# ADVANCED MACHINE LEARNING FOR ANOMALY DETECTION AND JAMMER LOCALIZATION

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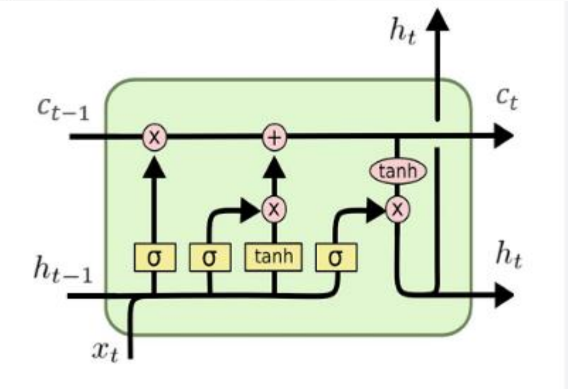
# RESEARCH GOALS

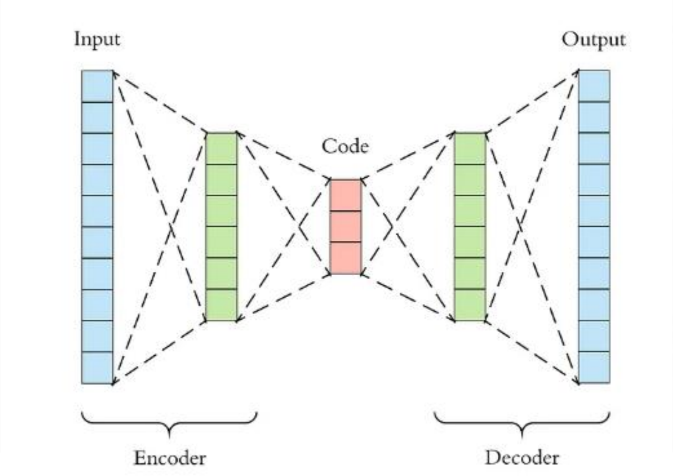
- Resilience and security of geospatial data for critical infrastructures (REASON)
  - Academy of Finland 2020 – 2023, with FGI, VTT
- In REASON UH's SDA group will develop
  - GNSS Fault Detection and Diagnosis system based on Long-Short Term Memory (LSTM) deep learning models for **anomaly detection**
  - Machine learning model for **localizing jammers**

# MACHINE LEARNING BASICS

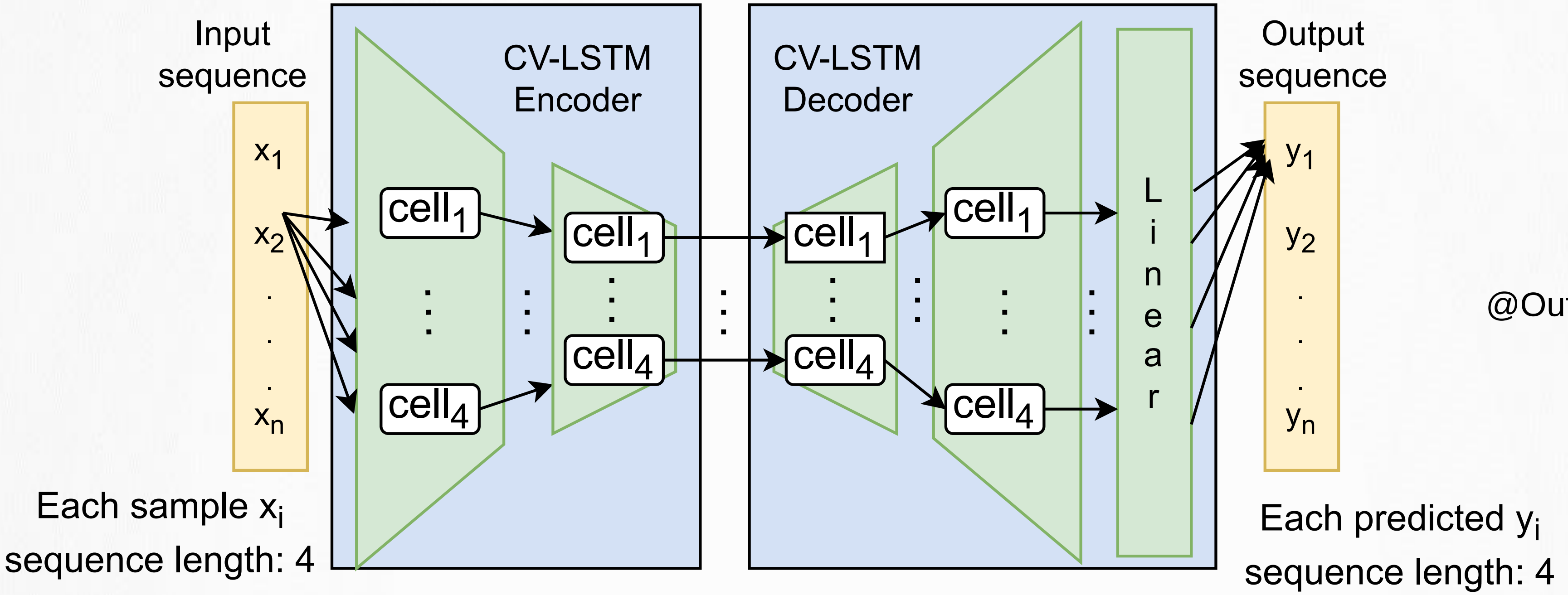
- Long Short-Term Memory network
  - Recurrent neural network capable of learning long sequence prediction problems




