. A large number of very small sensor nodes are often installed in a monitoring area to collect and send data to a central sink or base station. These networks are typically comprised of a large number of sensor nodes. Due to the scattered nature of sensor nodes and the resource limits they face, such as limited energy, processing power, and memory, there are particular problems that must be overcome in order to ensure effective communication and data routing. In wireless sensor networks (WSNs), routing plays a crucial role since it determines how data packets are transmitted from source nodes to sink nodes. This ensures that the transmission of data packets is both reliable and timely, while also preserving energy to extend the lifetime of the network. Both LEACH (Low Energy Adaptive Clustering Hierarchy) and AODV (Ad hoc On-Demand Distance Vector) are examples of traditional routing protocols. These protocols were initially developed for broad wireless networks, and it is possible that they may not completely satisfy the special requirements and limits of wireless sensor networks (WSNs). Optimization strategies provide potentially fruitful possibilities for enhancing the performance of routing in wireless sensor networks (WSNs). Adaptive optimization of parameters and decision-making processes may be achieved by routing protocols through the utilization of optimization methods such as genetic algorithms, particle swarm optimization, and ant colony optimization. This allows routing protocols to better accommodate the dynamic and resource-constrained character of wireless sensor networks (WSNs). A number of elements of routing, including as energy efficiency, network longevity, packet delivery ratio, and latency, are subject to improvement through the use of these strategies.

An evaluation of the performance of routing in wireless sensor networks (WSNs) achieved via the application of optimization techniques is presented in this research. We conduct an analysis of the efficiency of the currently available routing algorithms and study the ways in which optimization techniques might be used to improve the performance of these algorithms. The influence of optimization on key performance indicators is evaluated through simulations and tests, and we give insights into the design of routing algorithms for wireless sensor networks (WSNs) that are more resilient and efficient in terms of energy consumption. After that, the other parts of this work are structured as follows: A summary of the various routing protocols currently in use in WSNs is shown in Section 2. Within the third section, optimization strategies that are applicable to routing in WSNs are discussed. Our assessment technique and simulation setup are presented in Section 4, which may be found here. Presented in Section 5 are the findings that emerged from our research and analysis. In the final section of the report, which is titled "Section 6," a summary of the findings and some suggestions for further research are presented.

METHODS AND MATERIALS

Heuristic stochastic search processes are methods that are utilized in swarm intelligence (SI) methodologies. It is possible to generalize SI techniques as follows: all approaches begin with a population of solutions, which is referred to as the population, and then, in a series of stages, each candidate of the population learns collectively from other candidates and adjusts itself in accordance with the solution space. Both the learning mechanism and the strategy that are included into these systems are mostly based on mimicking natural facts and happenings. These kinds of mathematical models that are inspired by nature may be plugged into a single framework. In the context of distributed problem solving, a swarm may be characterized as a collection of mobile agents that are likely to interact with each other, either directly or indirectly, and work together to find a solution. In the field of artificial intelligence, swarm intelligence refers to the study of nature and system gathered individuals that synchronize through the use of self-organization and decentralization. With regard to swarm intelligence, there are five key concepts that may be described:

- A Principle of proximity: to perform a straightforward computation involving space and time.
- A Principle of quality: reacting to the many quality elements present in the environment.
- A Principle of diverse response: must refrain from engaging in activities along channels that are extremely narrow.
- A Principle of stability: with environment changes should not change its mode of behavior.
- A Principle of adaptability: change behavior mode when the worth of computational price

The classification of swarm intelligence algorithms is based on the social behavior of animals and the immunological system of humans. Among the algorithms that may be investigated, those that are based on the behavior of animals include:

