

IoT Challenge 3
Exercise Part

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EQ1:

EQ1) A LoRaWAN network in Europe (carrier frequency 868 MHz, bandwidth 125 kHz) is composed by one gateway and 50 sensor nodes. The sensor nodes transmit packet with **payload size of L byte** according to a Poisson process with intensity $\lambda = 1$ packet / minute. **Find the biggest LoRa SF** for having a success rate of at least 70%. Hint: use <https://www.thethingsnetwork.org/airtime-calculator> to compute the airtime of a packet.

Report the result in the form!!

For the payload size L of your packet, take it as follows:

Take **XY** = Last two digit of your person code (leader code)

L = 3 + XY bytes

e.g. personcode = 106929**11** -> **XY** = 11 -> **L = 3 + 11 = 14**

In our case, since the leader's person code ends with 28, our payload size is 3+28 bytes = 31.

To solve this exercise we consider the aloha success rate formula studied during the lesson:

$$\text{Succ. Rate} = \frac{S}{G} = e^{-2G} = e^{-2N*\lambda*t}$$

Where N is the number of Nodes, in our case equals to 50

λ is the tx. Rate, in our case we have 1 packet/minute so 1/60 packet/second

t is the packet airtime, which is unknown.

Using the formula we obtain that: $t = -\frac{\ln(SR)}{2*N*\lambda} = -\frac{\ln(0.7)}{100*\frac{1}{60}} = 0.214s$

We observe that if the packet airtime decrease, the success rate increases, it makes sense because intuitively less time on air → smaller collision window → less chance of two packets overlapping → better success.

So that means with t = 0.214s we have a Succ.Rate of 0.7, by increasing t the succ. rate would decrease, so 0.214s is the maximum value I can have.

Now using the airtime-calculator, we observe that:

The screenshot shows the LoRaWAN Airtime Calculator interface. At the top, there are four input fields: 'Input Bytes' (31), 'Spreading Factor' (SF8), 'Region' (EU868), and 'Bandwidth' (125 kHz). Below these fields, a large blue box displays the result '164.4 ms'. Underneath the blue box, the text 'Time on air' is visible.

Input Bytes	Spreading Factor	Region	Bandwidth
31	SF8	EU868	125 kHz

Result
164.4 ms
Time on air

Input Bytes [?]	Spreading Factor [?]	Region [?]	Bandwidth [?]
<input type="text" value="31"/>	<input type="text" value="SF9"/>	<input type="text" value="EU868"/>	<input type="text" value="125 kHz"/>

