**Hanoi University of Science and Technology**

**School of electrical engineering**



**GRADUATION THESIS**

**Energy efficient in wireless sensor network using Grey Wolf Optimization algorithm**

|  |  |
| --- | --- |
| **Author:**  **Supervisor:** | Dao Duc Nguyen  Dr. Nguyen Thanh Huong  Chữ ký của GVHD |
| **Department:** | Department of instrumentation and industrial informatics |
| **School:** | School of electrical engineering |
| **HÀ NỘI, 6/2021** | |

i

**CỘNG HÒA XÃ HỘI CHỦ NGHĨA VIỆT NAM**

**Độc lập - Tự do - Hạnh phúc**

-----------------

**BỘ GIÁO DỤC VÀ ĐÀO TẠO**

**TRƯỜNG ĐẠI HỌC BÁCH KHOA HÀ NỘI**

--\*\*\*--

**NHIỆM VỤ**

**THIẾT KẾ TỐT NGHIỆP**

Họ và tên: Dao Duc Nguyen Mã số sinh viên: 20162982

Khóa:  **61**

Viện: **Điện**

Ngành: **Kỹ thuật đo và Tin học công nghiệp**

*1. Đầu đề thiết kế/Tên đề tài*

* Energy efficient in wireless sensor network using Grey Wolf Optimization algorithm

*2. Các số liệu ban đầu*

*3. Các nội dung tính toán, thiết kế*

*4. Cán bộ hướng dẫn:* TS. Nguyễn Thanh Hường

*5. Ngày giao nhiệm vụ thiết kế: 01/2021*

*6. Ngày hoàn thành nhiệm vụ: 04/2021*

*Ngày...... tháng...... năm......*

CHỦ NHIỆM BỘ MÔN CÁN BỘ HƯỚNG DẪN

*(Ký, ghi rõ họ tên) (Ký, ghi rõ họ tên)*

SINH VIÊN THỰC HIỆN

*(Ký, ghi rõ họ tên)*

**ACKNOWLEDGEMENTS**

I would like to thank all of the people who made this thesis possible, starting with my wonderful supervisor - Dr. Nguyen Thanh Huong for her support, patience, and guidance in almost every step throughout my thesis. I am grateful to all the members in the class AP Automatic Control K61. It is their kind help and support that have made my study and life at the university a wonderful time. Further, I would like to express my sincere gratitude to Hanoi University of Science and Technology and all its member’s staff for all the considerate guidance. Also, I would like to thank my friends I have made along the way when I was studying at Hanoi University of Science and Technology. They have left wonderful memories for me. Finally, I would like to express my gratitude to my parents. Without their tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study.

ABSTRACT

Tóm tắt nội dung của đồ án tốt nghiệp trong khoảng tối đa 300 chữ. Phần tóm tắt cần nêu được các ý: vấn đề cần thực hiện; phương pháp thực hiện; công cụ sử dụng (phần mềm, phần cứng…); kết quả của đồ án có phù hợp với các vấn đề đã đặt ra hay không; tính thực tế của đồ án, định hướng phát triển mở rộng của đồ án (nếu có); các kiến thức và kỹ năng mà sinh viên đã đạt được.

Sinh viên thực hiện

Ký và ghi rõ họ tên

Contents

[Chapter 1. INTRODUCTION 8](#_Toc70109721)

[1.1 Background 8](#_Toc70109722)

[1.2 Related works 8](#_Toc70109723)

[1.2.1 LEACH protocol 9](#_Toc70109724)

[1.2.2 PEGASIS protocol 10](#_Toc70109725)

[1.3 Thesis Scope and Contributions 11](#_Toc70109726)

[1.4 Thesis Organization 11](#_Toc70109727)

[Chapter 2. THEORETICAL BACKGROUND 12](#_Toc70109728)

[2.1. Wireless sensor network 12](#_Toc70109729)

[2.2. Heuristic-based clustering algorithm 12](#_Toc70109730)

[2.3. Meta-heuristic approaches 12](#_Toc70109731)

[Chapter 3. GREY WOLF OPTIMIZATION 13](#_Toc70109732)

[3.1. Inspiration 13](#_Toc70109733)

[3.2. Mathematical model and algorithm 14](#_Toc70109734)

[3.2.1. Social hierarchy 14](#_Toc70109735)

[3.2.2. Encircling process 15](#_Toc70109736)