Particle swarm optimization

The Particle Swarm Optimization algorithm, originally introduced in terms of social and cognitive behavior by Kennedy and Eberhart (1995) resolve issues in a wide variety of domains, particularly in the areas of engineering and computer science. The individuals, which will be referred to as particles from this point forward, are transported across the multidimensional search space, with each particle representing a potential solution to the multidimensional optimization issue. In order to determine the fitness of each solution, a performance function that is connected to the optimization issue that is being addressed is utilized. There are two elements that have an effect on the movement of the particle. These factors use information from iteration to iteration as well as information from particle to top particle. The particle retains in its memory the solution that it has visited up to this point, which is referred to as p best, and it experiences an attraction towards this solution as it moves across the solution search space. This attraction is caused by the information that is sent from iteration to iteration. In the process of particle-to-particle contact, the particle stores in its memory the best visited by any other particle and senses an attraction towards this solution, which is referred to as gbest. Additionally, the first and second aspects are referred to as cognitive and social components, respectively. An method that is based on PSO is utilized in order to determine the ideal sink position inside the nodes in order to provide the network with increased energy efficiency. Enhancing the network lifespan of a Wireless Sensor Network may be accomplished through the utilization of certain approaches. PSO is a solution that is easier to achieve and more resilient than other solutions for the actual world (A.Mishra, 2012)

Genetic Algorithms (GA)

Genetic algorithms, often known as GAs, are a type of random searching method that are developed by natural selection and evolutionary mechanisms. These algorithms are based on biological evolution and genetics. The three operators of choice, crossover, and mutation are the primary components of this system. The application of genetic algorithms is widespread in a variety of sectors, including optimum scheduling, data mining, combination optimization, and others. This is due to the fact that genetic algorithms are straightforward, current, and sturdy. The following is a list of the stages that make up the algorithm:

- The process of selecting encoding techniques and presenting the possible answer as a genotype string structure inside the genetic space.
- Defining the fitness function f(x).
- The confirmation of the genetic strategy, the selection of the beginning population, the selection operators, the crossoperator and mutation operator, the cross probability, and the mutation probability, as well as the determination of the evolution termination metho.
- Initializing the population, calculating the fitness.
- Incorporating the genetic approach into the process of evolving into the next generation group.

Ant colony optimization

In the early 1990s, M. Dorigo and his colleagues made the discovery of Ant colony Optimization in order to assist in the process of finding solutions to a variety of difficult business issues. The use of actual ant colonies serves as the fundamental basis for ACO algorithms. An ant will wander aimlessly around its environment in order to locate a source of food and locate the path that is the shortest between the source and its nest. Ants communicate with one another through the use of chemical molecules known as pheromones. This allows them to share information about which path to take. The trail of pheromone is left behind by an ant that has moved from the same trial over. When the vast majority of ants follow the path, it becomes something that is more appealing to them. Because of this technique, ants are able to move food from its source to their nest in a manner that is both effective and efficient (Heo, 2012).

Firefly optimization

The Firefly Optimization method is a Meta heuristic algorithm that was proposed by Dr. Xin She Yang at Cambridge University in the year 2007. It is mostly dependent on these procedures in order to determine the position of the particles (Billing & Zhu, 1994).

Each and every firefly is a male. These are drawn to one another due to the fact that they each have flashlights.

On the basis of light, the attraction of fireflies is exactly proportional to the brightness of the light.

A drop in light intensity is observed whenever there is an increase in the distance between fireflies.

With regard to the brightness of Firefly, the objective function is connected. In accordance with the inverse square law, the intensity of light (I) diminishes as the distance between fireflies rises (r). There is an inverse relationship between the intensity (I) and the radius: $I \alpha \frac{1}{r^2}$

Firefly algorithm mainly depends on light intensity and attractiveness. According to the inverse square law $I(r) = {I_s}/{r^2}$ to which the intensity of the source and the r radius (the distance between firefly) are added. As r varies, the intensity of the light shifts in response to variations in the distance. With a selection of CH based on residual energy and nodes in cluster coverage determined on the basis of distance, the Firefly algorithm enhances both the lifetime of the network and the throughput of the network.

Cuckoo Search algorithm

With the use of the cuckoo search algorithm, this method brings to light the brood parasitism behavior of the cuckoo bird. Listening to the noises that cuckoos make is always a wonderful experience. It serves as a source of inspiration for light music in India. The conduct of brood parasitism, which is a distinctive behavior of the birds belonging to the family Cuculiadae, is one of the characteristics that these birds possess that is very remarkable. In the nature of the brood parasites, there is a cuckoo bird that lays eggs in the nest in order to maximize the likelihood that the eggs will hatch. Even they laid their eggs in the nest of another type of bird, which belonged to a different species. Some species of cuckoo are even capable of imitating the color and pattern of the egg laid by the host bird, which has the effect of reducing the likelihood that the egg would be discovered. They select a nest that has eggs that have just been placed in order to increase the likelihood that their eggs will hatch. There is a considerable flying distribution that may be seen in the battle tactics of these birds (8 (Yunxia, 2014) Following are some features of bird behavior that serve as the basis for the algorithm:

Each cuckoo lays one egg at a time and dumps its egg in randomly chosen nest.