Result

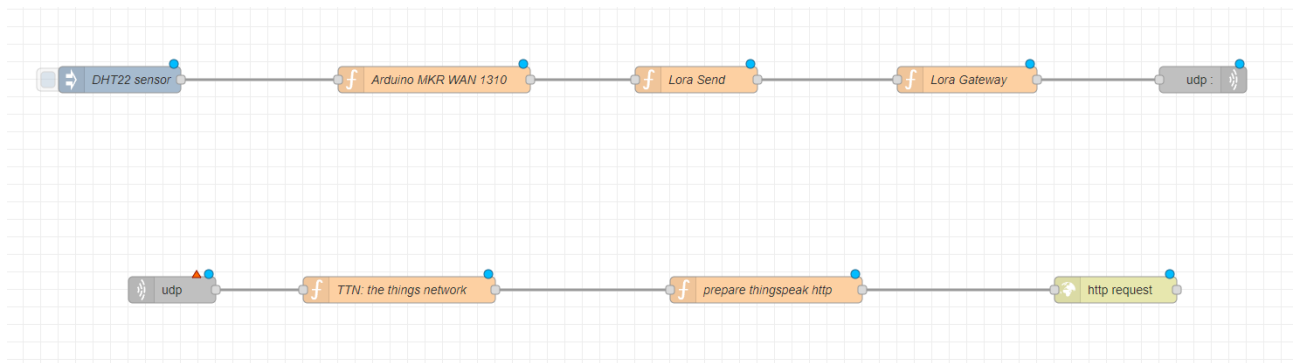
287.7 ms

Time on air

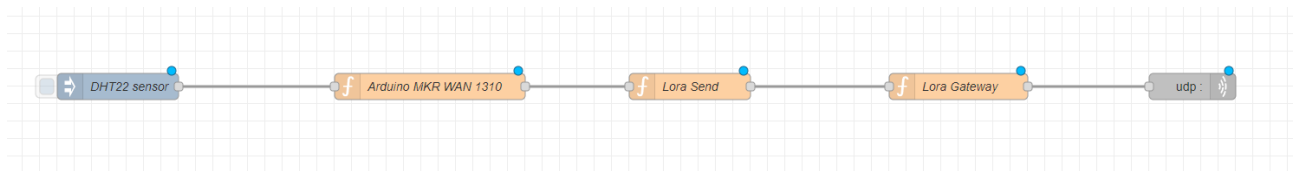
With the Spreading Factor 9 we obtain a $t > 0.214s$.

So in our case the biggest LoRa SF for having a success rate of at least 70% is **SF8**.

EQ2



Our system has two parts: the Arduino side and the TTN: the things network side.



The Arduino side starts with the DHT22 sensor, which measures the temperature and humidity and sends the data, for example every 5 minutes, to the Arduino MKR WAN 1310 board.

The Arduino board reads the sensor values and forwards them to the LoRa transceiver (built into the MKR WAN 1310).

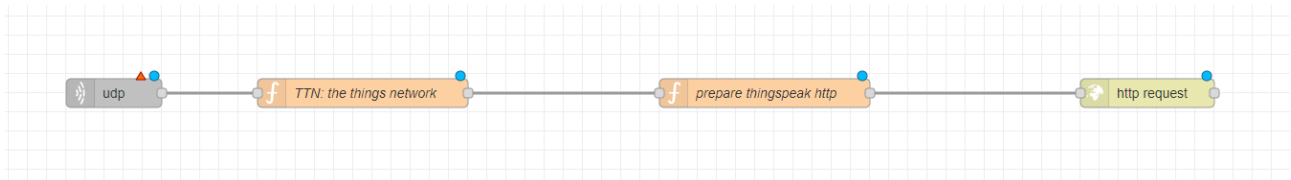
The LoRa transceiver packages the data into a LoRaWAN packet following the LoRaWAN protocol (adding headers frame counter)

This LoRaWAN packet is then transmitted wirelessly (over radio) to the nearby LoRa Gateway.

The LoRa Gateway receives the wireless LoRaWAN packet and wraps it inside a UDP packet, adding some extra metadata (like RSSI, SNR, timestamp, frequency, etc.).

The gateway is configured with the IP address and UDP port of the TTN router.

Then, through the UDP protocol — which is connectionless, lightweight, and faster than HTTP — the gateway forwards the packet to TTN.



Meanwhile, The Things Network (TTN) server is always listening on its UDP port, waiting to receive incoming packets from gateways.

When TTN receives a new packet, it decodes the LoRaWAN message to extract the original sensor data (temperature and humidity).

After decoding, TTN prepares a HTTP Webhook request containing the sensor data and sends it to ThingSpeak.

Finally, ThingSpeak receives the HTTP POST, stores the temperature and humidity values, and displays them in the channel.

EQ3

Figure 5 presents the second experiment from the paper.

We use LoRasim:

```
import subprocess

def simulate(n_nodes, tx_rate, exp, duration):
    env = os.environ.copy()
    env["MPLBACKEND"] = "Agg"

    # Use subprocess.run to execute the command and capture output
    result = subprocess.run(
        [
            "python2",
            "lorasim/loradir.py",
            str(int(n_nodes)),
            str(int(tx_rate)),
            str(int(exp)),
            str(int(duration)),
        ],
        env=env,
        capture_output=True,
        text=True,    # Capture output as text
    )
```

For Figure 5, we based our setup on the function provided in `lorasim/loradir.py`, as it is suitable for scenarios where multiple nodes (N nodes) transmit to a single sink (which is the case here).

