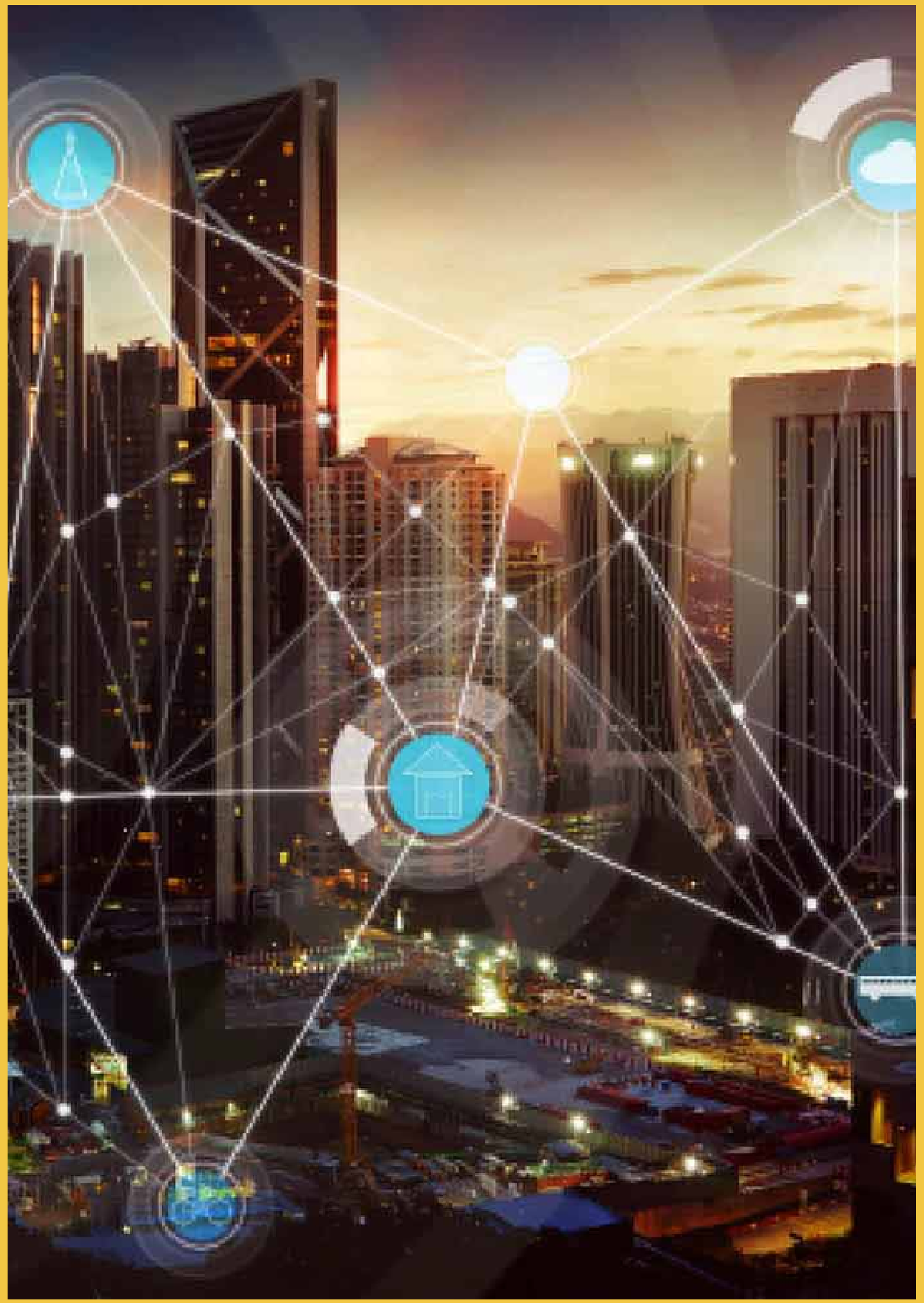
Vellore Institute Of Technology

# Review III

## Optimization of CH node selection for lifetime maximization of WSN and the application of CR-WSN



Abhishek Iyer
19BEC0806

Aryan Malik
19BEC0843

Faculty Guide:
Dr. Karthikeyan A.

Vellore Institute Of
Technology

# Overview

- Summary
- Animation of the proposed algorithm
- Flowchart of the algorithms
- First Order Radio Model
- Output of the proposed algorithm

- CRWSN - Introduction
- Difference between WSN-CRWSN
- Q learning and the implementation the of Cognitive Radio technology
- FGF outputs- Alive nodes, throughput, distance analysis
- CRWSN - evaluation of epsilon
- Future work

# Summary

## Maximizing the lifetime of the CH node and efficiently utilizing the under-utilized licensed spectrum using CR-WSN

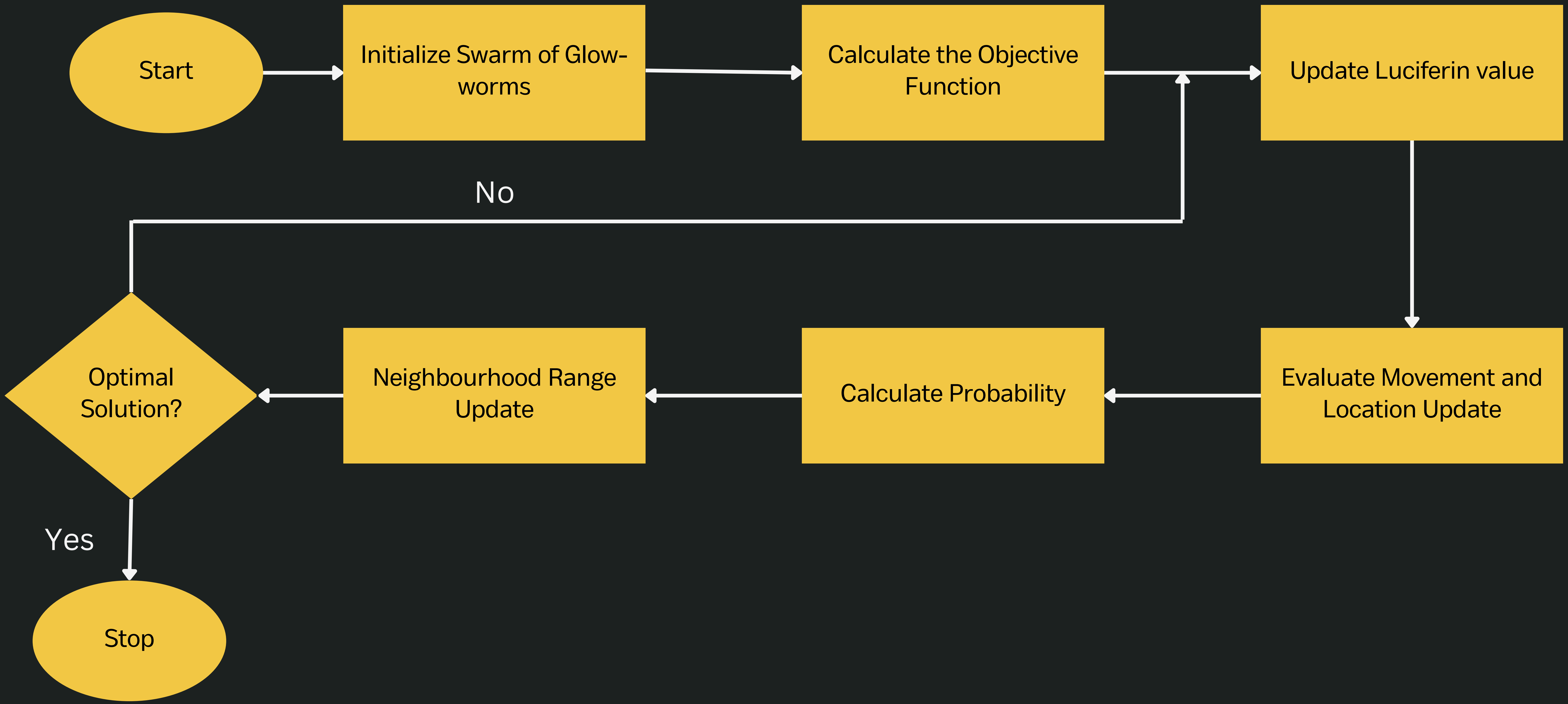
### Objectives

- Implementation of a Hybrid based Cluster Head selection algorithm to maximize the lifetime of the CH nodes.
- To minimize the delay and increase the throughput.
- To utilize the white spaces in the licensed spectrum to avoid degradation of the wireless sensor networks using reinforcement learning
- To implement the self-learning joint decision making algorithm.