- Autoencoders are neural networks that can compress and reconstruct data
- Reconstruction error can be used to identify anomalies



# COMPLEX-VALUED AUTOENCODER

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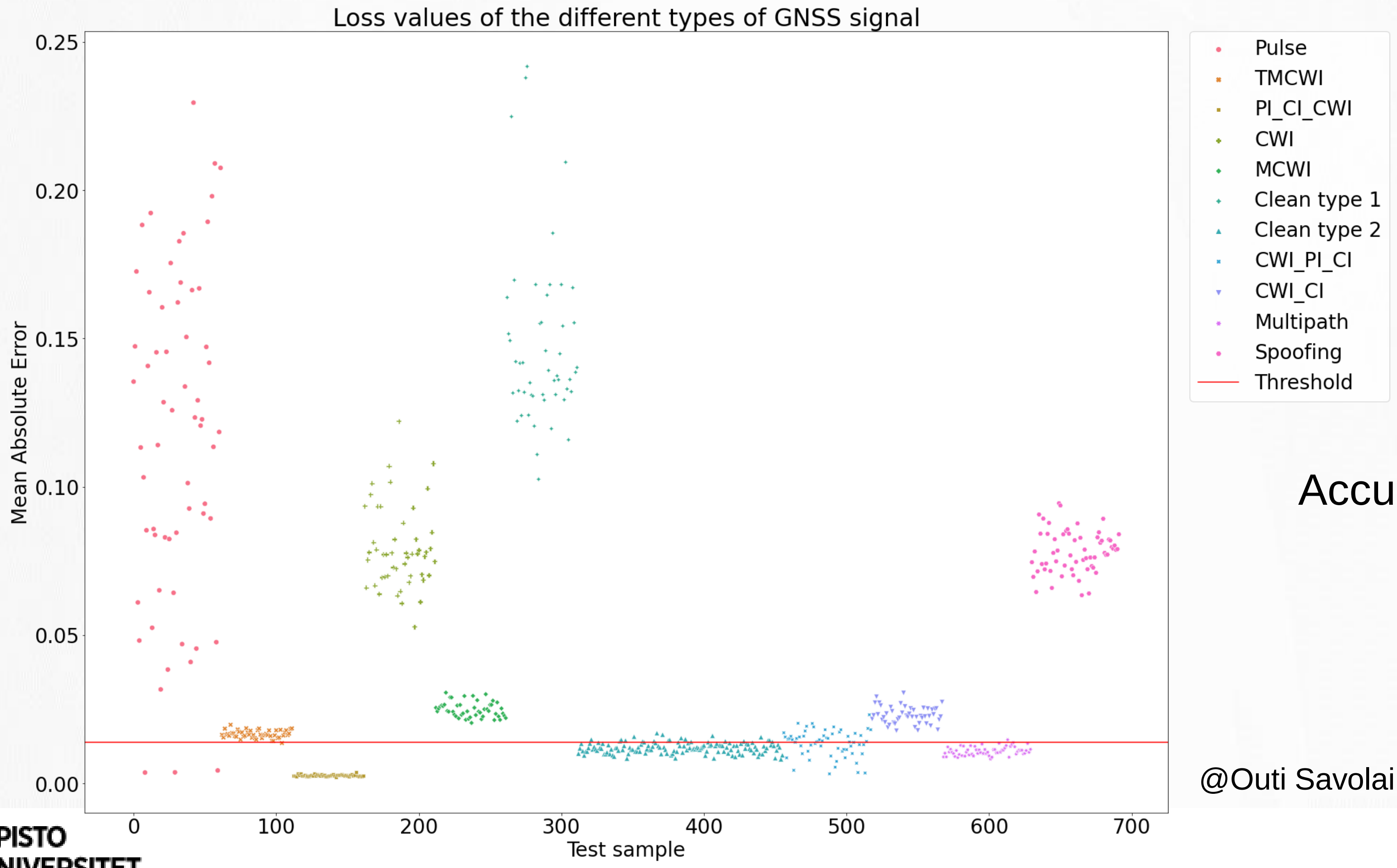
First **unsupervised** LSTM based autoencoder for GNSS anomaly detection
First fully **complex-valued** variant from the detector