We set up the variables as follows:

- Tx_rate: A 20-byte packet is sent every 16.7 minutes. The 20-byte size is the default setting in LoRasim, and we set `tx_rate` to `1e6`.
- CF: The carrier frequency is 868 MHz. We did not modify this setting, as it is already correctly set in `loradir.py`.
- Duration: The original experiment in the paper uses 58 days; however, we set the duration to only 1 day (86400000 ms), because our simulator cannot handle such a long simulation time. Moreover, there seems to be little difference between simulating 58 days and 1 day for our purposes.
- Number of nodes: We increase the number of nodes as follows:

```
duration = 86400000
tx_rate = 1e6

for n_nodes in list(range(1,10)) + list(range(10,300,10)) + list(range(300,1601,100)):
    print(f"Simulating {n_nodes} nodes")
    simulate(n_nodes, tx_rate, 4, duration)
    simulate(n_nodes, tx_rate, 3, duration)
    simulate(n_nodes, tx_rate, 5, duration)
```

Finally, for the experiment settings, we use `exp4` for SN3, `exp3` for SN4, and `exp5` for SN5, based on the following details from `loradir.py`:

```
if experiment==1 or experiment == 0:
    self.sf = 12
    self.cr = 4
    self.bw = 125

# for certain experiments override these
if experiment==2:
    self.sf = 6
    self.cr = 1
    self.bw = 500
# lorawan
if experiment == 4:
    self.sf = 12
    self.cr = 1
    self.bw = 125
```

```

if (experiment == 3) or (experiment == 5):
    minairtime = 9999
    minsf = 0
    minbw = 0

    print "Prx:", Prx

    for i in range(0,6):
        for j in range(1,4):
            if (sensi[i,j] < Prx):
                self.sf = int(sensi[i,0])
                if j==1:
                    self.bw = 125
                elif j==2:
                    self.bw = 250
                else:
                    self.bw=500
                at = airtime(self.sf, 1, plen, self.bw)
                if at < minairtime:
                    minairtime = at
                    minsf = self.sf
                    minbw = self.bw
                    minsensi = sensi[i, j]

    if (minairtime == 9999):
        print "does not reach base station"
        exit(-1)

```

After the simulation, we obtained the .dat files:

exp3.dat	X	exp4.dat	exp5.dat
1 #nrNodes		nrCollisions	nrTransmissions OverallEnergy
2 1 0	91	0.309044736	
3 2 0	185	0.492188928	
4 3 0	243	0.453682944	
5 4 0	330	0.859237632	
6 5 0	425	0.7934784	
7 6 0	491	1.028324352	
8 7 0	599	1.50978432	
9 8 0	691	1.290102528	
10 9 0	725	1.729736448	
11 10 0	869	2.133145344	
12 20 2	1689	4.038718464	
13 30 4	2507	5.925266688	
14 40 2	3492	8.655727872	
15 50 10	4265	9.653960448	
16 60 2	5233	12.467364096	
17 70 8	5985	14.849970432	
18 80 18	6789	15.740938752	
19 90 10	7733	17.526330624	
20 100 12	8593	22.229889792	
21 110 19	9554	21.909355776	
22 120 20	10498	26.054130432	
23 130 36	11268	25.615535616	
24 140 28	12005	29.329496064	
25 150 20	12872	30.888557568	
26 160 37	13811	32.900093952	
27 170 53	14738	36.156840192	
28 180 50	15532	35.747762688	
29 190 78	16589	39.319087104	
30 200 75	17518	41.989988856	

exp3.dat	exp4.dat ✕		exp5.dat	
1 #nrNodes	nrCollisions	nrTransmissions	OverallEnergy	
2 1 0 83	14.449999872			
3 2 2 177	30.815059968			
4 3 2 253	44.046385152			
5 4 2 356	61.978312704			
6 5 4 399	69.464457216			
7 6 0 503	87.570481152			
8 7 16 595	103.58734848			
9 8 18 677	117.863251968			
10 9 12 782	136.143372288			
11 10 14 859	149.548793856			
12 20 92 1775	309.0210816			
13 30 158 2634	458.569875456			
14 40 355 3396	591.231320064			
15 50 555 4306	749.659029504			
16 60 724 5093	886.672883712			
17 70 1041 6105	1062.85842432			
18 80 1282 6936	1207.53251942			
19 90 1542 7576	1318.95420518			
20 100 2066 8653	1506.45601075			
21 110 2382 9502	1654.26384077			
22 120 2767 10339	1799.98251418			
23 130 3390 11405	1985.56925952			
24 140 3575 12050	2097.8614272			
25 150 4095 12857	2238.35720909			
26 160 4609 13597	2367.18853325			
27 170 5265 14674	2554.69033882			
28 180 5757 15566	2709.98431334			
29 190 6308 16340	2844.73491456			
30 200 7219 17326	3016.39394918			