Back to Overview

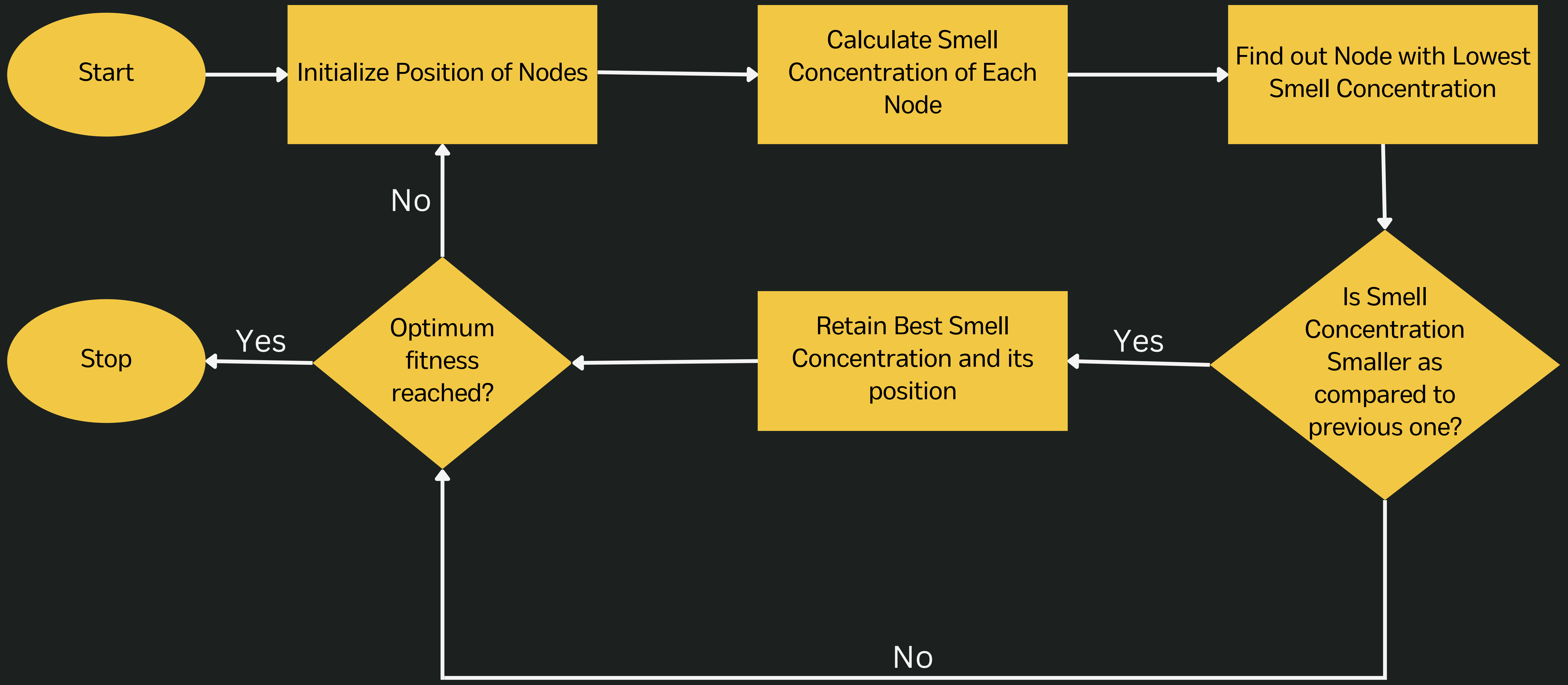
# Conventional GSO Flowchart

Back to Overview



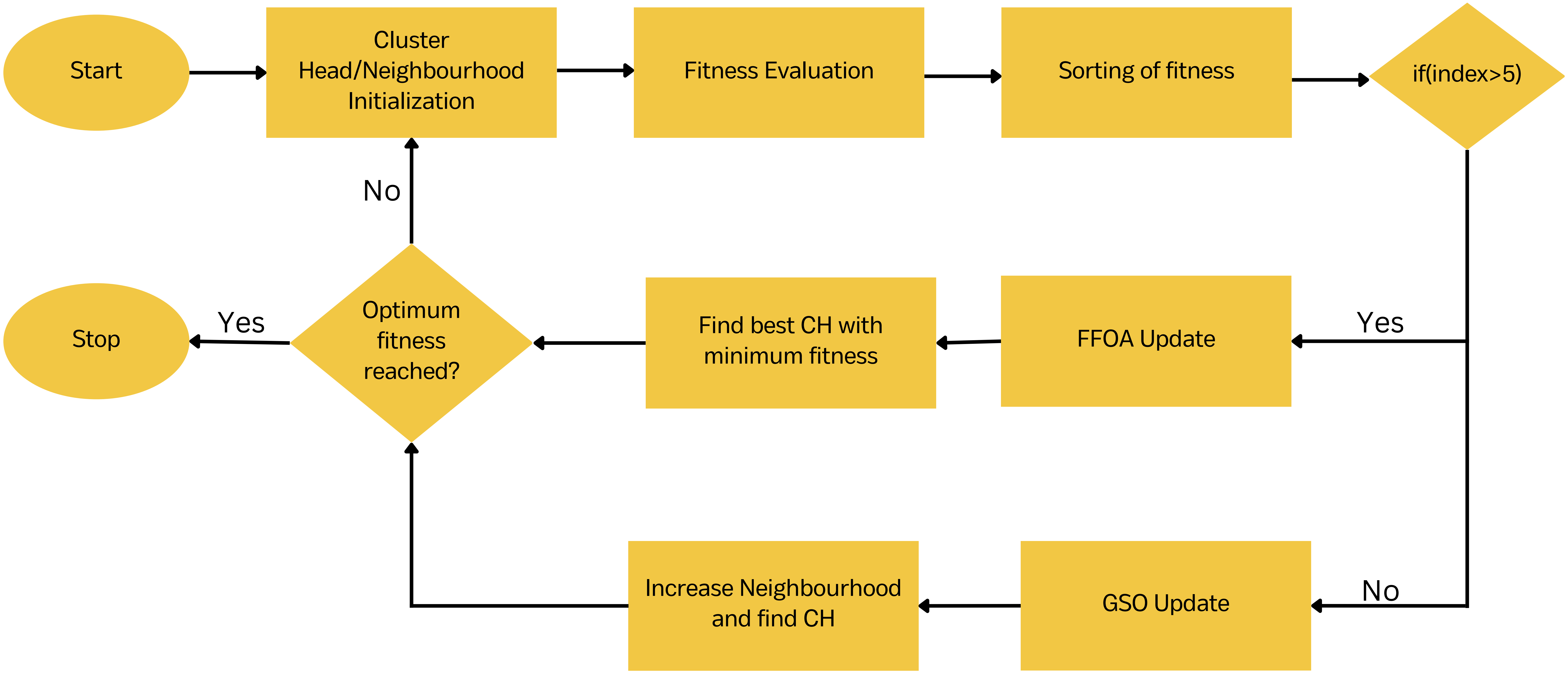
# FFOA Flowchart

Back to Overview

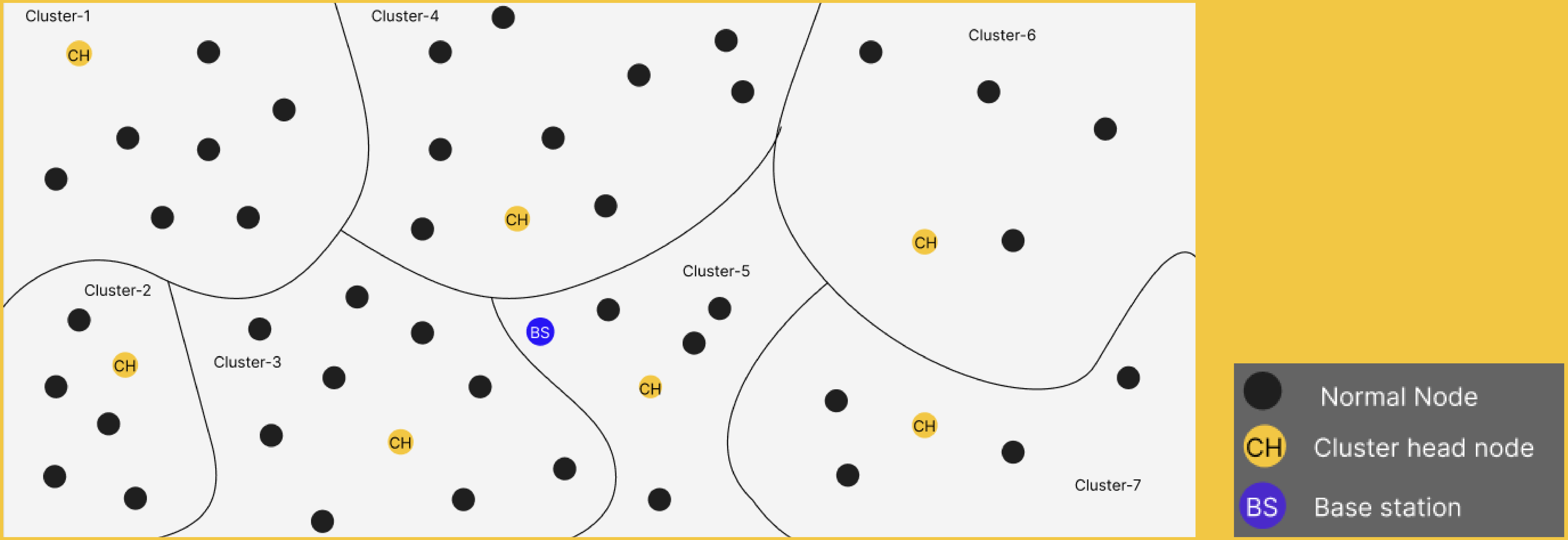


# FGF Flowchart

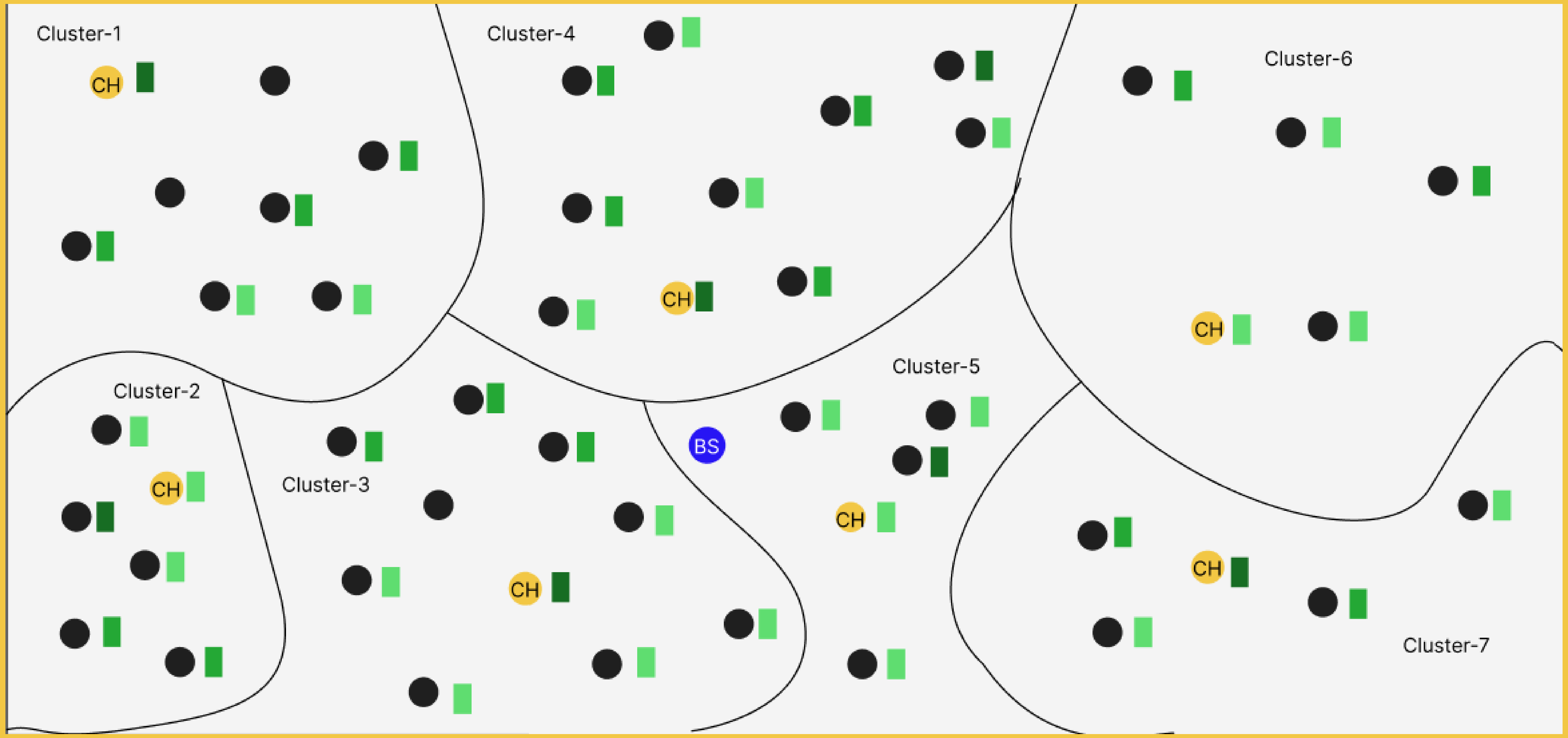
Back to Overview



# STEP 1: CH Initialization

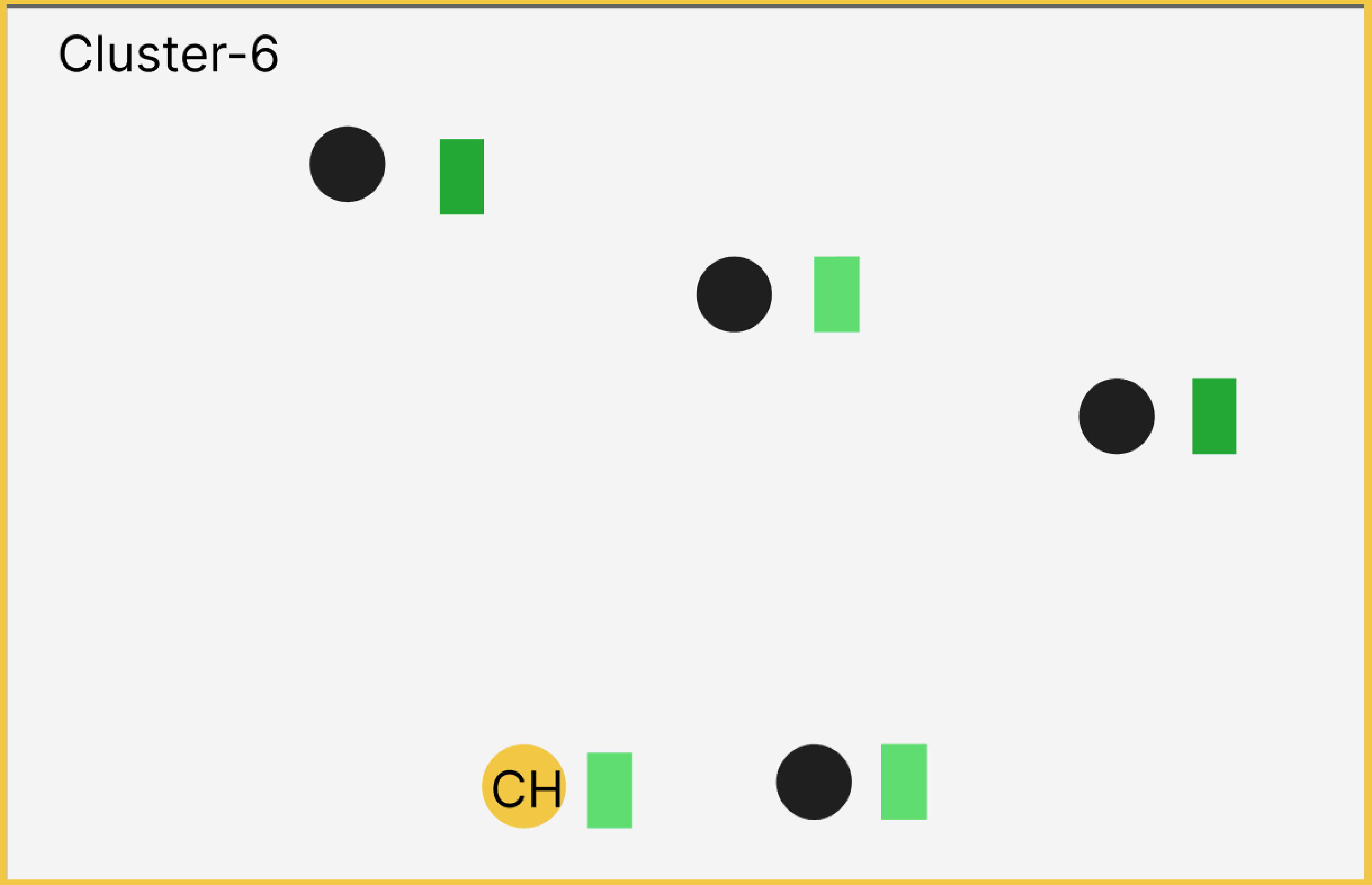