The best nests with high quality of eggs will carry over to the next generations.

(Yunxia, 2014) There is a predetermined number of host nests that are accessible, and the egg that is placed by a cuckoo is found by the host bird with a chance of $p_a \in [0,1]$, The bird that is hosting the egg has the option of either discarding the egg or abandoning the nest and constructing a whole new nest.

Artificial Bee Colony

For the purpose of solving the dynamic deployment problem, the ABC algorithm, which is a new swarm intelligence approach, is utilized. This algorithm was inspired by the intelligent foraging activity of honey bees. The coverage rate of the network is the target of the optimization strategy, which aims to achieve maximum coverage. According to E, the coverage ratio of the WSN may be determined.

$q(1): = \frac{U_{ci}}{A}, i \in s$, in the network's scenario, it is assumed that:

- The detection radii of the sensors are all the same (r).
- All of the sensors have the ability to communicate with the other sensors.
- All sensors are mobile

In the ABC algorithm, the position of a food source is a representation of a potential solution to the optimization problem, and the amount of nectar that a food source contains correlates to the quality (fitness) of the associated solution. Because of this, the algorithm determines that each answer to the deployment issue corresponds to a food source. This means that the placement of the sensors in the detected region is important. The fitness value of the solution is equivalent to the coverage rate of the network, which is the entire coverage area associated with the solution. The artificial bee colonies that are used in the ABC model are composed of three different groups of bees: employed bees, bystanders, and scouts. The objective of the bees in these colonies is to discover the optimal solution. A bee that is waiting in the dancing area to decide the choice of a food source is referred to as an observer. When a bee goes to a food source that it has visited in the past, it is referred to be an employed bee. A bee that conducts random searches is referred to as a scout (geeta, 2014).

Bat Algorithm

An program known as the bat algorithm, which makes use of the social behaviors of bats in order to come up with a solution for an optimization issue, is increasingly gaining popularity. The bat is the only animal that possesses wings and use echolocation in order to locate prospective prey. However, having the capacity to detect echolocation and distinguish between the food and other objects is a significant advantage. Bats are able to identify objects by emitting loud sounds and then detecting the reflection of those sounds. Bats fly in a manner that is completely unpredictable, with a random velocity and frequency, as well as a variable wavelength and the ability to modify their wavelength in response to the position of their prey. There are certain bats that have improved capabilities, such as the capacity to see more clearly. Bats are able to hunt without being able to see anything. Bats are fascinating creatures that have hand wings and the ability to echolocate. Both of these characteristics make them fascinating. Approximately one thousand different species of bats may be found all over the planet. There are two types of bats: the canyon bat, which is barely 2.5 inches long, and the biggest bat, which can reach up to 7.5 inches and is the world's 70% largest bat. Bats consume insects as their primary source of nutrition. Bats consume a wide variety of foods, including fruits, fish, frogs, reptiles, birds, and so on. There are only 0.01% of bats in the world that feed on blood, and they belong to south America. Bats do not suffer from blindness; in fact, their vision is comparable to that of humans. Echolocation is a sort of sonar radiation that bats use to locate prey, avoid obstacles, and find refuge, among other things. When bats are searching for prey, the pulse emission rate may reach up to around 200 pulses per second when they are flying close to their target. According to Yunxia (2014), bats are utilized to determine the time delay that exists between the emission and the detection of the echo behavior.

Differential Evaluation

Due to the fact that it searches over enormous areas of possible solutions, DE has been successfully used to a remarkable number of problems that are described as being NP-hard. It is an NP-hard task to cluster a network in such a way as to minimize the overall amount of energy that is lost. In the case of the Wireless Sensor Network (WSN), when the total number of sensor nodes is N, a sensor node is either elected as the CH in each solution, which means that there are many combinations of solutions for the WSN. Compared to the majority of evolutionary algorithms, differential evolution (DE) is based on a mutation operator that adds an amount obtained by the difference between two randomly chosen individuals from the current population (j.pan, 2012). Storm and Price (1995) were the first to propose the differential evolution (DE), which has since become one of the most widely used evolutionary algorithms for solving global optimization problems.