exp3.dat ✕	exp4.dat	exp5.dat ✕	
1 #nrNodes	nrCollisions	nrTransmissions	OverallEnergy
2 1 0 84	0.092671488		
3 2 0 182	0.297321024		
4 3 0 253	0.579984		
5 4 0 344	0.700161408		
6 5 0 413	0.8490336		
7 6 0 529	0.974678016		
8 7 0 612	1.09457856		
9 8 0 682	1.043397504		
10 9 0 776	1.162806528		
11 10 0 843	1.653111552		
12 20 2 1647	2.934328896		
13 30 0 2601	5.100284352		
14 40 8 3469	6.109875072		
15 50 8 4341	7.746935616		
16 60 2 5085	8.385372288		
17 70 2 5893	11.431347264		
18 80 10 6947	13.702473792		
19 90 16 7691	13.269643776		
20 100 8 8593	15.626239872		
21 110 26 9691	15.469831296		
22 120 19 10135	17.88523872		
23 130 16 11240	20.90629824		
24 140 18 12199	20.805533568		
25 150 30 12951	24.03960096		
26 160 56 13895	23.121468288		
27 170 50 14777	26.627817792		
28 180 54 15509	28.011558528		
29 190 78 16503	29.307442176		
30 200 66 17331	29.866023744		

Then we calculate the Data Extraction Rate:

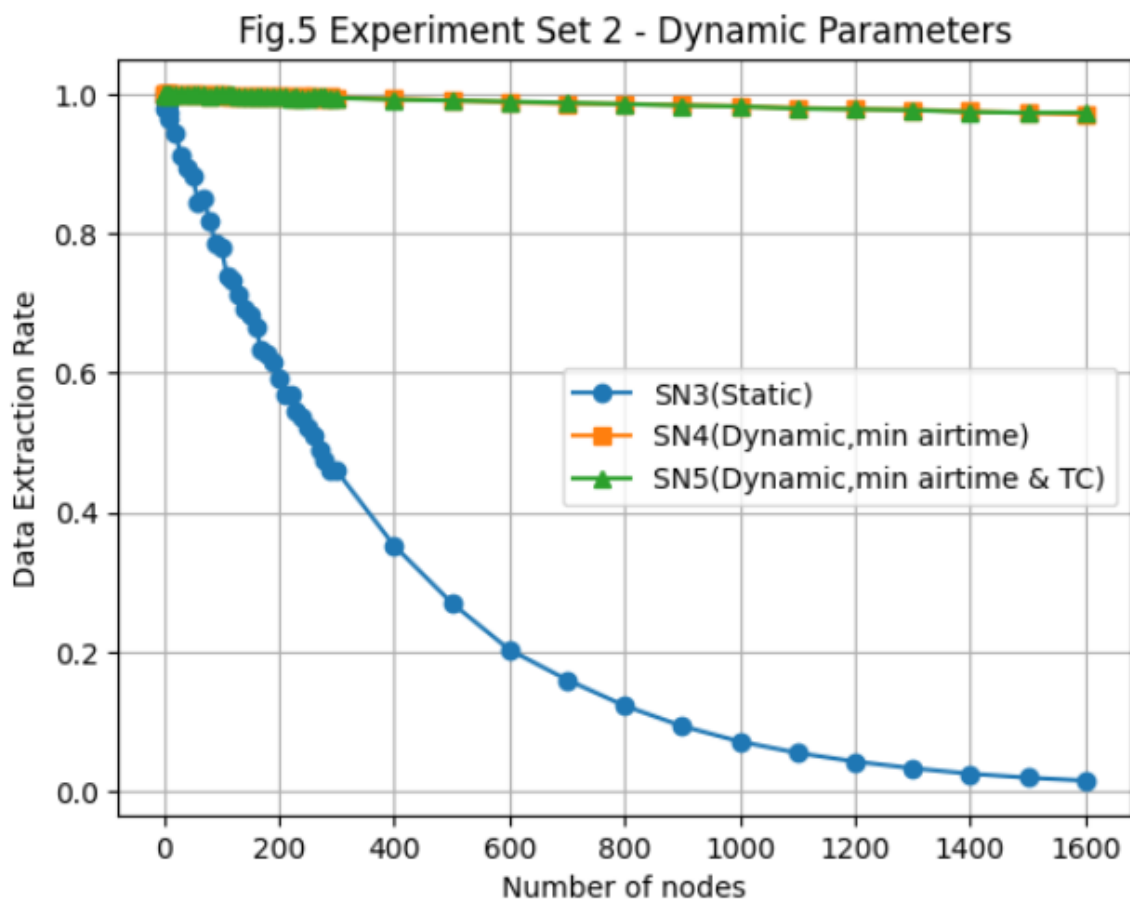
```
sn3 = pd.read_csv("exp4.dat", sep=" ")
sn4 = pd.read_csv("exp3.dat", sep=" ")
sn5 = pd.read_csv("exp5.dat", sep=" ")
```