# RESULTS WITH SIMULATED DATA




Accuracy 75%

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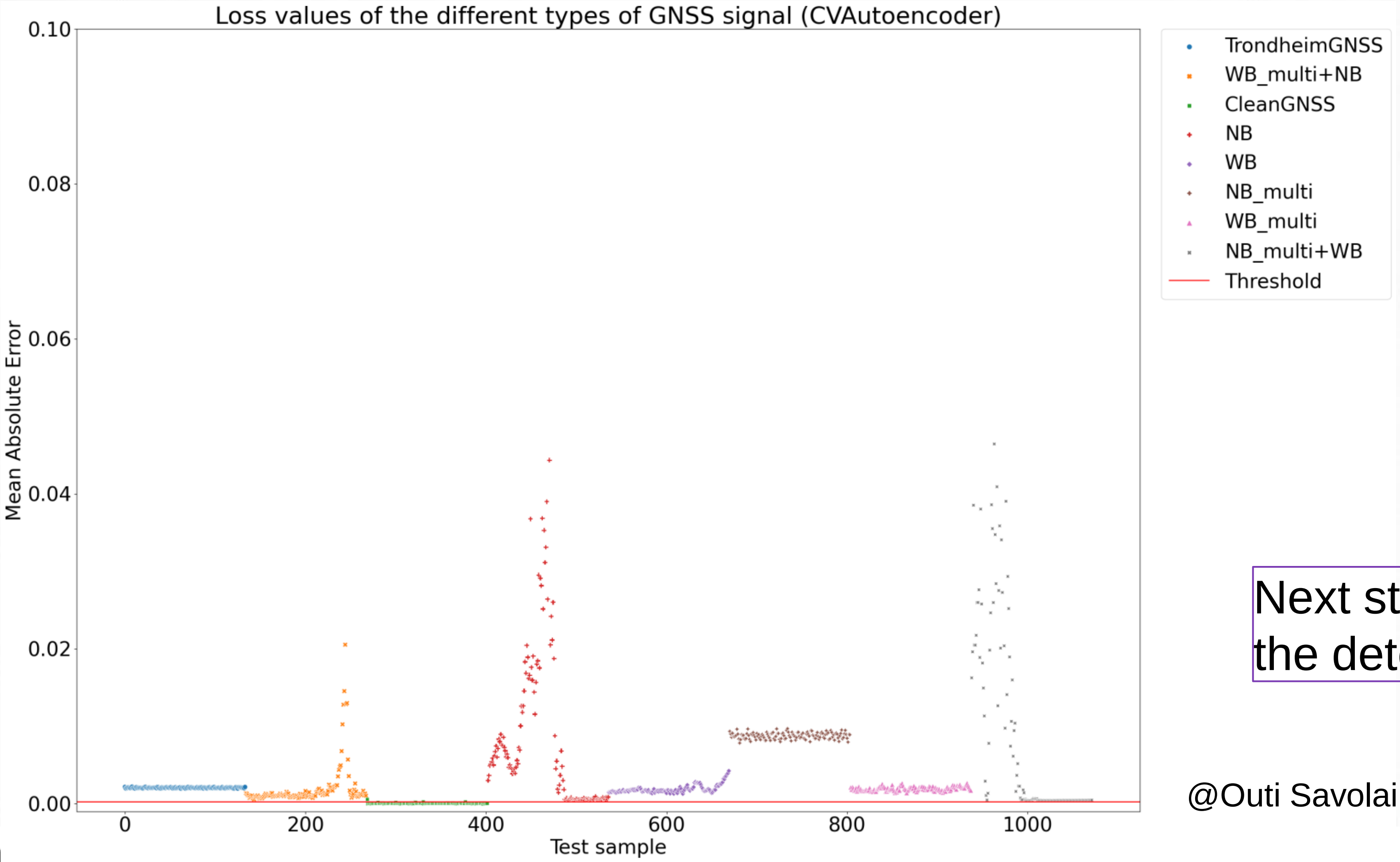
# VERIFICATION WITH REAL WORD DATA (JAMMING)




Accuracy 99.8%

Next step: classification of the detected anomalies

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# Jammer localization – setup