# STEP 2: Fitness evaluation and luciferin energy calculation




# Cluster specific steps

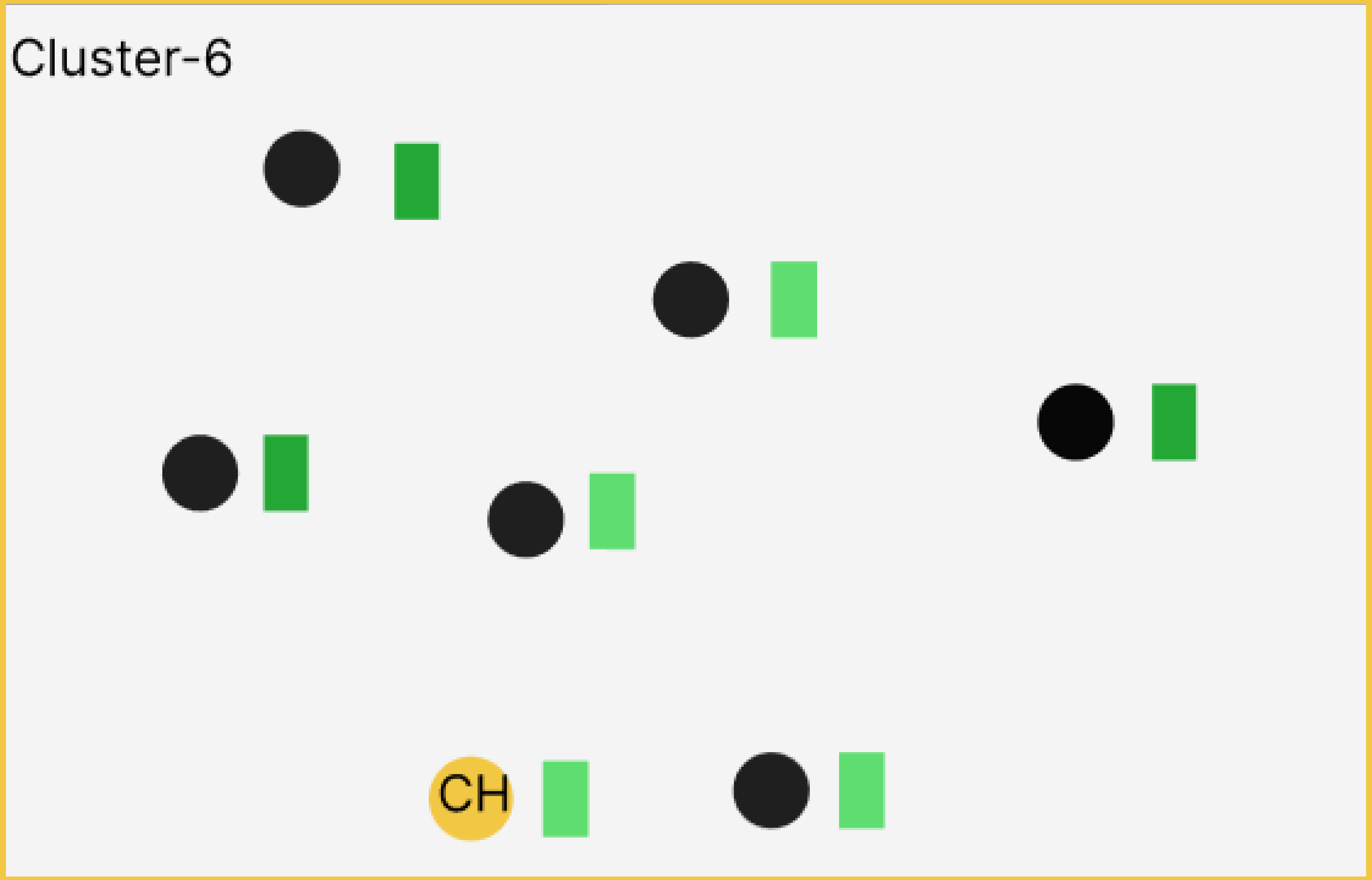
## STEP 3a: Calculating the luciferin density of the neighborhood




GWO update track

# Cluster specific steps

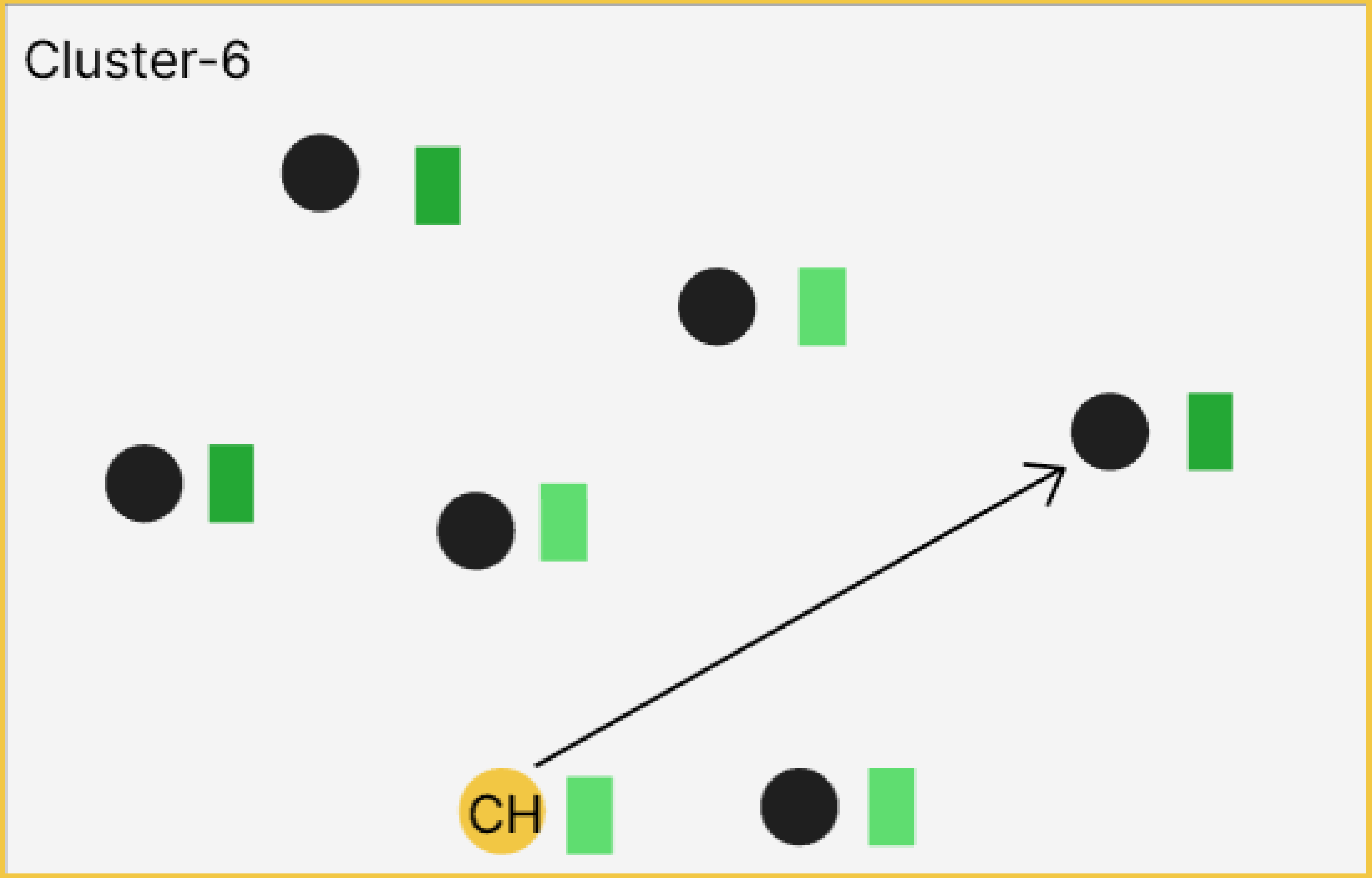
## Step 3b: Increasing the neighborhood




GWO update track

Cluster specific steps

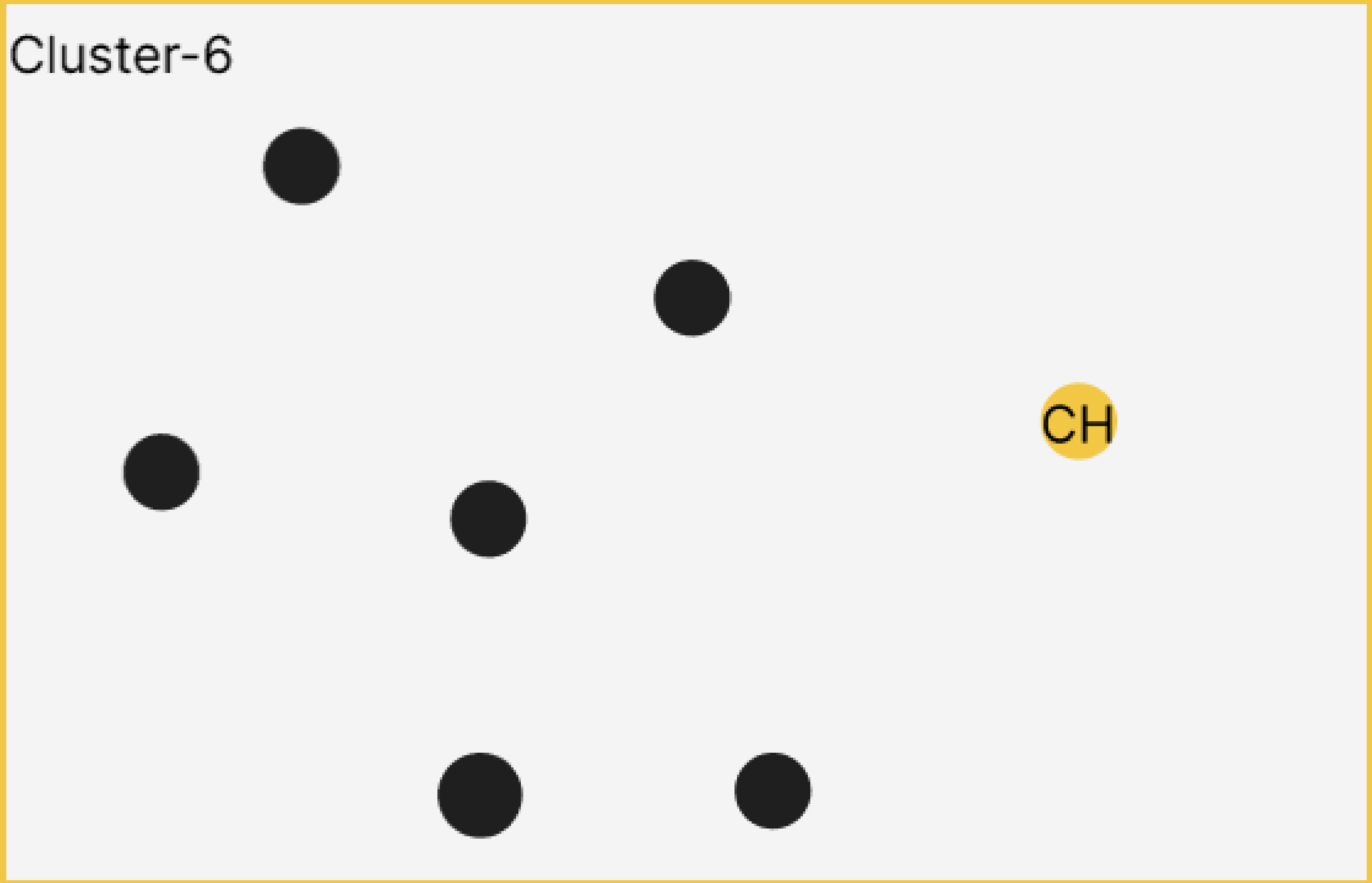
Step 3c: Movement of the CH node based on the luciferin energy