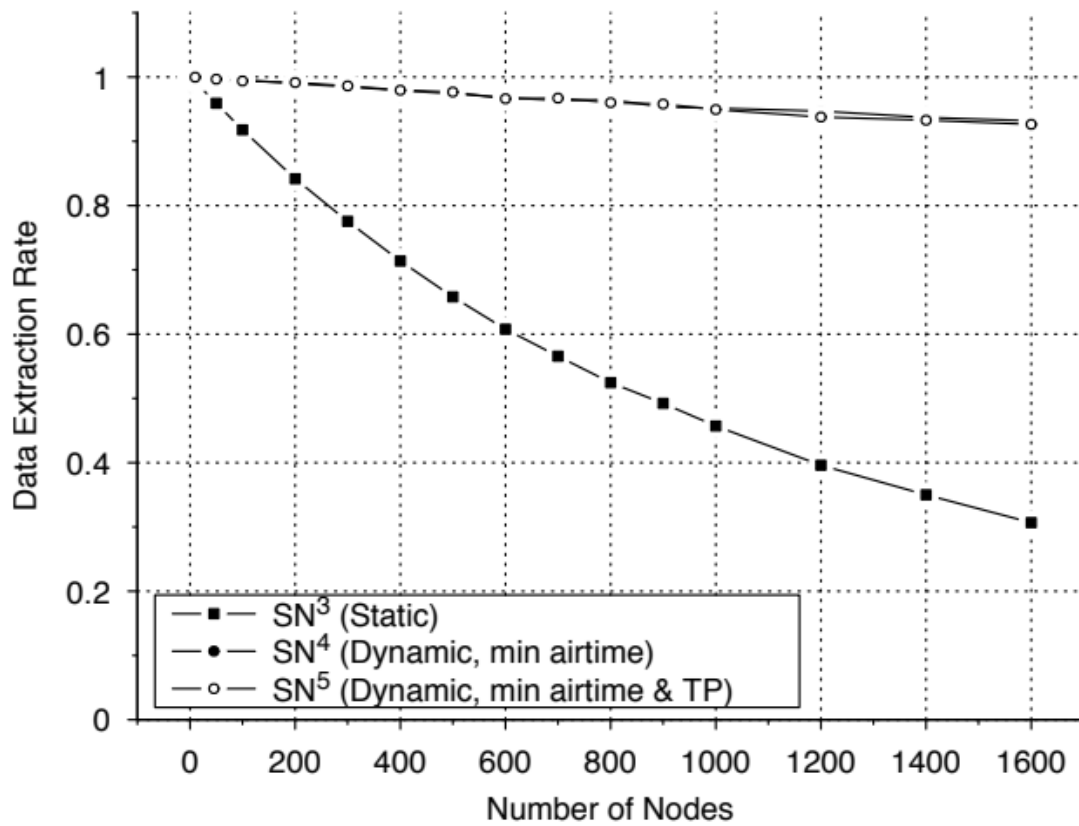
```
sn3["der"] = (sn3["nrTransmissions"] - sn3["nrCollisions"]) / sn3["nrTransmissions"]
sn4["der"] = (sn4["nrTransmissions"] - sn4["nrCollisions"]) / sn4["nrTransmissions"]
sn5["der"] = (sn5["nrTransmissions"] - sn5["nrCollisions"]) / sn5["nrTransmissions"]
```