[3.2.3. Hunting process 16](#_Toc70109737)

[3.2.4. Seeking and attacking the prey 17](#_Toc70109738)

[Chapter 4. ENERGY CONSUMPTION MODEL 19](#_Toc70109739)

[4.1. Network model and assumptions 19](#_Toc70109740)

[4.2. Energy consumption 19](#_Toc70109741)

[Chapter 5. PROPOSED ALGORITHM 21](#_Toc70109742)

[5.1. Selection of Initial Clusters 21](#_Toc70109743)

[5.2. Modified Grey Wolf Optimizer 21](#_Toc70109744)

[5.3. Selection of the Optimal Cluster Set 23](#_Toc70109745)

[5.4. Pseudo code 24](#_Toc70109746)

[Chapter 6. RESULTS AND ANALYSIS 25](#_Toc70109747)

[6.1. Network lifetime 25](#_Toc70109748)

[6.2. Residual energy 25](#_Toc70109749)

[6.3. Impact of cluster heads 25](#_Toc70109750)

[Chapter 7. CONCLUSION 26](#_Toc70109751)

[Chapter 8. REFERENCE 27](#_Toc70109752)

**TABLE OF CONTENTS**

**LIST OF FIGURES**

[Figure 1 9](#_Toc69767605)

[Figure 2 11](#_Toc69767606)

[Figure 3 12](#_Toc69767607)

[Figure 4 13](#_Toc69767608)

[Figure 5 15](#_Toc69767609)

[Figure 6 16](#_Toc69767610)

**LIST OF TABLES**

[Bảng 1.1 Thống kê các thiết bị và giá thành 8](#_Toc20580109)

# Chapter 1. INTRODUCTION

## Background

In recent years, wireless sensor networks (WSNs) have a wide range of application area, such as military reconnaissance, medical aid, urban management, smart home and target tracking thanks to the development of low-power digital circuits and wireless communication technology. WSNs consists of a base station (BS) and a large number of randomly distributed sensor nodes. The energy of the sensor node is mainly powered by the battery and it is very difficult to charge or replace the battery. Therefore, to increase the lifetime of the network, energy efficiency is the most important and critical task in the design WSN routing protocols.

The routing protocol is a process to select suitable path for the data to travel from source to destination. The process encounters several difficulties while selecting the route, which depends upon, type of network, channel characteristics and the performance metrics.

In the routing protocol of WSNs, clustering algorithms are considered to be one of the most energy efficient approach for wireless sensor networks. Clustering divides the nodes into multiple regions, a region is known as a cluster. For each cluster, there is a sensor node which is chosen as a leader, called the cluster head (CH). All the remaining node in that cluster send their perceived data information to CH, which will conduct data information fusion and send date to the BS. Clustering avoids long distance communication of member nodes and only cluster heads are communicating to base station. To balance the network, role of cluster head is rotated among all nodes.

## Related works

In recent years, the routing protocols of WSNs have attracted the attention of many scholars because of the rapid evolution and development of wireless sensor networks. Clustering routing protocol is an efficient way to reduce the energy consumption of sensor nodes and lengthen the life cycle of networks.

Thus, many routing protocols based on clustering have been presented, such as Low-Energy Adaptive Clustering Hierarchy (LEACH), Threshold Sensitive Energy Efficient Sensor Network Protocol (TEEN), Adaptive TEEN (APTEEN), The power-efficient gathering in sensor information systems (PEGASIS), Hybrid Energy-Efficient Distributed Clustering (HEED), LEACH-centralized (LEACH-C), etc.

However, heterogeneous wireless sensor networks (HWSNs) which consider heterogeneity of energy are now widely used in practice; meanwhile, most clustering routing protocol of WSNs are based on homogenous network. Many HWSNs routing protocols with heterogeneity of nodes energy have been proposed such as Power-Efficient Gathering in Sensor Information Systems (PEGASIS), Stable Election Protocol (SEP), Modified SEP (M-SEP), Distributed Energy-Efficient Clustering Algorithm (DEEC), etc.