GWO update track

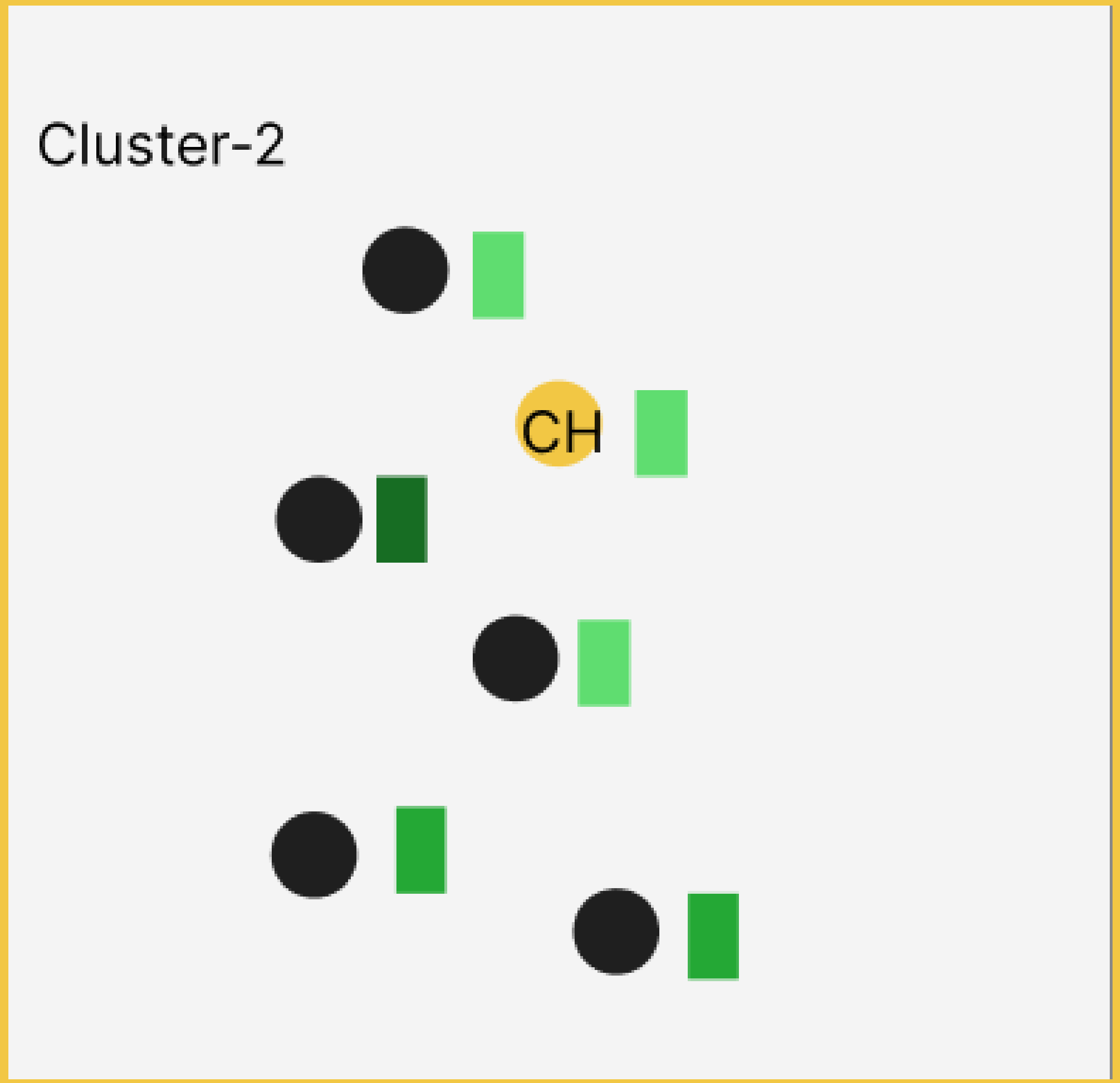
# Cluster specific steps

# Step 3d : Initialzing the new CH node




GWO update track

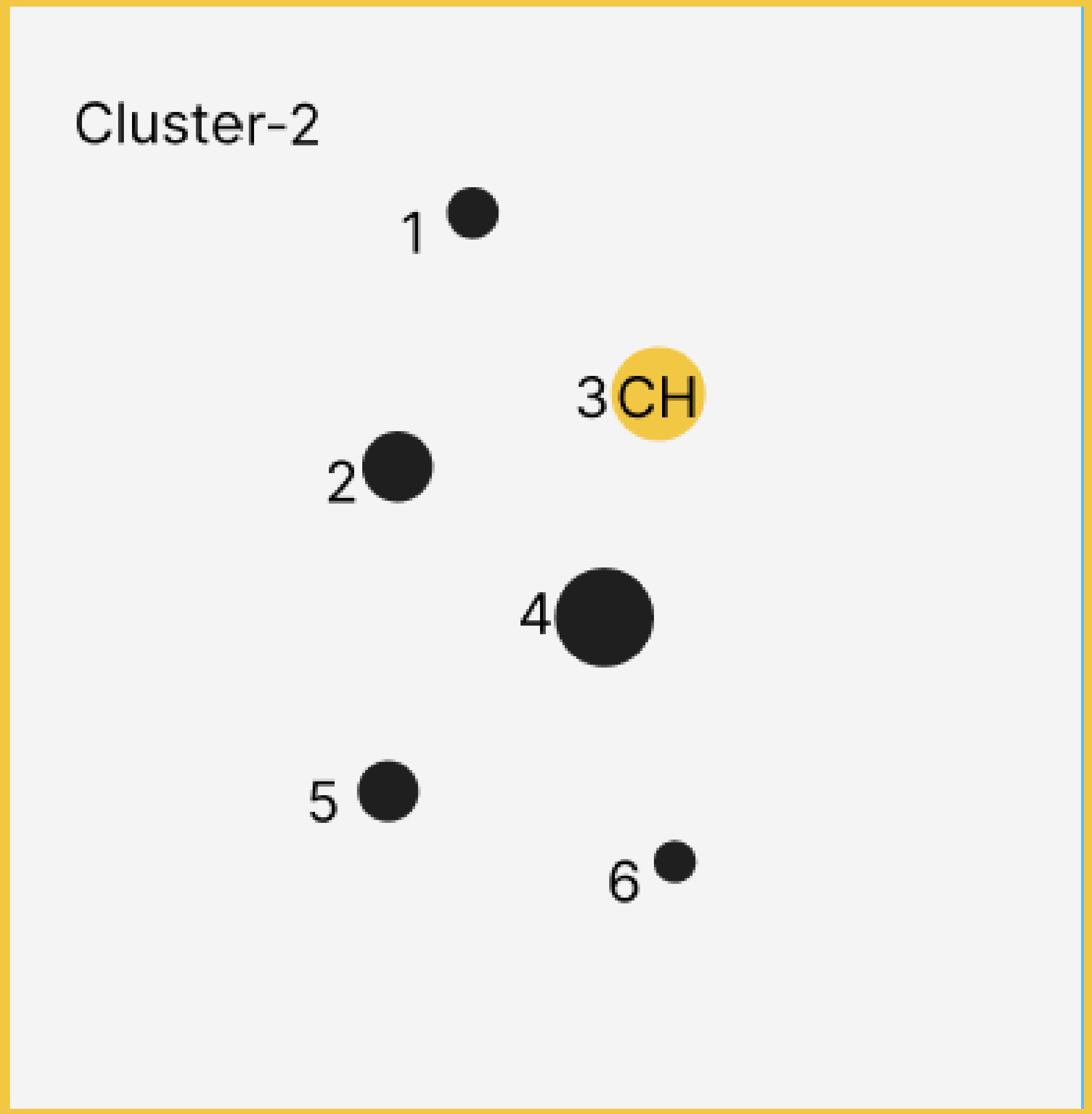
# Cluster specific steps
# Step 4a : Fruitfly initialization




FFOA update

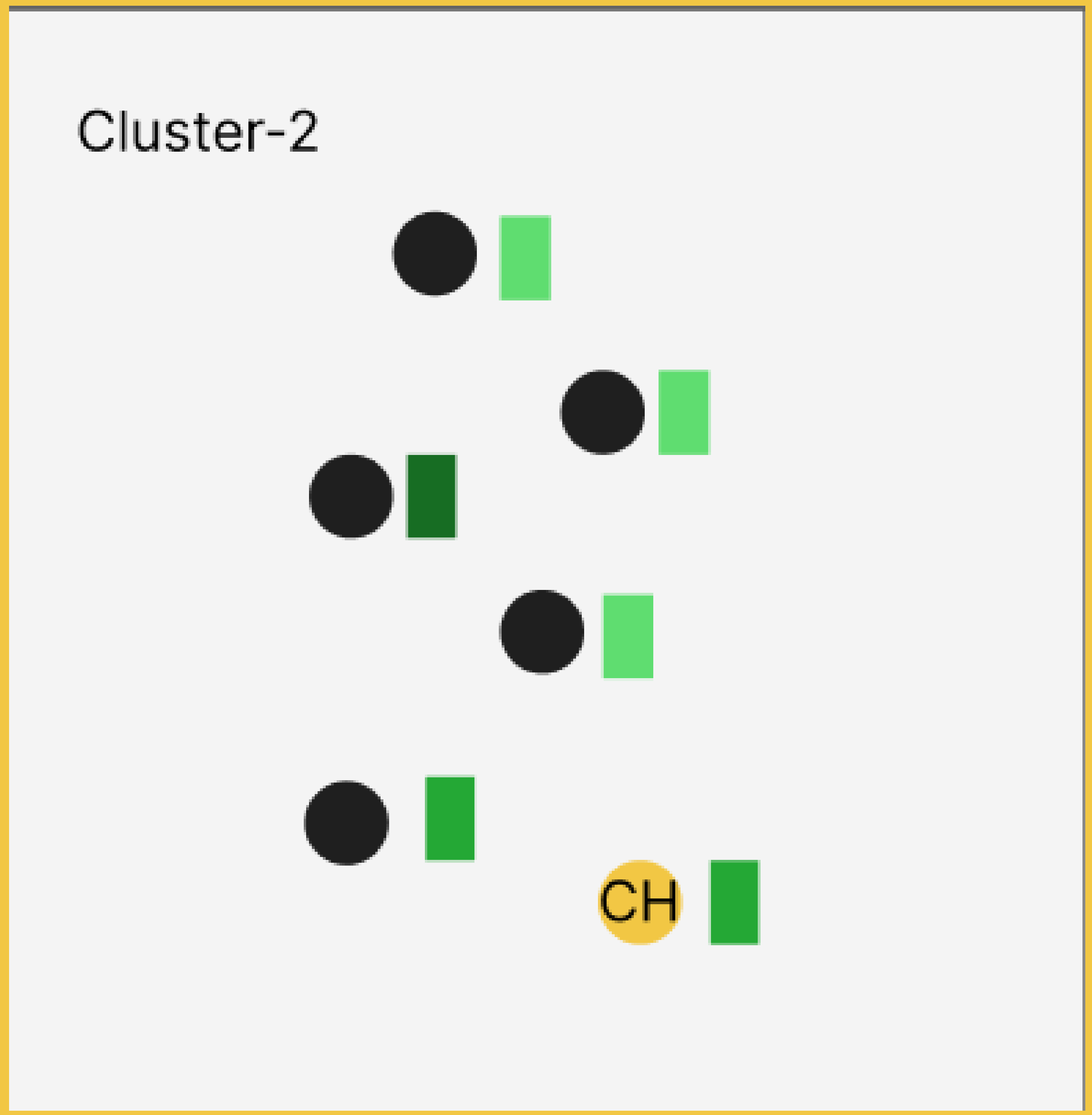
# Cluster specific steps

# Step 4b : Calculation of smell factor



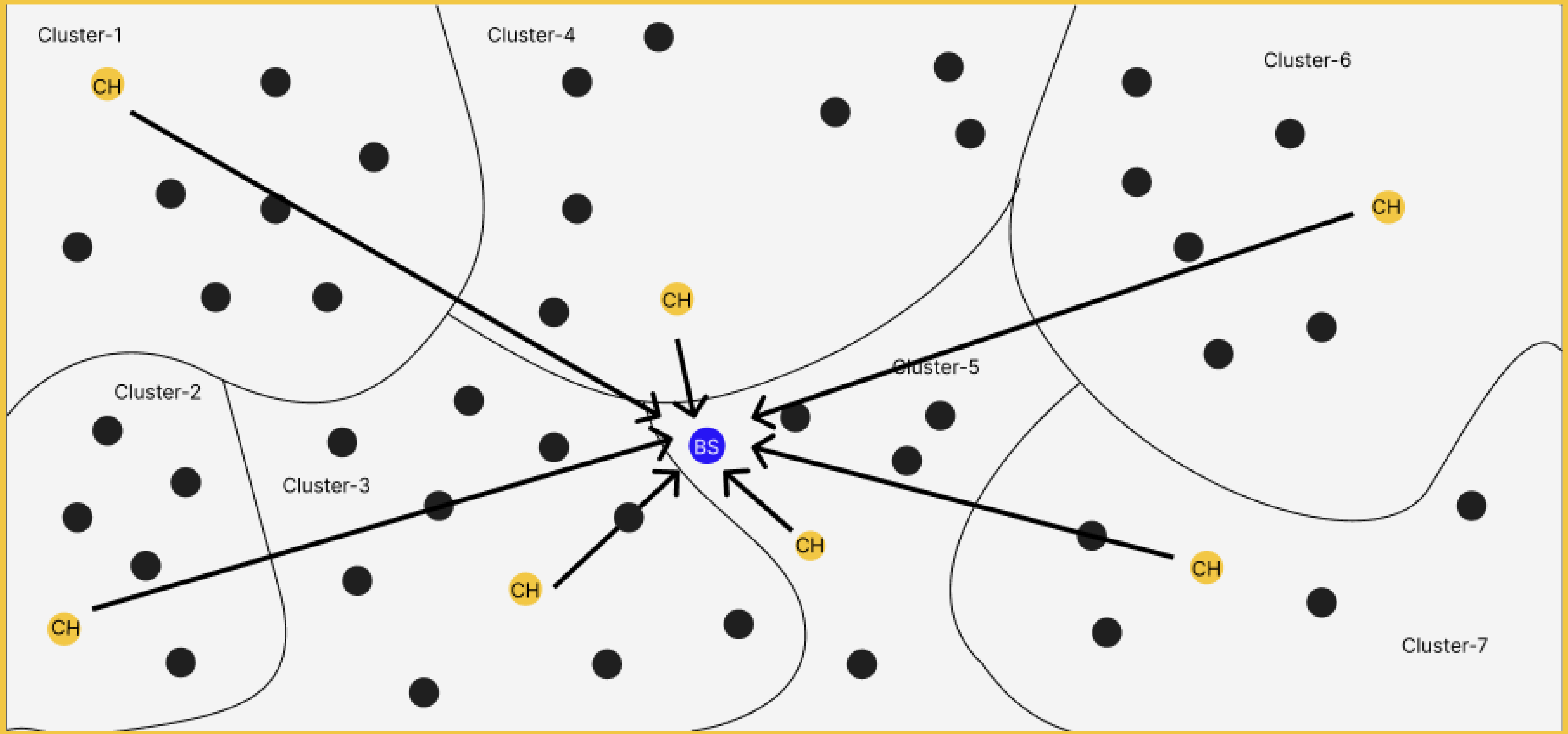

A greater radius signifies a greater smell factor

# Cluster specific steps
# Step 4c: CH selection




FFOA update

# Step 5: Communication to the base station



# Algorithm used for FFOA

- Initialize the X and Y parameters
- Determine the distance and smell concentration
- Evaluate the fitness functions
- Identify the fruitfly with high smell concentration between the fruitfly swarm and update the best solution