Finally, we plotted the data, and the figure looks very similar to the one in the paper.

```
import matplotlib
import matplotlib.pyplot as plt

plt.plot(sn3["#nrNodes"], sn3["der"], label="SN3(Static)", marker='o')
plt.plot(sn4["#nrNodes"], sn4["der"], label="SN4(Dynamic,min airtime)", marker='s')
plt.plot(sn5["#nrNodes"], sn5["der"], label="SN5(Dynamic,min airtime & TC)", marker='^')
plt.title("Fig.5 Experiment Set 2 - Dynamic Parameters")
plt.xlabel("Number of nodes")
plt.ylabel("Data Extraction Rate")
plt.legend()
plt.grid()
plt.show()
```





In both cases, we observe that optimal allocation of settings in terms of airtime (and airtime plus TP) has a huge impact on achievable DER. With minimized airtime (SN4) and a DER > 0.9 requirement, well over N = 1600 nodes can be supported. This is a dramatic improvement compared to the N = 120 nodes achieved with the static, conservative settings used in LoRaWAN.

For Figure 7, we proceed in a similar way as for Figure 5, but in this case, we use the functions in `lorasim/loraDirMulBS.py`, because in this experiment the number of sinks also increases (not just a single sink as before).

Most of the variables remain the same, but we run a simulation for each number of sinks (1, 2, 3, 4, 8, 24). In particular, we set `collision = 1`, whereas by default it is 0. However, due to an unknown issue, passing the parameter `collision = 1` in the “simulate” function does not work. Therefore, for this particular case, we manually edit `loraDirMulBS.py` and change the default value of “full_collision” from False to True.

```
65 # do the full collision check
66 full_collision = True
67
```

```
import subprocess

def simulate(n_nodes, tx_rate, exp, duration, n_sinks):
    env = os.environ.copy()
    env["MPLBACKEND"] = "Agg"

    # Use subprocess.run to execute the command and capture output
    result = subprocess.run(
        [
            "python2",
            "lorasim/loradirMulBS.py",
            str(int(n_nodes)),
            str(int(tx_rate)),
            str(int(exp)),
            str(int(duration)),
            str(int(n_sinks))
        ],
        env=env,
        capture_output=True,
        text=True, # Capture output as text
    )
```

```
duration = 86400000
tx_rate = 1e6

for n_nodes in list(range(1,10)) + list(range(10,300,10)) + list(range(300,1601,100)):
    print(f"Simulating {n_nodes} nodes")
    simulate(n_nodes, tx_rate, 0, duration, 1)
    simulate(n_nodes, tx_rate, 0, duration, 2)
    simulate(n_nodes, tx_rate, 0, duration, 3)
    simulate(n_nodes, tx_rate, 0, duration, 4)
    simulate(n_nodes, tx_rate, 0, duration, 8)
    simulate(n_nodes, tx_rate, 0, duration, 24)
```