## Measurement

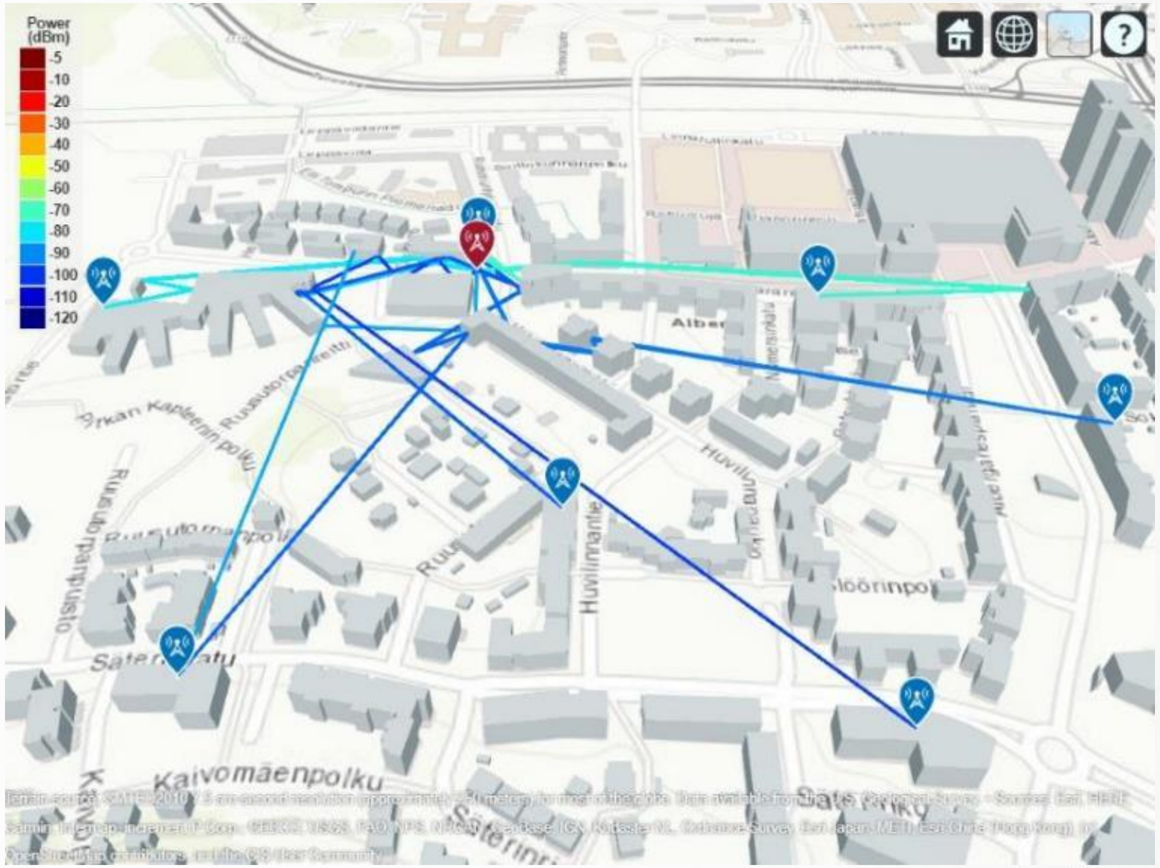
- Carrier-to-noise ratio (C/N0) + Automatic gain control (AGC)

## Multipath environment

- City model + ray-tracing

## Localization method

- Raw classification + fine searching

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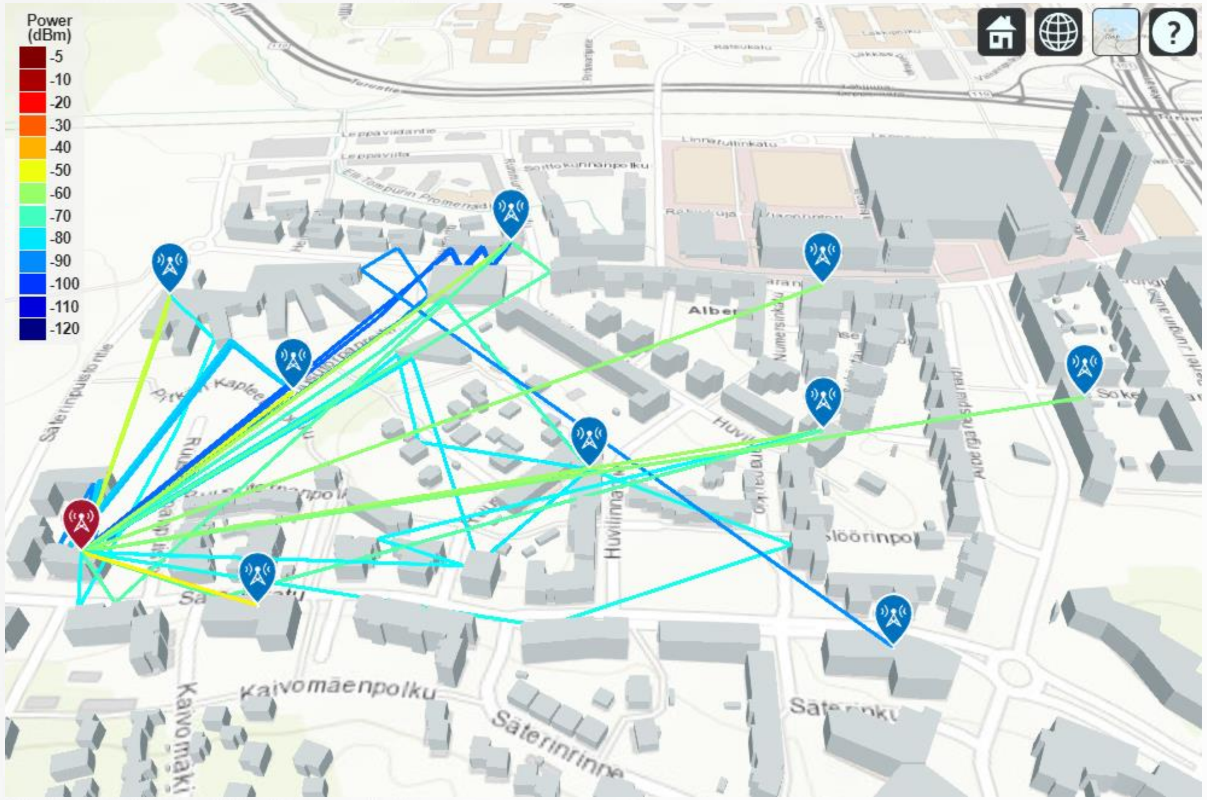
# Multipath Simulation Settings