# Formula

$$X_i = X_a xis + rv$$

$$Y_i = Y_a xis + rv$$

$$Distance_i = \sqrt{X_i^2 + Y_i^2}$$

$$SM_i^C = \frac{1}{Distance_i}$$

$$smell_i = function\left(SM_i^C\right)$$

$$smell^{best}, index^{best} = \max(smell_i)$$

$$BEST\ SMELL = smell^{best}$$

$$X_a xis = X\left(index^{best}\right)$$

$$Y_a xis = Y\left(index^{best}\right)$$

# Algorithm used for GSO

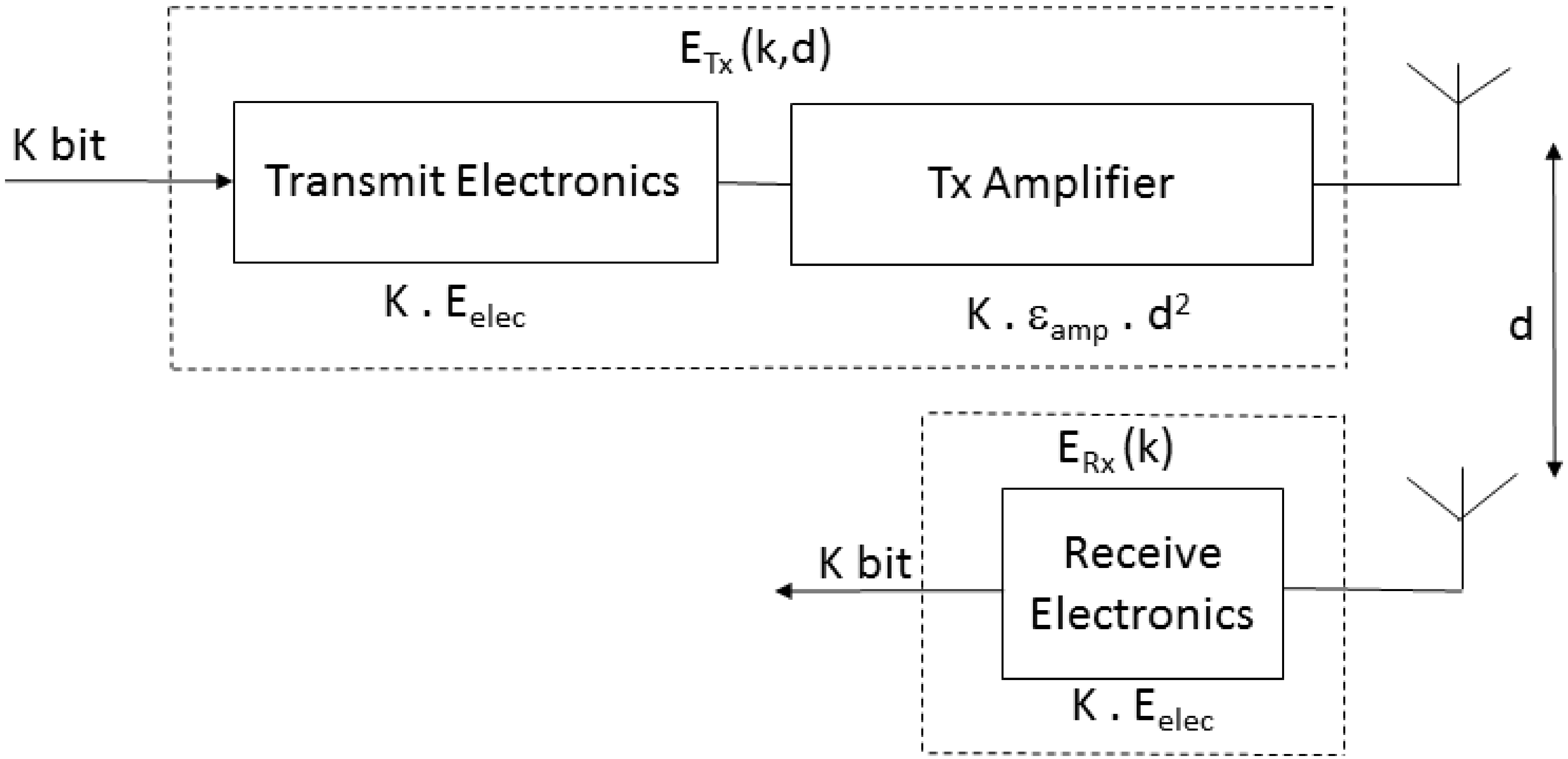
- Initialization phase: Initialize the luciferin level of the nodes
- Luciferin update phase: The luciferin intensity is related to the location fitness. It also depends on the objective function.
- Movement: In this phase the glowworm choose their neighbor and follows it with a distinctive probability
- Neighborhood range update: Based on the luciferin density of a cluster, the range of the neighborhood either gets increased or decreased

$$LU_g(t) = (1 - \upsilon)LU_g(t-1) + \eta(J(X_g(t)))$$

$$X_g(t+1) = X_i(t) + size * \left(\frac{X_w(t) - X_g(t)}{||X_w(t) - X_g(t)||}\right)$$

$$GM_e^g(t+1) = \min\{GM_u, \max\{0, GM_e^g(t) + \lambda|N_g(t)|\}\}$$

# First Order Radio Model



## Algorithm used for the implementation of First Order radio model

- Initialization of Energies
- Defining the parameters
- Implementing the formula
- Mapping the alive nodes to number of rounds

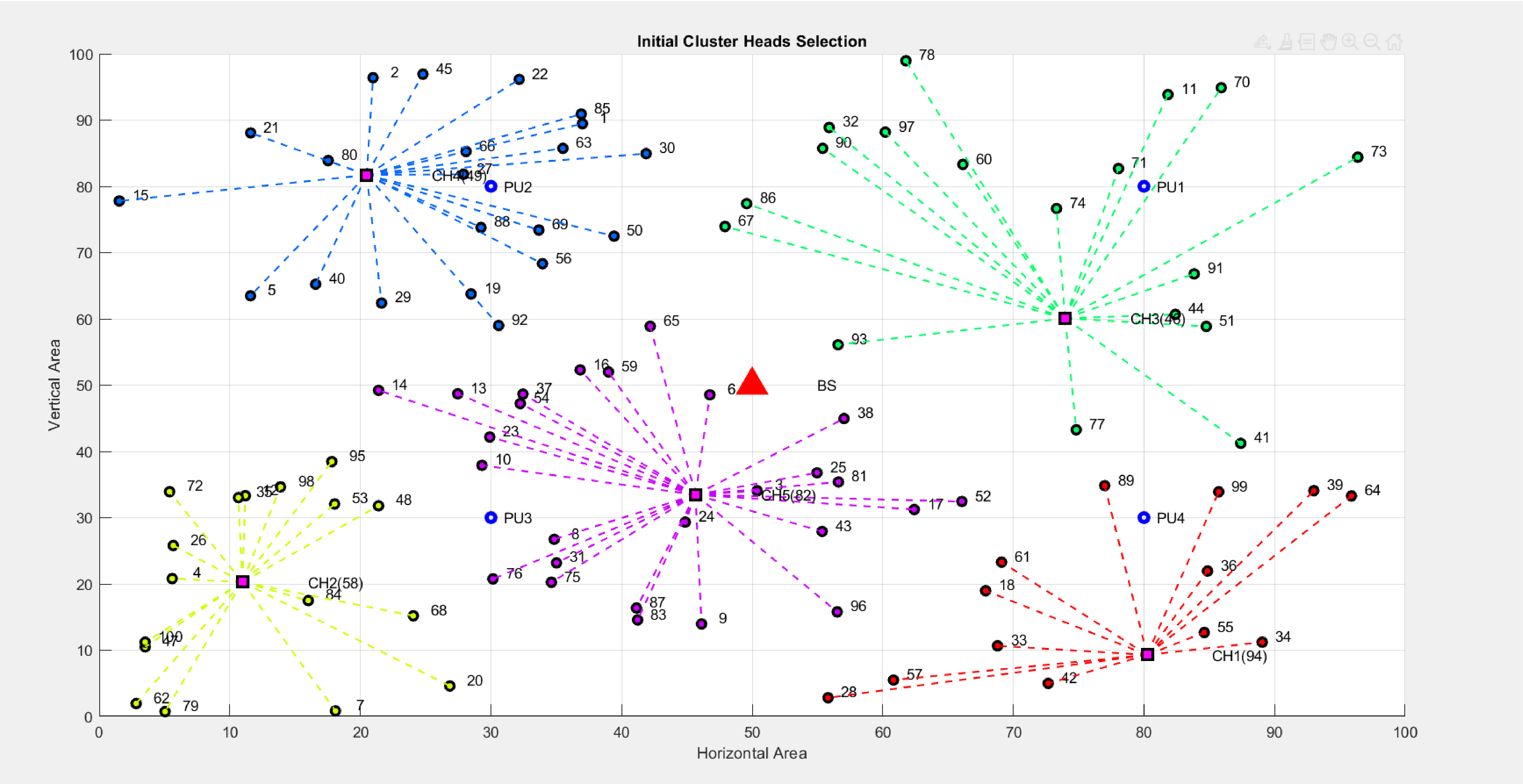
## Formulas

$$E_{Tx}(k,d) = E_{Tx-elec}(k) + E_{Tx-amp}(k,d)$$

$$E_{Tx}(k,d) = E_{elec} * k + \varepsilon_{amp} * k * d^2$$

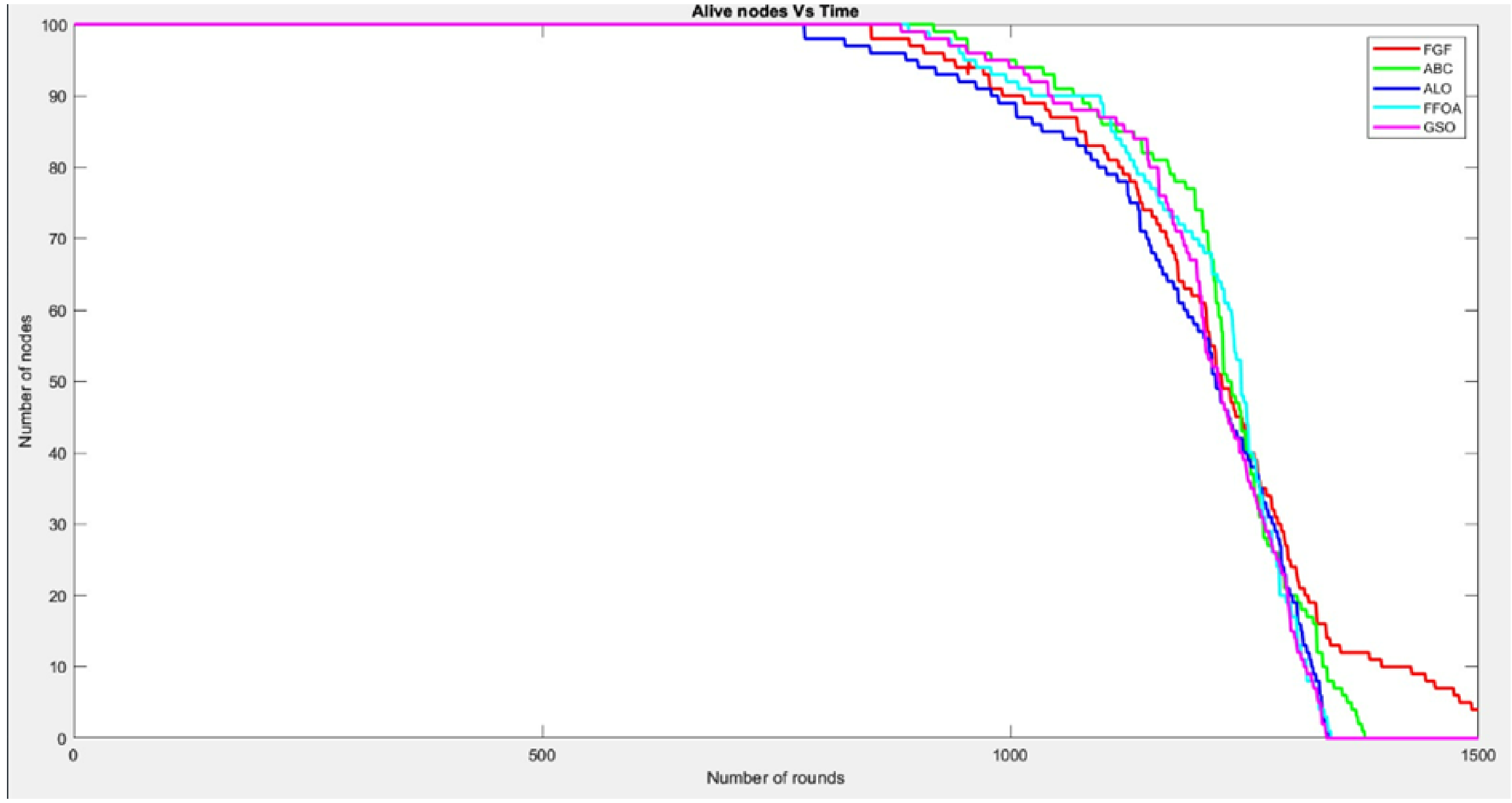
$$E_{Rx}(k) = E_{Rx-elec}(k)$$

$$E_{Rx}(k) = E_{elec} * k$$


Initial Cluster Heads Selection
Vertical Area
Horizontal Area
BS
PU1
PU2
PU3
PU4
CH1(94)
CH2(58)
CH3(46)
CH4(49)
CH5(82)