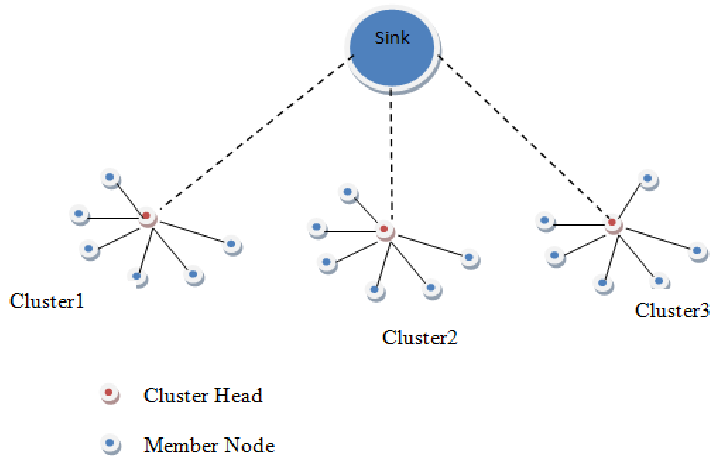
### LEACH protocol

LEACH is the most famous clustering routing protocol among homogeneous WSNs.

Low-energy adaptive clustering hierarchy (LEACH) is a TDMA-based MAC protocol which is integrated with clustering and a simple routing protocol in wireless sensor networks (WSNs). This is the protocol for collecting and distributing data to sinks especially base stations. The main goals of LEACH are:

* Expand network lifetime.
* Reduce energy consumption by each sensor node.
* Use data concentration to reduce message transmission in the network.

To achieve these goals, LEACH adopted a hierarchical model to organize the network into clusters, each managed by the master node. The master node is responsible for performing many tasks. This master node is called cluster head (CH). This routing algorithm uses cluster formation based on the received signal strength and uses the CHs as the local sink while BS receives all the gathered data from cluster heads. Network topology of LEACH which uses single hop routing is shown below in Figure 1.



* Figure 1

In LEACH, the CHs are randomly selected and the sensor nodes are periodically rotated into CHs. The network energy consumption is evenly allocated to each sensor node to lengthen the network life cycle and enhance the network throughput. Nodes that have been cluster heads cannot become cluster heads again for P rounds, where P is the desired percentage of cluster heads. Thereafter, each node has a 1/P probability of becoming a cluster head again. At the end of each round, each node that is not a cluster head selects the closest cluster head and joins that cluster. The cluster head then creates a schedule for each node in its cluster to transmit its data.

The advantage of LEACH is significant energy savings. And this saving depends mainly on the data concentration coefficient of the cluster's master nodes.

However, LEACH also has some of the following shortcomings: It is impractical to assume that all of the host nodes in the network transmit to the base station in a single hop, and because the energy reserves and capabilities of the nodes change over time from node to node. In addition, the steady-state interval is key to achieving the energy reduction required to compensate for the amount of crest caused by cluster selection processing. Short cycle will increase the amount of overhead, long cycle will quickly consume the energy of the host node.

Many improved protocols based on LEACH have been proposed, such as LEACH-B, LEACH-C, E-LEACH, H-LEACH, O-LEACH, etc. The lifecycle of these above protocols raised relative to LEACH in homogeneous WSN, but they still perform poorly in HWSNs.

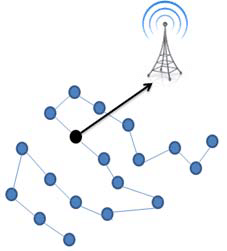
B-LEACH [25] communication is entirely depending upon the position of the cluster heads which needs no information about all the other nodes inside the cluster. Therefore, the residual energy of the CHs gets drained which further reduces the lifetime of the network.

In E-LEACH [14], the cluster head communication between different clusters is highly efficient, but in the case of larger networks, it fails to select the nodes with low energy.

LEACH-C [26, 27] outperforms LEACH-A, LEACH-B because the CPU handles locations and energy of all the nodes; therefore, formation and maintenance of the cluster is not affected. The only disadvantage is that it is not vigorous. In the case of multi-hop communication E-LEACH is much energy efficient. It enhances the cluster head selection process by considering the higher residual energy available at a particular time within a cluster.

### PEGASIS protocol

Power Efficient Gathering in Sensor Information Systems (PEGASIS) is one such hierarchical routing protocol which follows a chain based approach and a greedy algorithm. The sensor nodes organize themselves to form a chain. A leader or a cluster head node is assigned and it takes care of transmitting data to the base station/ sink node. The main goal of PEGASIS is to receive and transmit data to and from the neighbor and take turns being the cluster head for transmission to the Sink Node.