Description of the ray-tracing paths between the jammer and monitors in Sello shopping center area, Espoo, Finland.

- An urban area about 0.5 km2
- 9 monitoring nodes, 2 m above the roofs
- 5 × 9 blocks with 60 × 60m
- 1500 samples in each block
- 3 GPS satellites' *C/N0* + 1 front-end AGC
- 45 blocks × 1500 samples × 4 features

## Ray tracing

- Maximum reflections: 5
- Maximum relative pass loss with the first path: 40dB (otherwise discard it)
- Materials of the building and terrain : concrete

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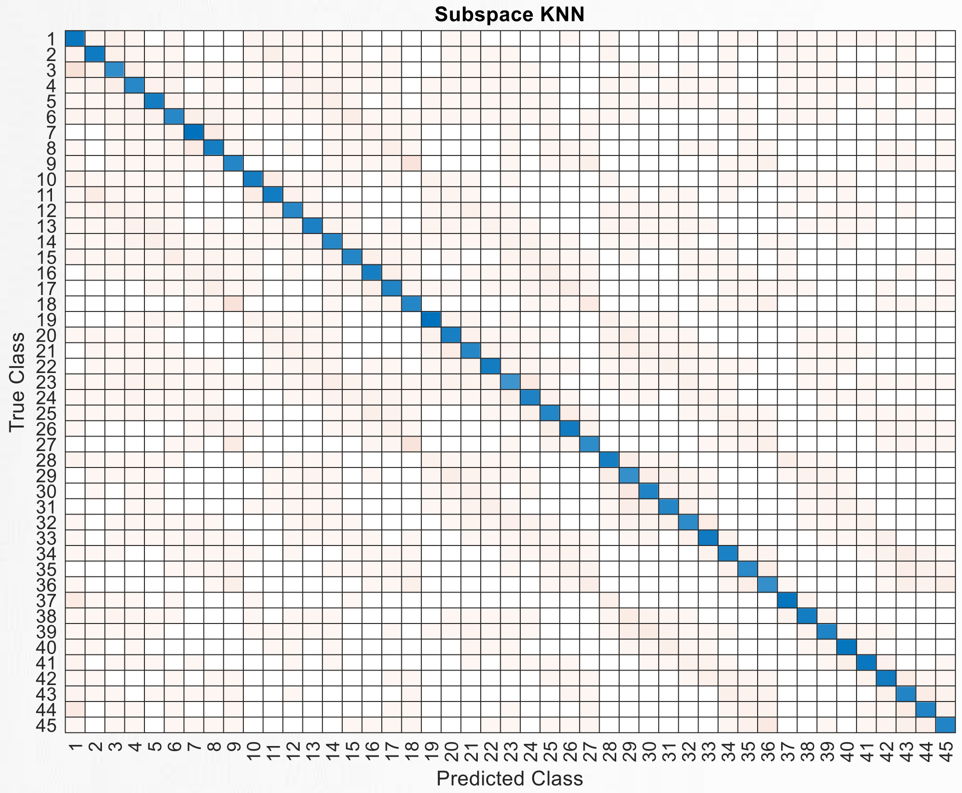
# Localization method (Raw classification)

- First step: the raw localization is described as a classification problem




| Method | Accuracy |
|---|---|
| Cubic SVM | 71.9% |
| Fine Gaussian SVM | 70.1% |
| Fine KNN | 70.2% |
| Weighted KNN | 70.8% |
| Subspace KNN | **78.0%** |
| Wide Neural Network | 70.2% |
| Bagged Trees | 77.1% |

Traditional supervised machine learning methods

# Localization method (Fine searching)

- Second step: optimization method is used in the finer searching within the block

Objective:

Minimize

$$\frac{\sum C/N_0(\text{Optional jmmer location}) - \sum C/N_0(\text{Real jmmer location})}{\text{Amount of the stations}}$$

Problem: common optimization method cannot be used because the cost function value is given by ray-tracing simulation, but the mathematic expression of the cost function cannot be given.