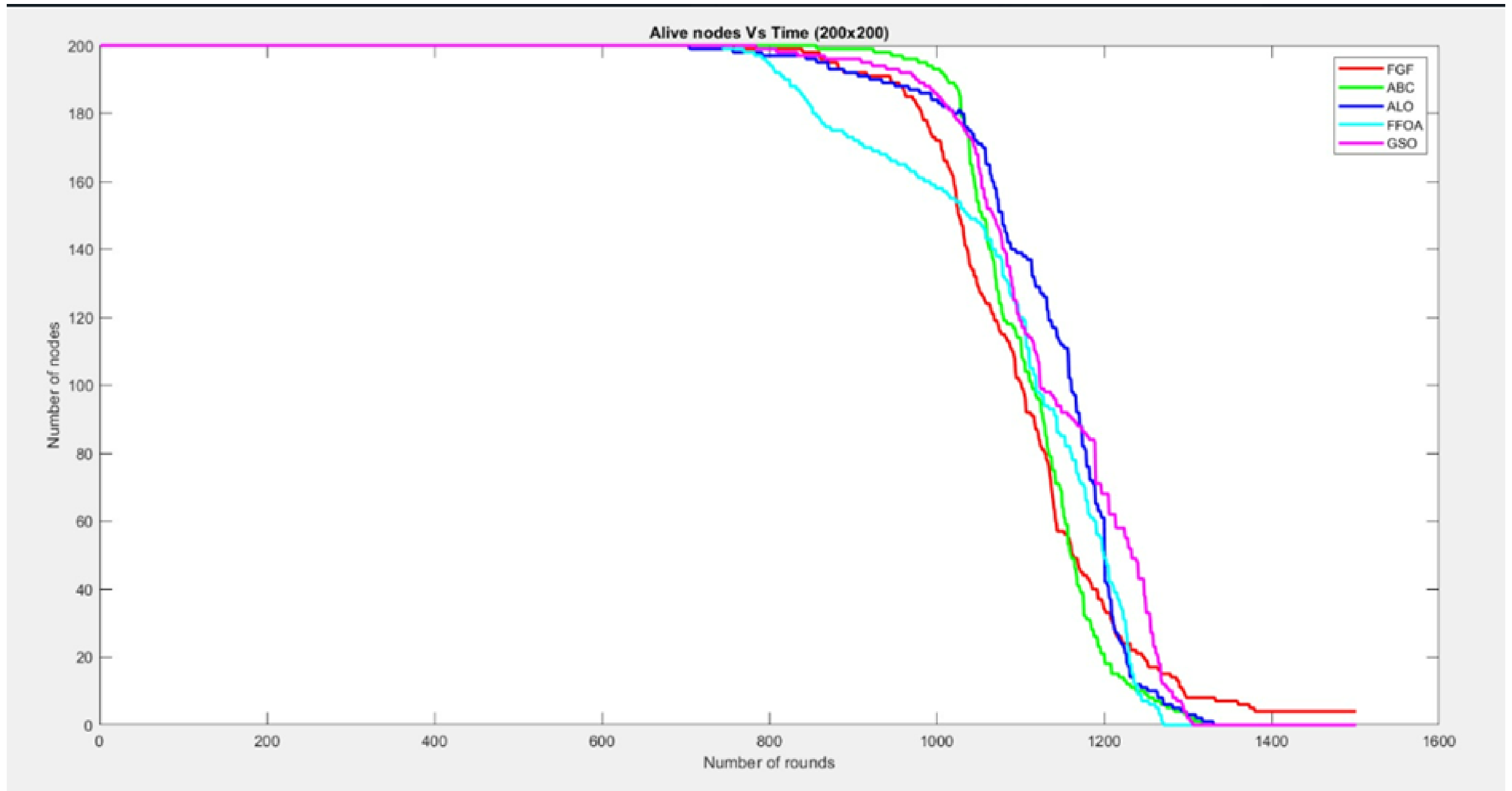
Back to Overview

# Output – Alive nodes Vs Number of rounds




Network area: 100x100
Number of nodes: 100
Number of rounds: 1500
Initial energy of each node: 0.5J
BS: (50,50)
k:4000bits

# Output – Alive nodes Vs Number of rounds




Network area: 200x200
Number of nodes: 200
Number of rounds: 1500
Initial energy of each node: 0.5J
BS: (100,100)
k:2000bits

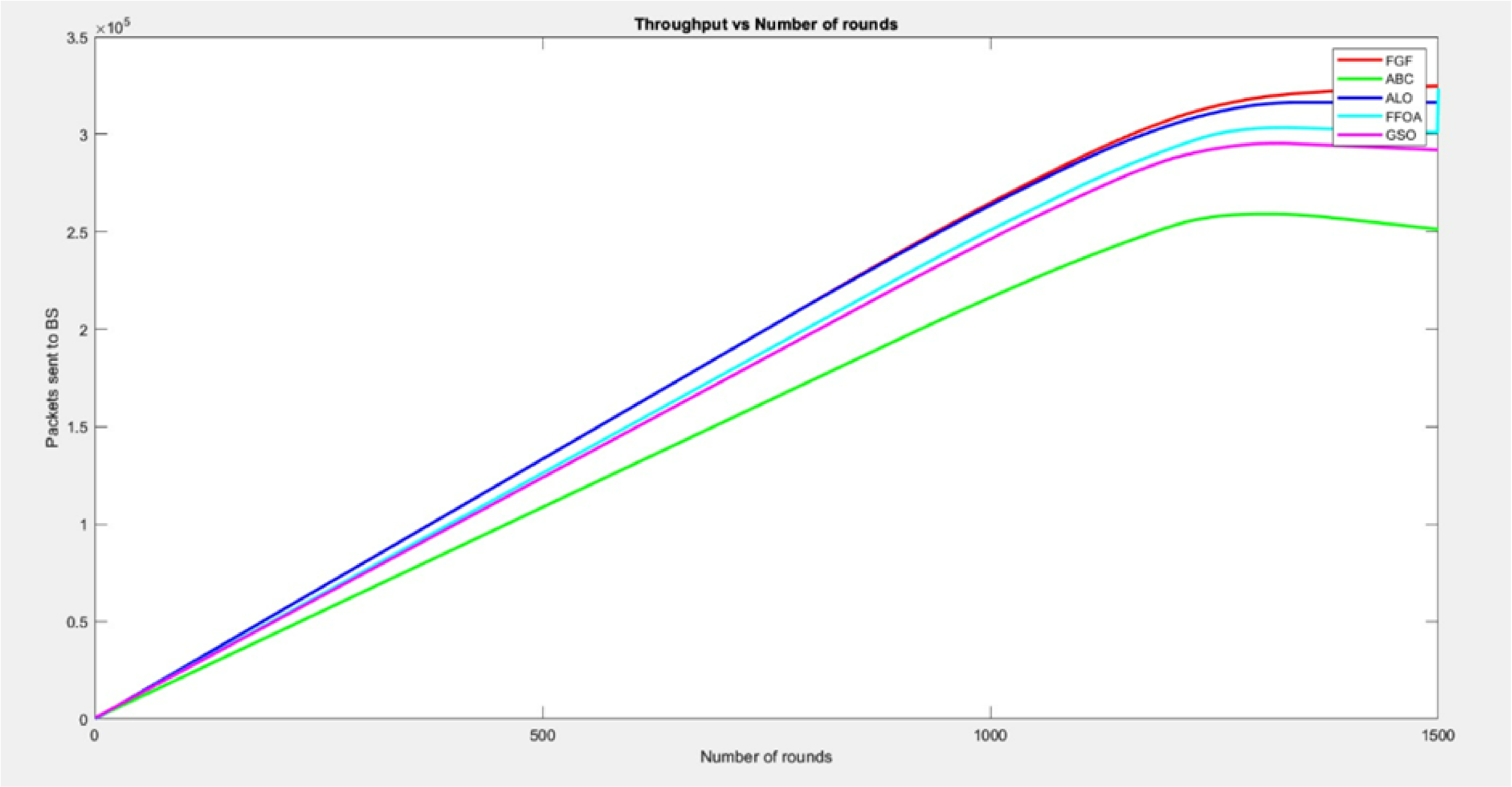
# Analysis

| Algorithm | 100 X 100 with 100 nodes | | 200 X 200 with 200 nodes | |
|---|---|---|---|---|
| | First node death | Last node death | First node death | Last node death |
| GSO | 885 | 1339 | 786 | 1307 |
| FFOA | 893 | 1344 | 746 | 1272 |
| ABC | 920 | 1380 | 858 | 1318 |
| ALO | 782 | 1342 | 706 | 1332 |
| FGF | 853 | 1587 | 759 | 1549 |

The alive nodes analysis for the proposed and compared algorithms. At the 1300th round, 25%, 20%, 20%, 17%, 19% of the nodes are alive for FGF, ABC, ALO, GSO, FFOA respectively.
The proposed algorithm has a better network lifetime compared to the other algorithms.

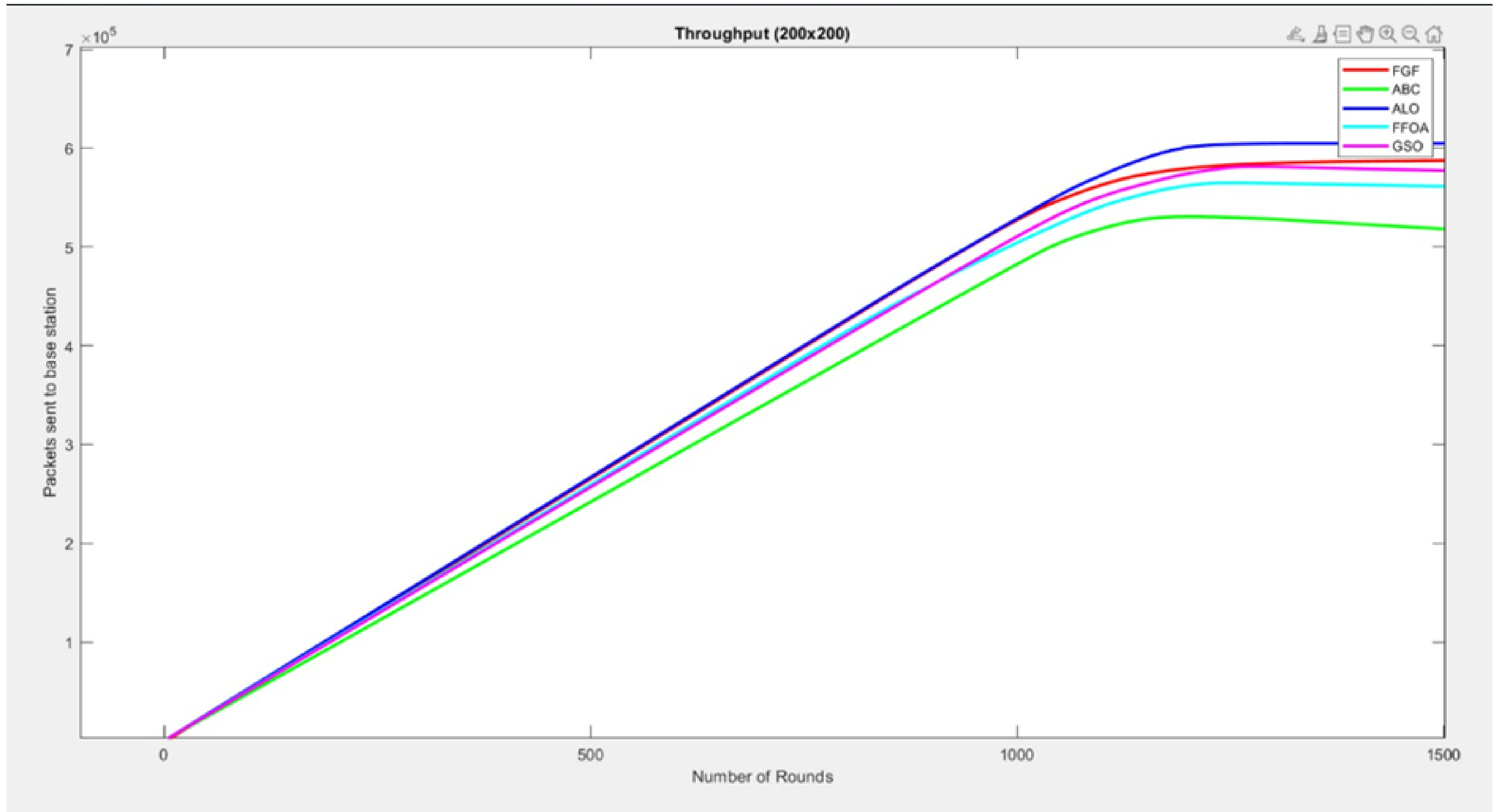
Back to Overview

# Output – Throughput Vs Number of rounds




Network area: 100x100
Number of nodes: 100
Number of rounds: 1500
Initial energy of each node: 0.5J
BS: (50,50)
k:4000bits