Figure

PEGASIS is a near optimal chain-based protocol that is an improvement over LEACH. In PEGASIS, each node communicates only with a close neighbor and takes turns transmitting to the base station, thus reducing the amount of energy spent per round.

However, it introduces an additional lag if nodes are distant. It is unsuitable for large scale WSNs which involves multi-hop communication.

## Thesis Scope and Contributions

## Thesis Organization

# Chapter 2. THEORETICAL BACKGROUND

## Wireless sensor network

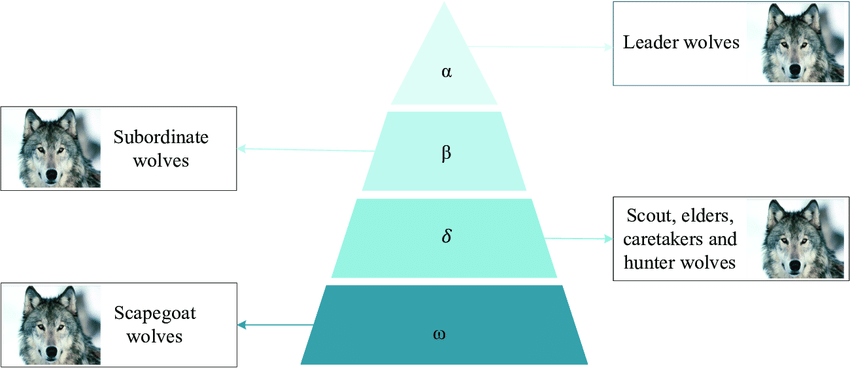
## Heuristic-based clustering algorithm

## Meta-heuristic approaches

# Chapter 3. GREY WOLF OPTIMIZATION

## Inspiration

Grey wolf (Canis lupus) belongs to Canidae family. Grey wolves are considered as apex predators, meaning that they are at the top of the food chain. Grey wolves mostly prefer to live in a pack. The group size is 5-12 on average. Of particular interest is that they have a very strict social dominant hierarchy.



Figure

The leaders are a male and a female, called alphas. The alpha is mostly responsible for making decisions about hunting, sleeping place, time to wake, and so on. The alpha’s decisions are dictated to the pack. However, some kind of democratic behavior has also been observed, in which an alpha follows the other wolves in the pack. In gatherings, the entire pack acknowledges the alpha by holding their tails down. The alpha wolf is also called the dominant wolf since his/her orders should be followed by the pack. The alpha wolves are only allowed to mate in the pack. Interestingly, the alpha is not necessarily the strongest member of the pack but the best in terms of managing the pack. This shows that the organization and discipline of a pack is much more important than its strength.

The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alpha in decision-making or other pack activities. The beta wolf can be either male or female, and he/she is probably the best candidate to be the alpha in case one of the alpha wolves passes away or becomes very old. The beta wolf should respect the alpha, but commands the other lower-level wolves as well. It plays the role of an adviser to the alpha and discipliner for the pack. The beta reinforces the alpha's commands throughout the pack and gives feedback to the alpha.

The lowest ranking grey wolf is omega. The omega plays the role of scapegoat. Omega wolves always have to submit to all the other dominant wolves. They are the last wolves that are allowed to eat. It may seem the omega is not an important individual in the pack, but it has been observed that the whole pack faced internal fighting and problems in case of losing the omega. This is due to the venting of violence and frustration of all wolves by the omega(s). This assists in satisfying the entire pack and maintaining the dominance structure. In some cases, the omega is also the babysitters in the pack.

If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). Delta wolves have to submit to alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category. Scouts are responsible for watching the boundaries of the territory and warning the pack in case of any danger. Sentinels protect and guarantee the safety of the pack. Elders are the experienced wolves who used to be alpha or beta. Hunters help the alphas and betas when hunting prey and providing food for the pack. Finally, the caretakers are responsible for caring for the weak, ill, and wounded wolves in the pack.

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. According to Muro et al.[1] the main phases of gray wolf hunting are as follows:

* Tracking, chasing, and approaching the prey.
* Pursuing, encircling, and harassing the prey until it stops moving.
* Attack towards the prey.