Solution: Gravitational Search Algorithm (GSA), no cost function expression is needed

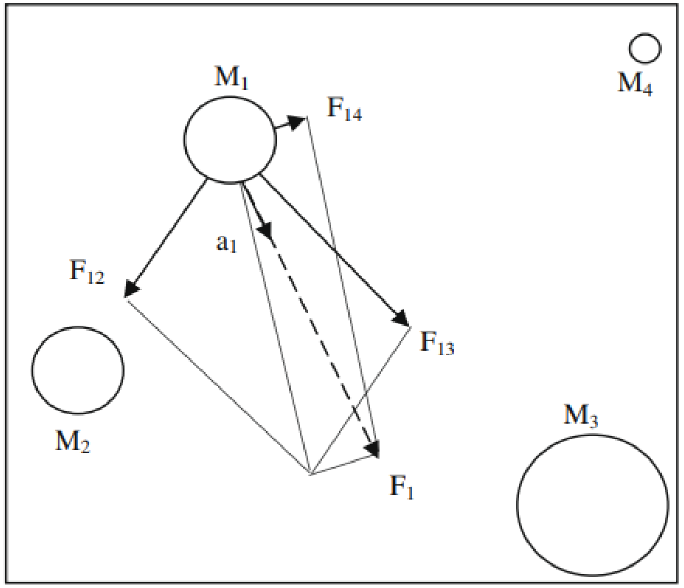
# Localization method (Fine searching)

Basic idea of Gravitational Search Algorithm (GSA)

- Optional location points are assigned with different mass according to their fitness (value of the cost function)
- By the forces among the optional points, they are attracted to move towards the best solution.

Newton's law on universal gravitation

$$F_{ij}(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}$$




From the equation on the previous slide

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}$$

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Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2009). GSA: a gravitational search algorithm. Information sciences, 179(13), 2232-2248.

# Localization method (Fine searching)

Examples of the searching process of GSA

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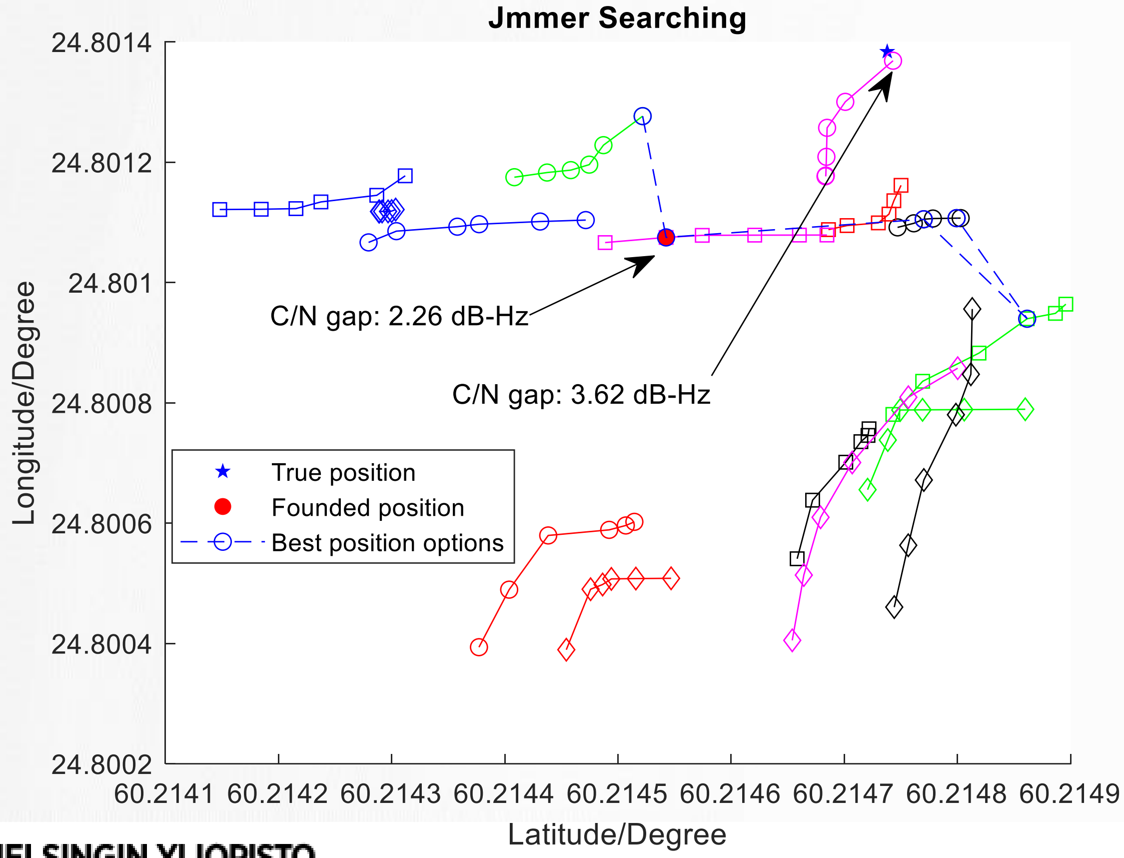