# Output – Throughput Vs Number of rounds




Network area: 200x200
Number of nodes: 200
Number of rounds: 1500
Initial energy of each node: 0.5J
BS: (100,100)
k:2000bits

# Analysis

| Algorithm | Throughput for 100 nodes | Throughput for 200 nodes |
|---|---|---|
| GSO | 291973 | 577188 |
| FFOA | 300949 | 561286 |
| ALO | 316330 | 604824 |
| ABC | 251231 | 518101 |
| FGF | 324746 | 587546 |

The proposed algorithm gives 11.21% more throughput than GSO, 7.9% more throughput than FFOA, 2.66% more than ALO and 29.2% more than ABC algorithm in an area of 100x100 for 100 nodes

Whereas it is 1.79% more throughput than GSO, 4.6% more throughput than FFOA, 13.40% more throughput than ABC but the ALO algorithm gives the most throughput when we consider 200 nodes in an area of 200x200.

Hence, we can say that this algorithm is most efficient for smaller number of nodes in a smaller area.

# Why CR-WSN??

- With rapid developments in the wireless sensor networks domain, spectrum scarcity is becoming a major issue.
- On the contrary, the licensed spectrum is barely being used compared to the unlicensed spectrum.
- The goal of CR is to opportunistically use the licensed spectrum without hindering the functionalities of the primary user.

- The cognitive radio technology can be divided into various sections such as the spectrum sensing, spectrum detection, spectrum sharing and spectrum handoff. All of which comprises into the spectrum decision process.
- We will be implementing the Joint Spectrum Decision process.

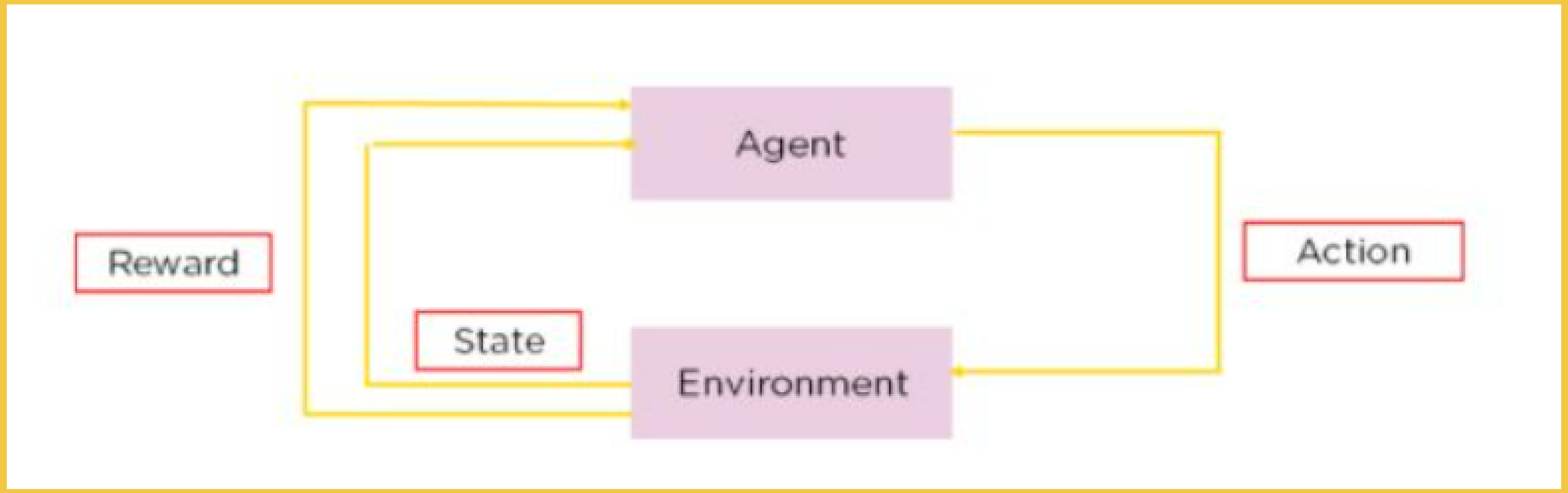
# WSN vs CR-WSN

| Parameter | Wireless Sensor Network (WSN) | Cognitive Radio Sensor Networks (CRWSN) |
|---|---|---|
| Medium Used | Wireless- ISM Bands | Wireless- Licensed Bands for Data channels<br>Licensed or ISM band for control channel |
| Channel Used | Single Channel | Multi-channel so can switch channels easily |
| Channel Requirement | Possible to create multi channel environment | Required to create multi channel environment |
| Memory | Restricted | Have huge capacity |
| Communication Range | Short | Short but intelligently controllable |

# Q learning

Q learning is a model free, off policy reinforcement learning that will find the best course of action given the current state of the agent.

**States**: The State, S, represents the current position of an agent in an environment.
**Action:** The Action, A, is the step taken by the agent when it is in a particular state.
**Rewards:** For every action, the agent will get a positive or negative reward.
**Episodes**: When an agent ends up in a terminating state and can't take a new action.
**Q-Values**: Used to determine how good an Action, A, taken at a particular state, S, is. Q (A, S).



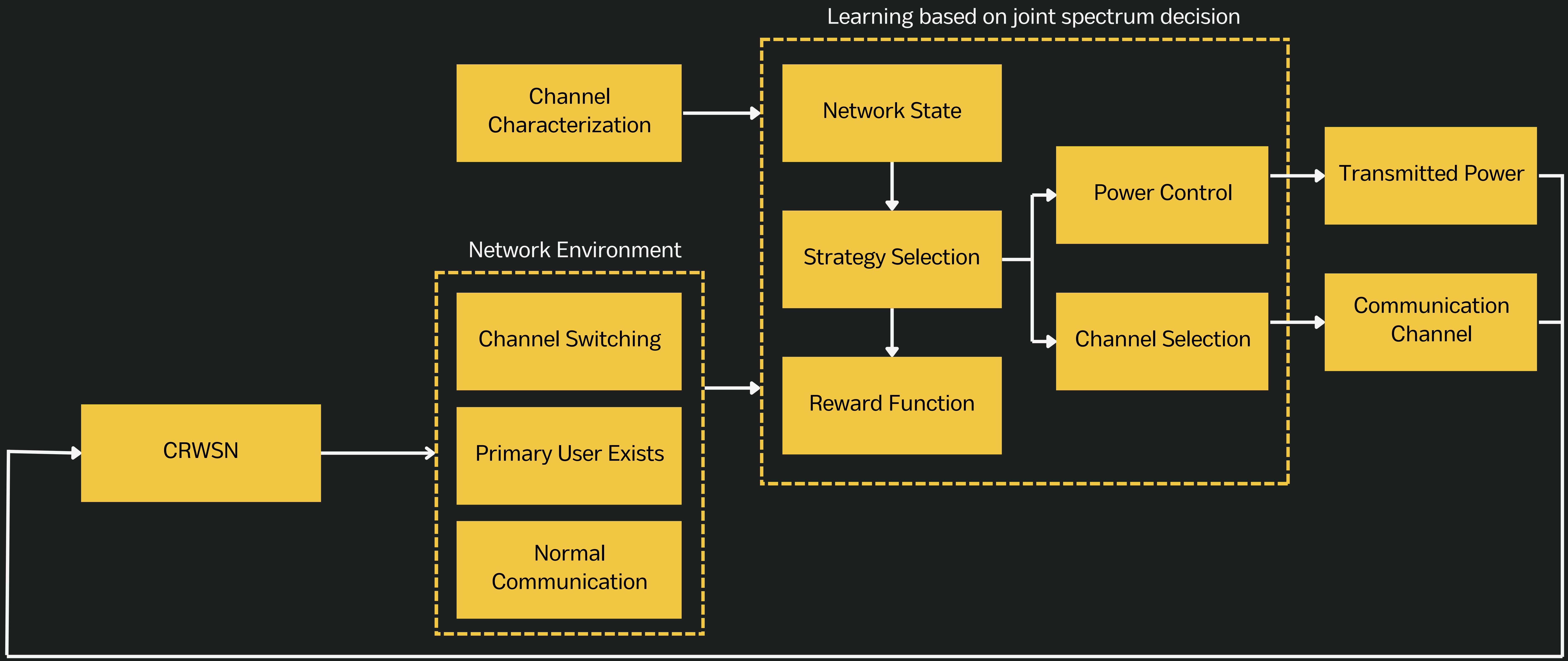

Reinforcement learning

$$Q_{i,t+1}(s_t, a_t) = (1 - \alpha_t) Q_{i,t}(s_t, a_t) + \alpha_t r_{i,t+1} + \alpha_t \left[ \gamma \max_{a' \in A} Q_{i,t}(s', a') \right],$$

Bellman's equation

# CRWSN Block Diagram

Back to Overview



# Q learning in CRWSN

**State:** The network state st is a set of available bands, st=[Dt], where Dt=d1,d2,d3,…dk

**Action:**Each state has one or more associated actions. Any change of a network property is considered as an action.The action at=[dt,pt] where dt is the selected band and pt is the communication power. Each network node can switch to a better channel or adjust the transmission power of the current channel.

**Channel Characterization:** In order to select an appropriate channel, the current channel characteristics is vital for a good decision making. In our project, we will consider the bandwidth $W_d$, signal interference $I_{d,t}$, false alarm rate of spectrum detection $P_d$, and the idle time of band $T_{idle}$.

$$\theta_{d,t} = \varepsilon_1 W_d + \varepsilon_2 I_{d,t} + \varepsilon_3 (1 - P_d)\, T_{idle\ d}$$

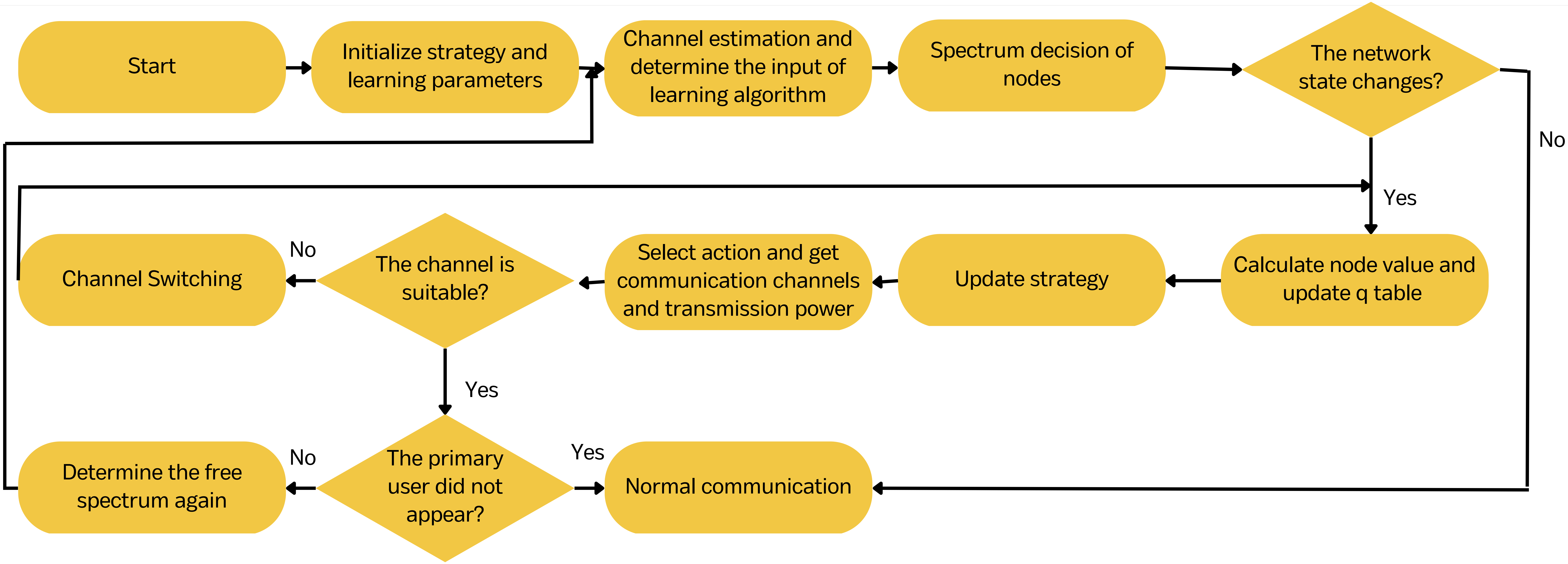
,Where epsilon is a weighting factor

**Strategy selection:** Based on the theta value we either decide to switch the channel, acquire a channel or drop a channel.
**Reward function:** Based on different outcomes, we have different rewards that are given to our model.