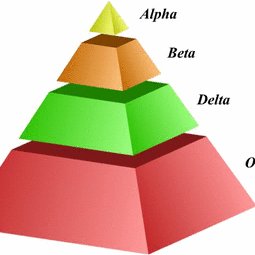


Figure

## Mathematical model and algorithm

### Social hierarchy

In order to mathematically model the social hierarchy of wolves when designing GWO, we consider the fittest solution as the alpha (α). Consequently, the second and third best solutions are named beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). In the GWO algorithm the hunting (optimization) is guided by α, β, and δ. The ω wolves follow these three wolves.



Figure

### Encircling process

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space, we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution) beta and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agent.

During hunting, the location of the prey is assessed by α, β, and δ wolves, and the remaining wolves calculate the distance between themselves and the prey; then, the wolves encircle the prey.

The following is the calculation formula of the wolf’s position:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 1 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | | Eq 2 | |
|  |  |  | |

Where:

* is the wolf’s position in the (t+1)th iteration
* is the prey’s position at the tth iteration
* linearly decreases from 2 to 0 over the course of iterations
* is the convergence factor
* is a random vector in the range [0,1]
* is the distance from the wolves to the prey, and is calculated as follow:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 3 |
|  |  |  |
|  |  | Eq 4 |
|  |  |  |

Where

* and are the positions of the prey and the wolf at the tth iteration
* is the convergence factor
* is a random vector in the range [0, 1]

### Hunting process

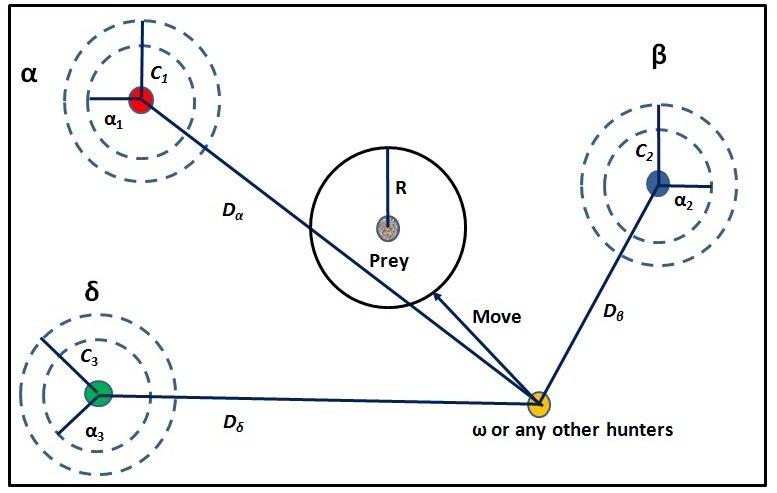
Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution) beta, and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agent. The following formulas are proposed in this regard.

|  |  |  |
| --- | --- | --- |
|  |  | Eq 5 |

Where:

* is the prey’s position at the (t+1)th iteration
* are the positions of alpha wolf, beta wolf and delta wolf at the (t+1)th iteration. They are calculated by equation (3.1).

At the end of the iteration times, α wolves have the highest fitness value.

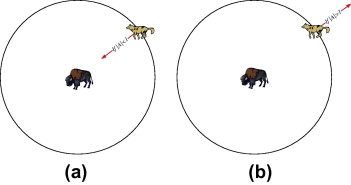


Figure

shows how a search agent updates its position according to alpha, beta, and delta in a 2D search space. It can be observed that the final position would be in a random place within a circle which is defined by the positions of alpha, beta, and delta in the search space. In other words, alpha, beta, and delta estimate the position of the prey, and other wolves updates their positions randomly around the prey.

### Seeking and attacking the prey

As mentioned above the grey wolves finish the hunt by attacking the prey when it stops moving. In order to mathematically model approaching the prey we decrease the value of . Note that the fluctuation range of is also decreased by . In other words, is a random value in the interval [-a, a] where a is decreased from 2 to 0 over the course of iterations. When random values of are in [-1, 1], the next position of a search agent can be in any position between its current position and the position of the prey. Fig shows that |A| < 1 forces the wolves to attack towards the prey.



Figure

With the operators proposed so far, the GWO algorithm allows its search agents to update their position based on the location of the alpha, beta, and delta; and attack towards the prey. However, the GWO algorithm is prone to stagnation in local solutions with these operators. It is true that the encircling mechanism proposed shows exploration to some extent, but GWO needs more operators to emphasize exploration.