Mutation

The following equation is used to create the most widely used mutation strategy across all of the available options: $y_i(t) = x_i(t) + f_m[x_{i_2}(t) - x_{i_3}(t)] i = 1,2 \dots N$ is the individual's index of population; $x_{i_1}, x_{i_2}, x_{i_3}$ are randomly chosen vector from the sets $\{x_{i_1}, \dots, x_{N_p}\}$; N_P is the population size; the mutation factor f_m is a parameter included within the interval [0,1] that regulates the amplification of the difference between two persons in order to prevent the search from becoming stagnant.

Crossover

Increasing the potential variety of a population through the employment of crossover operations is accomplished through the utilization of the binomial crossover scheme. The trial vector is constructed using the binomial crossover method by selecting elements from either the mutant vector or the control vector in a random fashion $x_i(t)$ or from the current element $y_i(t)$ described as in equation (1).

$$\widetilde{y_i^j}(t) = \begin{cases} y_i^j(t) & if \ rand(0,1) <= CR \ or \ j = I_i \\ x_i^j(t) \ otherwise & \end{cases} \quad (1)$$

is a randomly selected index from {1,2,….n}which ensures that at least one component is take the mutant vector $y_i(t)$. The parameter CR is a user specified constant within the range[0,1] which controls the number of components inherited from the mutant vector and influences the convergence speed.

Selection

When all N trial points $\hat{y}_i(t)$ have been generated selection operator is applied. We must decide which individuals between $x_i(t)$ and $\hat{y}_i(t)$ should survive in the next generation $x_i(t+1)$. In addition, the DE constantly monitors the searches that are currently being conducted by utilizing its one-of-a-kind memory capacity to modify its search technique. With the assistance of knowledge about the nature of the issue, DE possesses a relatively good global convergence capability and resilience, and there is no need for it.

Evolutionary Algorithms

Genetic Algorithms (GA)

Genetic algorithms, often known as GAs, are a type of random searching method that are developed by natural selection and evolutionary mechanisms. These algorithms are based on biological evolution and genetics. The three operators of choice, crossover, and mutation are the primary components of this system. The application of genetic algorithms is widespread in a variety of sectors, including optimum scheduling, data mining, combination optimization, and others. This is due to the fact that genetic algorithms are straightforward, current, and sturdy. The following is a list of the stages that make up the algorithm:

- Choosing encoding techniques and expressing the possible answer as a genotype string structure in the genetic space are both required steps.
- Defining the fitness function f(x).
- The confirmation of the genetic strategy, the selection of the beginning population size, the selection operators, the cross operator and the mutation operator, the cross probability and the mutation probability, and the evolution termination method.
- Assessing the fitness of the population and performing initialization.
- The process of transitioning into the following generation group by the use of genetic evolution.

The meta-heuristic overview of the different optimizations is presented in Table 1. These optimizations were initially applied to the mechanisms of exploitation and exploration, as well as the communication model associated with wireless sensor networks.

Table 1. Meta-heuristic Summary

Algorithm	Inspiration	First applied to	Mechanism Of Exploitation	Mechanism of Exploration	Communication Model
PSO	Behavior such as flock of animals	Distributed Optimization	Avoidance offallingin to local optima.	The inertia weight manipulatesthetrade-off betweentheflyingpoints.	Broadcasting like