- Collision with primary user:  -0.5
- Channel switching: -0.1 (As it takes some amount of energy to switch a channel)
- Normal communication: theta

# CRWSN Flowchart

Back to Overview



# Q learning in CRWSN

**Channel Characterization:** In order to select an appropriate channel, the current channel characteristics is vital for a good decision making. In our project, we will consider the bandwidth $Wd$, signal interference $Id,t$, false alarm rate of spectrum detection $Pd$, and the idle time of band $T$idle.

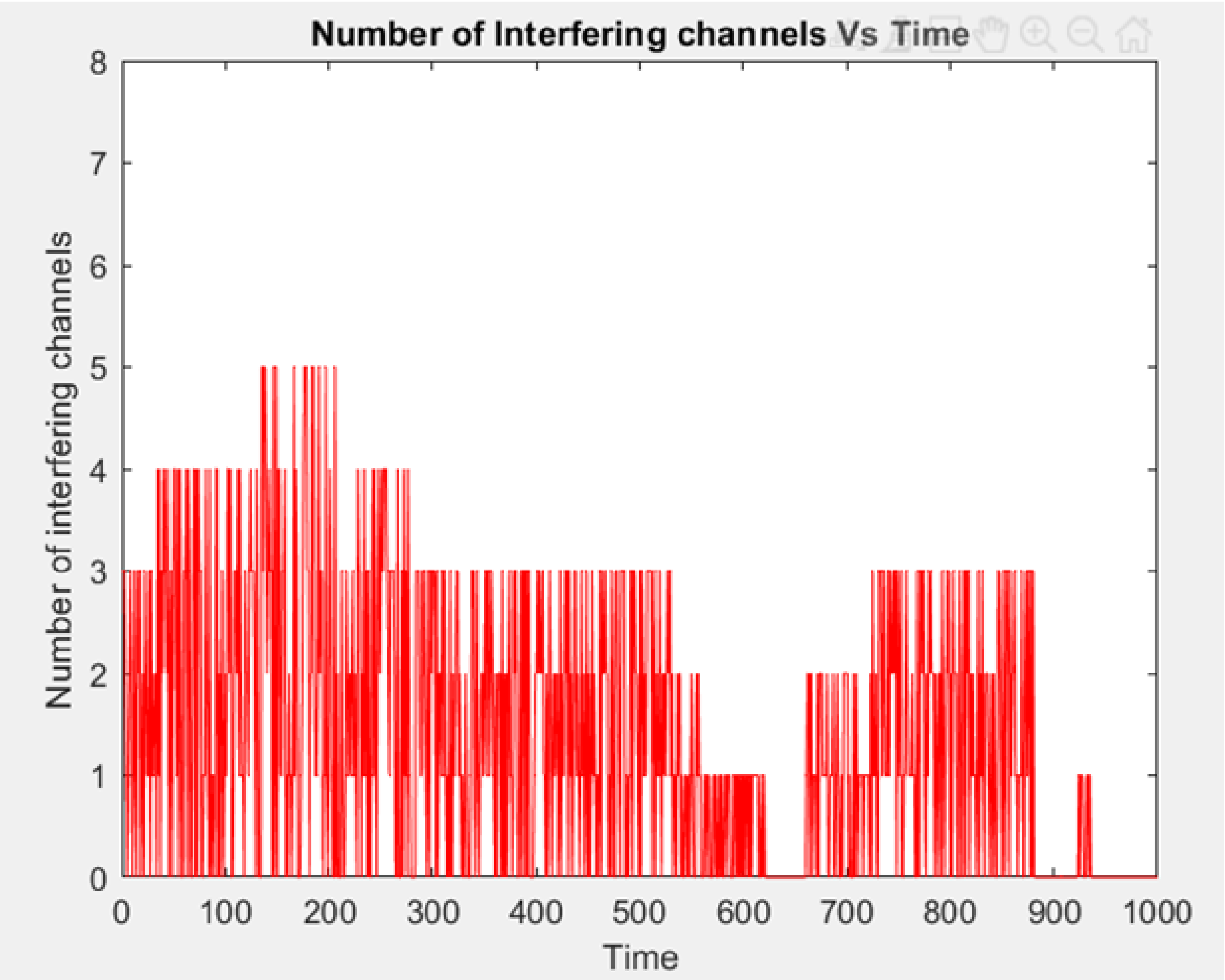
$$\theta d,t = \varepsilon 1 Wd + \varepsilon 2 Id,t + \varepsilon 3\ (1 - Pd)\ T\mathrm{idle}\ d$$

,Where epsilon is a weighting factor

**Strategy selection:** Based on the theta value we either decide to switch the channel, acquire a channel or drop a channel.
**Reward function:** Based on different outcomes, we have different rewards that are given to our model.

- Collision with primary user:  -0.5
- Channel switching: -0.1 (As it takes some amount of energy to switch a channel)
- Normal communication: Omega
    - Where the value of omega = (Wd*log2(1+SINR))/p

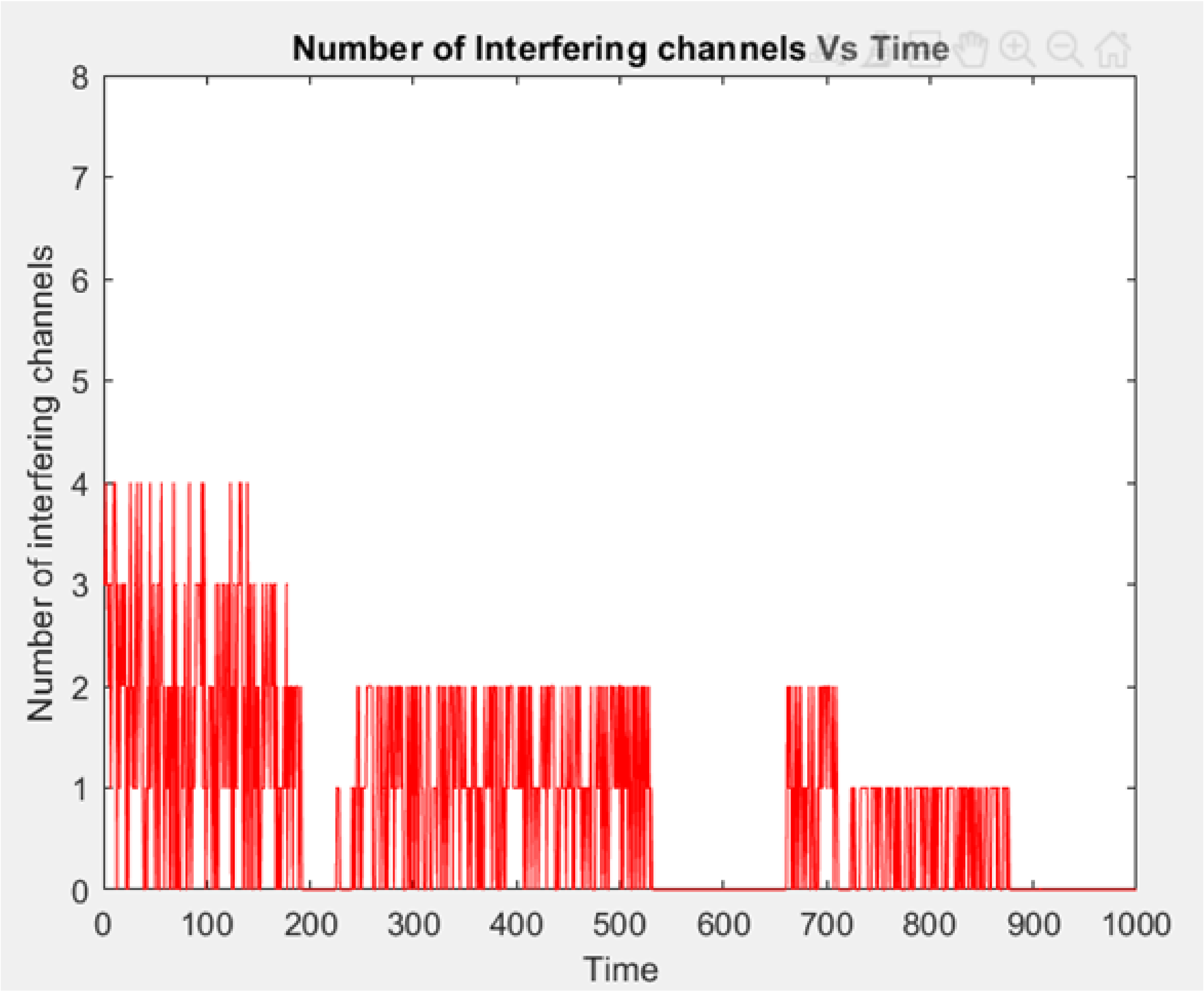
# Output – DCA




Number of channels: 8
Number of rounds: 1000
learning rate=0.8
discount factor=0.8
epsilon=0.4

None of the channels are being interfered on 38% of the time, whereas one channel is being interfered on 22% of the time, two channels are being interfered on 16% of the time, and three channels are being interfered on 7% of times, four channels are being interfered 11% of the time and five channels are being interfered on for 6%.

# Output – DCA




Number of channels: 8
Number of rounds: 1000
learning rate=0.8
discount factor=0.8
epsilon=0.8

None of the channels are being interfered on 54.5% of the time, one channel is being interfered 22.6% of times, two channels are being interfered on 16.6%, three channels are being interfered on 37% and four channels are being interfered on 8% of times.

# Conclusion and remarks

- In this project, a CH selection algorithm was proposed along with the implementation of a dynamic channel allocation using Q learning and the following were observed
- While considering the alive nodes analysis, at the 1300th round, 25%, 20%, 20%, 17%, 19% of the nodes are alive for FGF, ABC, ALO, GSO, FFOA respectively. The proposed algorithm has a better network lifetime compared to the other algorithms for 100 nodes
- While considering the throughput, the proposed algorithm gives 11.21% more throughput than GSO, 7.9% more throughput than FFOA, 2.66% more than ALO and 29.2% more than ABC algorithm in an area of 100x100 for 100 nodes
- When we look into the dynamic channel allocation, we consider two different values of the exploration-exploitation model. When the strategy is not being allowed to explore more, the number of interfering channels increase. When the ε value was 0.8, 545 channels that were selected for communication had no presence of PU whereas when the ε value was 0.4, 381 channels were selected for communication that had no presence of PU for 1000 rounds.

# Future work

- This algorithm uses the epsilon greedy algorithm where all actions are chosen coequally which would lead the best and worst action being chosen with the same probability during the random search phase. However, a soft-max approach can be implemented in the future for better efficiency of the learning algorithm.
- A communication efficiency index can be implemented that takes into consideration the channel gains, SINR, communication frequency as well as the communication bandwidth as the reward function for normal transmission.

# References

Back to Overview


- *Kale Navnath Dattatraya, K. Raghava Rao* ***- Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN (2019) -*** ScienceDirect Journal of King Saud University - Computer and Information Sciences

- *Kok-Lim Alvin Yau; Peter Komisarczuk; Paul D. Teal -* ***Cognitive Radio-based Wireless Sensor Networks: Conceptual design and open issues (2009) -*** IEEE 34th Conference on Local Computer Networks

- *Masoud Moradkhani, Paeiz Azmi, Mohammad Ali Pourmina -* ***Optimized energy limited cooperative spectrum sensing in cognitive radio networks (2015) -*** ScienceDirect Computers & Electrical Engineering Volume 43

- *Md Azharuddin, Prasanta K. Jana* ***- Particle swarm optimization for maximizing lifetime of wireless sensor networks (2016)*** *-* ScienceDirect Computers & Electrical Engineering Volume 51

- *R.Ramyaa, Dr. T.Brindha -* ***A Comprehensive Review on Optimal Cluster Head Selection in WSN-IoT (2022) -*** *ScienceDirect Advances in Engineering Software Volume 171*