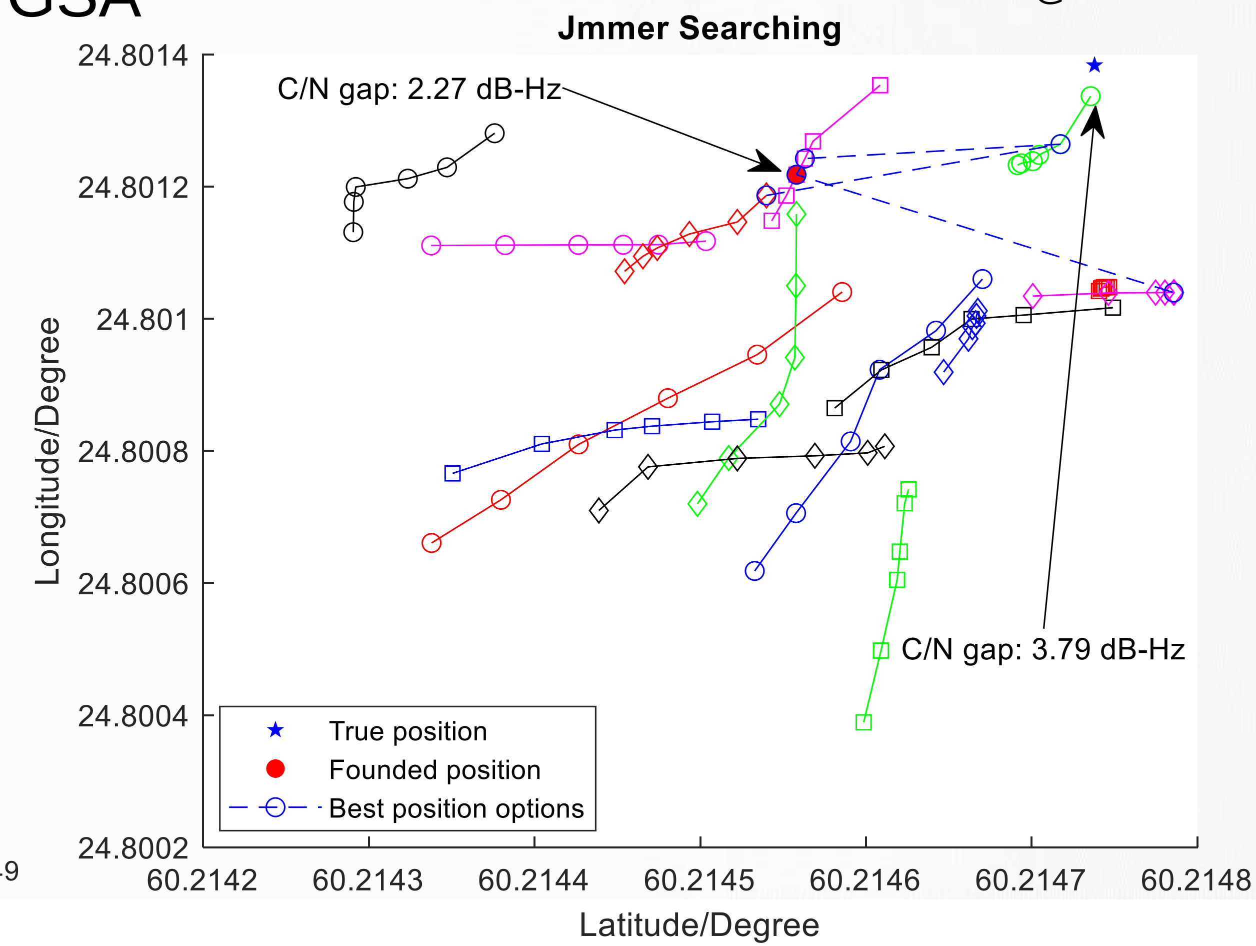


Limited accuracy due to closest point not having the lowest C/N0

# Localization method (Fine searching)

The other reason that we can only obtain a limited accuracy