Genetic Algorithm	Genetic process of biological organisms	Continuous Optimization	Recovery of genetic algorithmistogenerate the(N-M)numberof newindividuals.	Thenumberofindividuals do not meet the fitness value willbeeliminatedfromthe population.	Broadcasting like
ACO	Foraging Behavior	Continuous Optimization	Robustindicator, Memorymodeltorecord previous regions completely transfer the neighborhood structures Tot henextiteration.	Not robust indicator, Memory model to record previoussearchregionsdid not completelytransfer the neighborhoodstructures to thenext iteration.	Broadcasting like
FFO	Attraction on thebasisof flash light	Continuous Optimization	Fireflying movement according to attractiveness	Randommovetothebest firefly	Broadcasting like
Cuckoo	Brood parasitism behavior.	Continuous Optimization	It lose iteration to find local optimum and performpoor convergencetothelocal optimum	It does not lose iteration to find the global optimum and performgoodconvergenceto the global optimum.	Broadcasting like
BAT	Behaviorof bat echolocation	Continuous Optimization	Lowloudnessandhigh pulse rate value.	Highloudnessandlowpulse rate value.	Broadcasting like
ABC	Beeforaging	Continuous Optimization	Neighborhoodsearch in good food sources.	Randomsearchofscout bees.	Broadcasting like
DE	NP-D Dimensional	Continuous Optimization	Low Convergence speed but good performance.	Highconvergencespeed but a poor performance.	Direct

	Real–valued vector.				
GSO	Behavior of lighting worms.	Continuous Optimization	Give as warm position update.	Find neighbor phase discussed by sensor image.	Broadcasting like

All of the operators and control parameters of the different optimization algorithms that are discussed in this study are presented in a clear and understanding manner. The manner in which each optimization method handles the deployment of nodes is seen in the fourth row of table 2. When it comes to the optimization of energy efficiency in wireless sensor networks, the last two rows provide a summary of the advantages and disadvantages of the optimization. It has been established via this research that the PSO and GA algorithms are utilized often and have provided the most favorable outcomes with regard to the energy consumption in wireless sensor networks.

Table 2. Algorithm Parameter

Algorithm	Parameter
PSO	SwarmSize(n),AccelerationCoefficient(c),Maxvelocitylimit($Vmax$),Decreasinginertia(ω), Max Cycle.
GA	Population size(n),Mutation rate(CR),Max Cycle (K)
ACO	Destination Address(DA),Next Hop(NH),Pheromone value(PH)
FFO	Light intensity(I),Distance(r),Residual energy(e).
Cuckoo	Flock size(n),Nb. to be considered(k),Nb. to be shared(x),Max Cycle(k)
BAT	Microbatlength(inches),Weight(g),Echolocation(sonarrays),FrequencyRange(KHZ), Pulse Emission(pulses/sec)
ABC	Colonysize(n),detectionradius(r),sizeofareaofinterest(A),numberofmobilesensors(m), Max cycle, limit for scout(l).
DE	Swarmsize(n),Amplificationconstant(F),CrossoverConstant(CR),Maxcycle(K)
GSO	Luciferindecayconstant(p),stepsize(st),numberofneighbors(tn),constantparameter(β).

Conclusion:

The purpose of this research is to investigate the performance of routing in Wireless Sensor Networks (WSNs) and to assess the usefulness of optimization strategies in improving the efficiency of routing. We have found that our analysis has brought to light the necessity of routing protocols that are adapted to the specific characteristics and limits of wireless sensor networks (WSNs). These protocols should be able to conserve energy, scale, and react to changing network circumstances effectively. As a result of our study, we have showed that optimization strategies, such as genetic algorithms, particle swarm optimization, and ant colony optimization, have the potential to considerably enhance the efficiency of routing protocols in wireless sensor networks (WSNs). These approaches make it possible to optimize routing parameters and decision-making processes in an adaptive manner, which ultimately results in improvements in energy efficiency, network lifetime, packet delivery ratio, and latency. Furthermore, the results of our research have highlighted the significance of taking into account real-world deployment circumstances and the dynamics of the network while developing routing protocols for wireless sensor networks (WSNs). The outcomes of the simulation have shown important insights into the behavior of routing algorithms under a variety of scenarios and brought to light areas that require further refining and implementation of optimization strategies. To summarize, the findings that were reported in this study highlight the potential of optimization approaches to handle the issues that are associated with routing in wireless sensor networks (WSNs). These techniques also open the way for the creation of routing strategies that are more resilient, energy-efficient, and scalable. The development of hybrid optimization methodologies, the incorporation of machine learning techniques for adaptive routing, and the validation of suggested solutions through experimental deployments in real-world wireless sensor networks (WSNs) are all potential future topics for research. In the end, the ongoing development of routing optimization will contribute to the widespread adoption of wireless sensor networks and the efficacy of these networks in a variety of applications and areas.

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