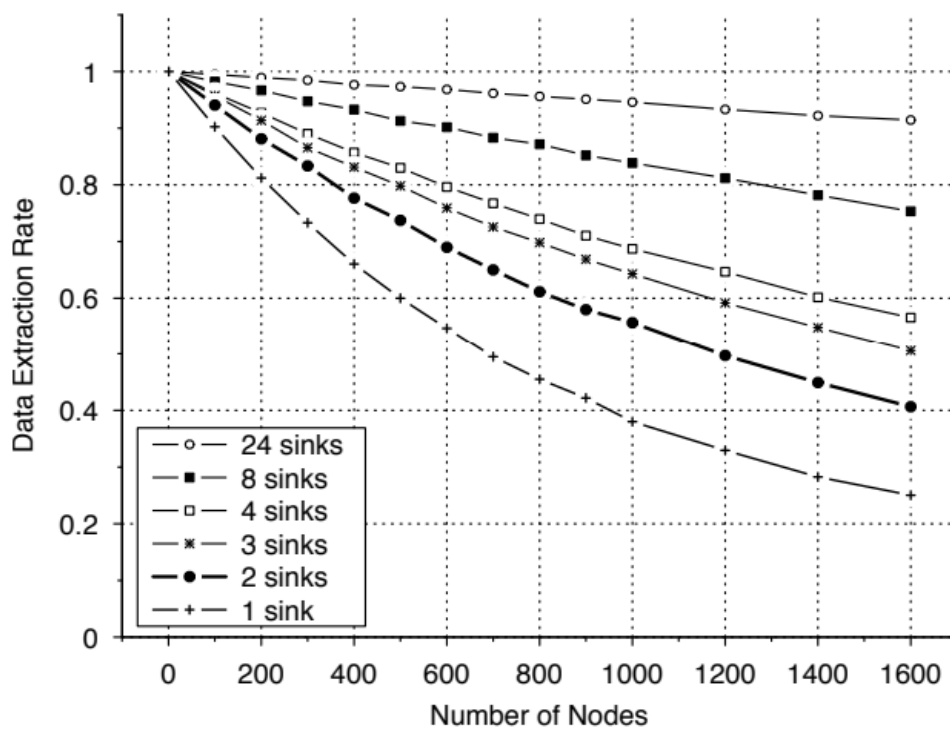
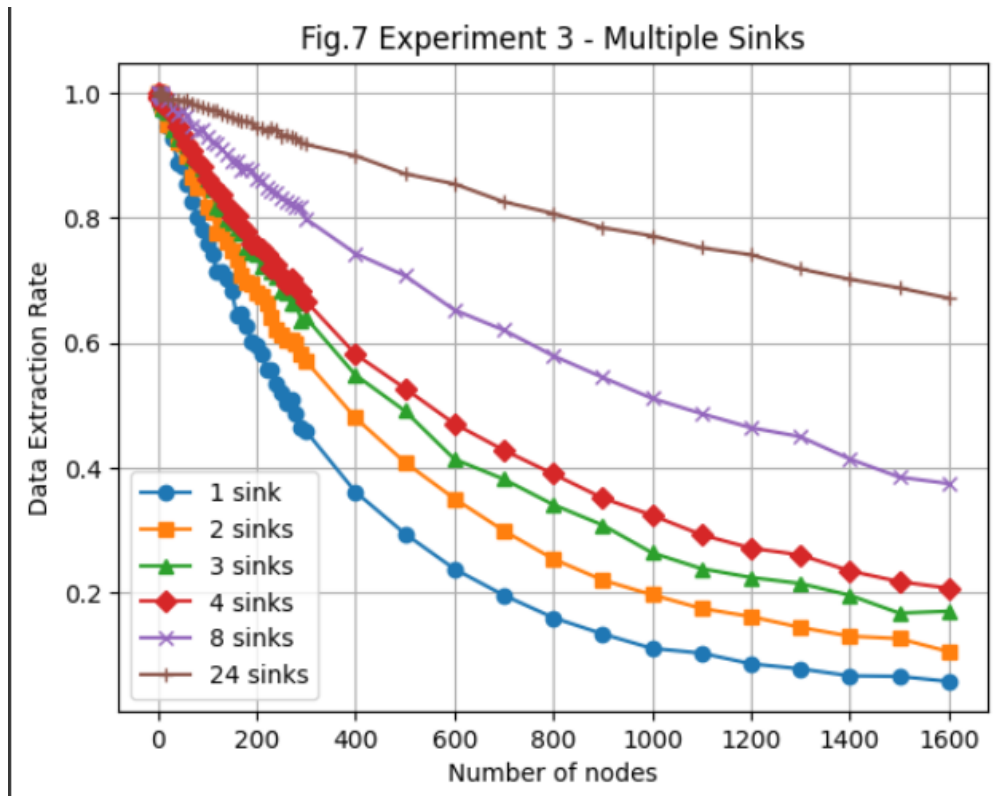
For all simulations we decided to use exp0.

```
if experiment==1 or experiment == 0:
    self.sf = 12
    self.cr = 4
    self.bw = 125
```

Here, we do not need to calculate the DER separately, as it is already contained in the .dat file. We simply read the data from the file and plot it in a figure.

(There is a problem with the simulator file: there is a space between the “#” and “nrNodes”, so the system recognizes “#” as the number of nodes and “nrNodes” as the DER.)

Again, our plot is similar to the one in the paper:



With more sinks, the chances increase that a packet finds a sink where the capture effect works to its advantage. With an infinite number of sinks, each node could potentially find a sink and avoid packet loss.