To sum up, the search process starts with creating a random population of grey wolves (candidate solutions) in the GWO algorithm. Over the course of iterations, alpha, beta, and delta wolves estimate the probable position of the prey. Each candidate solution updates its distance from the prey. The parameter a is decreased from 2 to 0 in order to emphasize exploration and exploitation, respectively. Candidate solutions tend to diverge from the prey when || > 1 and converge towards the prey when || < 1. Finally, the GWO algorithm is terminated by the satisfaction of an end criterion.

# Chapter 4. ENERGY CONSUMPTION MODEL

## Network model and assumptions

In the network model, the following assumptions are made:

1. All nodes are randomly distributed in the two-dimensional geographical area. Once the location is determined, no matter what happens, the location of the nodes will not change.
2. In HWSNs, all sensor nodes are assigned different initial energy levels.
3. The BS is located in the center of the sensing area, and its power is externally supplied.
4. The energy of the sensor node is limited, and the battery cannot be charged.
5. When the sensor node power is exhausted, the node will be considered dead.

## Energy consumption

In WSNs, nodes are randomly deployed, and the locations of the nodes are not pre-designed. Most of the energy of a node is dissipated due to communication between nodes, depending on the distance between the nodes. Both data transmission and reception consume energy. Therefore, to transmit an (m − bit)-long data packet over the distance d, the required energy is:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 6 |

Where:

* is the energy consumed when the node transmits data.
* is the energy dissipation of the process of transmitting 1 bit of data and the process of receiving 1 bit of data.
* is the coefficient of energy dissipation in the free-space model
* is the coefficient of energy dissipation in the multi-path attenuation model
* is the threshold of the transmission distance, which is calculated as:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 7 |

The energy consumption required by the receiving node to receive an m bit data packet is calculated as follows:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 8 |

The energy consumption of CH can be calculated by the above model. The energy consumption of CH mainly includes three aspects: the energy consumption of receiving data packets of member nodes, fusing data and transmitting fusing data to the base station. The calculation formula is as follows:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 9 |

Where:

* is the number of member nodes in the cluster.
* is 1 bit of data aggregation energy cost.
* is the packet length.

The energy consumption of the non-CH node is only the energy consumption of sending data to the CH, and its mathematical expression is as follows:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 10 |

The total residual energy in the rth round is calculated as follows:

|  |  |
| --- | --- |
|  | Eq 11 |

Where:

* is the total residual energy in the (r − 1)th round
* is the number of CHs in the rth round
* is the number of alive nodes in the network in the rth round
* is the energy consumed by the ith CH
* is the energy consumed by the jth non-CH.

# Chapter 5. PROPOSED ALGORITHM

In order to avoid the randomness of CHs selection, an algorithm is proposed. In the first stage of cluster formation, all the sensors in network send their positions and initial energy to the base station and then the base station saves them. It should be noted that the sensors’ locations are all fixed and cannot be changed. After receiving these information, energy consumed each round can be calculated; therefore, locations and energy are sent to the BS once only.

## Selection of Initial Clusters

To establish the initial clusters of the network, energy of the nodes and the distance of them to the BS are 2 parameters that the protocol uses, thereby limiting the number of CHs in each round. The following rules are used to select the initial clusters. All the sensors are divided into m sets of clusters and the cluster heads of these clusters are chosen based on the result of fitness value ranked from high to low. Nodes which are close to the BS and have high residual energy should be selected as the CH. Here, it is proposed to use the remaining energy and distance between the nodes to the BS as parameters of fitness function. The fitness function is expressed as:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 12 |

Where:

* is the weight.
* is the initial energy of the node.
* is the residual energy of the node.
* is the distance from the node to the BS.
* and are respectively the maximum and the minimum distance between a node and the BS of the network.

Node with the higher fitness value are more likely to become the BS.

## Modified Grey Wolf Optimizer

After the initial cluster is established, the MGWO is used to form new clusters and select new CHs. In the original GWO, based on the average weight of alpha, beta and delta wolves, the prey’s position was calculated. The three best wolves are chosen based on Equation 12. They are 3 nodes which have the highest fitness value F1. Consequently, based on the GWO and formula (12), the initial position of prey is computed as:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 13 |
|  |  |  |
|  |  | Eq 14 |

Where:

* α, β and δ are the 3 respective nodes have the highest fitness value calculated through Equation 12.
* , and are respectively the initial weights of alpha, beta and delta wolf.
* , and are respectively the first, the second and the third best fitness value calculated through Equation 12.

It should be noted that, if we use GWO algorithm to implement the protocol, the fitness of all the nodes change after completing one data transmission. However, the weight of alpha, beta and delta wolf will not change. Thus, to further improve the global search capacity of GWO, the weights should be updated for each transmission. A modified algorithm for GWO is proposed to update the weights based on vectors A and D. A is the coefficient vector, D is the distance between the wolf and the prey and they are calculated according to Equations 2 and 3. At the (t + 1)th iteration, the location of the prey and the weight updating formula are as follows:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 15 |
|  |  |  |
|  |  | Eq 16 |

Where:

* , and are respectively the positions of alpha, beta and delta wolf in the (t + 1)th iteration. They can be calculated by using equation 1.

After the iteration done, the node closer to the prey is more likely to become the CH. However, distance is not the only parameter we care about. The remaining energy of that node could not be enough to complete tasks of the CH, causing the node to die soon. Therefore, node which has more residual energy and close to the prey is consider to be selected as the CH. The fitness function to select the CH is then proposed based on the above parameters. It should be noted that the node with smaller fitness value will indicate that the CH selection is more reasonable. The fitness function is defined as:

|  |  |  |
| --- | --- | --- |
|  |  | Eq 17 |

Where:

* is the weight.
* is the residual energy of the node.
* and are the maximum and minimum residual energy in the cluster.
* is the distance from the node to the prey.
* and are respectively the maximum and the minimum distance between a node and the prey in the cluster.

## Selection of the Optimal Cluster Set

According to the clustering algorithm, a network can be divided into multiple clusters, and multiple clusters in the network are called a cluster set. To get the optimal cluster set; first, the initial cluster set which was calculated in 5.1 is taken as the current optimal set and its objective function is calculated. This cluster set is then randomly changed by MGWO algorithm to form new cluster sets and these new sets’ objective value are calculated. When the objective value of the new set is better than the old one, this set is accepted as the current optimal set. At the end of the iteration, the optimal cluster set is established. The objective function is expressed as:

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  | | --- | --- | --- | |  |  | Eq 18 | | |  |  |  | | --- | --- | --- | |  |  | Eq 12 | | |  |  |  | | --- | --- | --- | |  |  | Eq 12 | |

Where:

The objective function is designed based on the intra-cluster communication distance, the total communication distance from the CH to the BS and the residual energy of the nodes. A smaller objective value makes the CH selection more reasonable.

## Pseudo code

# Chapter 6. RESULTS AND ANALYSIS

To verify the performance, we use MATLAB software to simulate the HGWO algorithm. The simulation parameters are shown below:

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| The area of the sensing region | 100 (m2) |
| Number of Sensor Nodes | 100 |
| Packet Size | l = 4000 bits |
| Data Aggregation Energy Cost | = 5 nJ/bit |
| Energy Cost of Transmitter/Receiver | = 50 nJ/bit |
| Transmission Coefficient of Amplifier (free space) | = 10 pJ/bit/m2 |
| Transmission Coefficient of Amplifier (multi-path space) | = 0.0013 pJ/bit/m4 |
| Initial energy of normal node | 0.5 J |
| Ratio of Advanced Node | 0.2 |
| Weight of Fitness Function | a1 = a2 = a3 = 0.2 |
|  |  |

Table

At the beginning of each round, the BS selects CHs using algorithm as described above and each round last for 1 second.

## Network lifetime

## Residual energy

## Impact of cluster heads

# Chapter 7. CONCLUSION

# Chapter 8. REFERENCE

|  |  |
| --- | --- |
| [1] | Heinzelman, W.R.; Chandrakasan, A.; Balakrishnan, H., "Energy-Efficient Communication Protocol for Wireless Microsensor Networks," in *33rd Annual Hawaii International Conference on System Sciences*, 2000. |
| [2] | Tong, M.; Tang, M, "LEACH-B: An Improved LEACH Protocol for Wireless Sensor Network," in *2010 6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM), Chengdu, China)*, 2010. |
| [3] | Marappan, P.; Rodrigues, P, "An energy efficient routing protocol for correlated data using CL-LEACH in WSN," *Wirel. Netw,* p. 1415–1423, 2015. |
| [4] | Vinod Kumar, Ajay Khunteta, "Energy Efficient PEGASIS Routing Protocol for Wireless Sensor Networks," in *2nd International Conference on Micro-Electronics and Telecommunication Engineering*, 2018 . |