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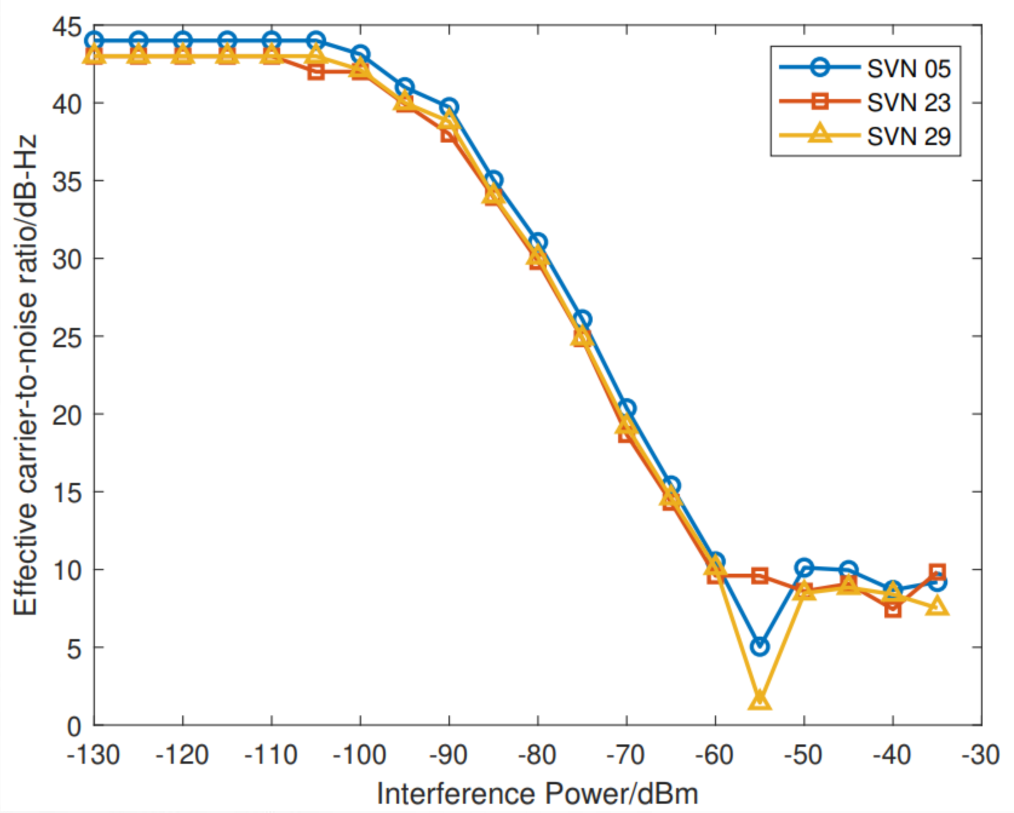


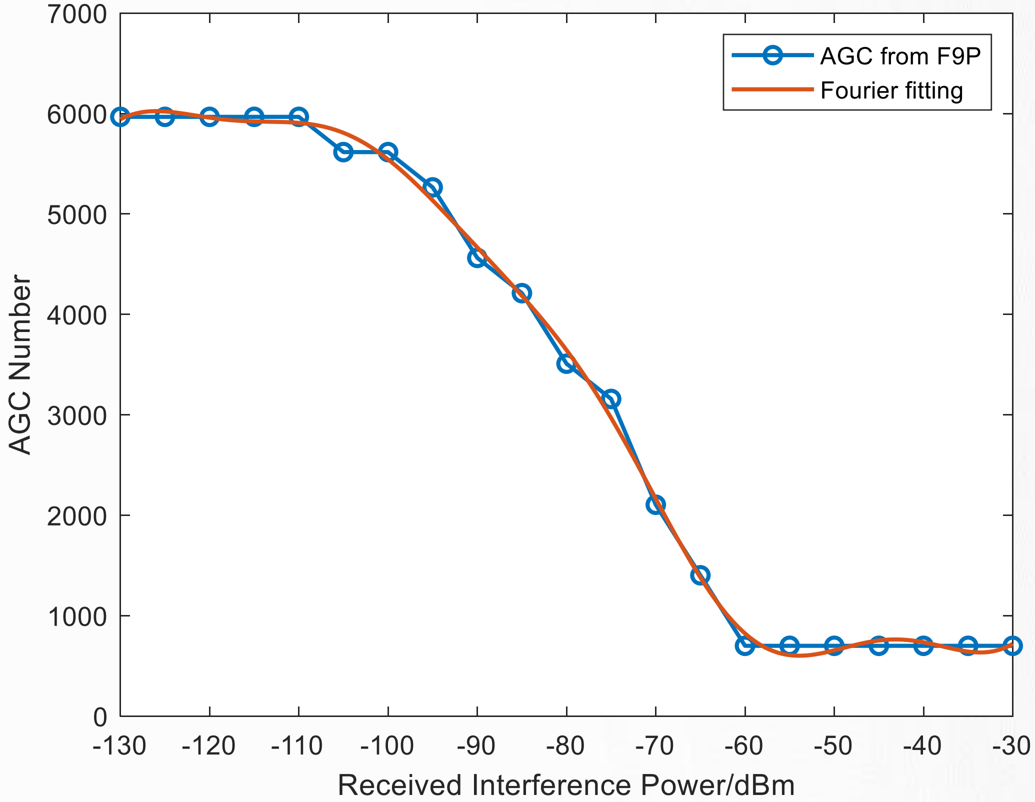


While getting close to the jammer, the C/N0 becomes unreliable and the AGC saturates

# Test results

- Randomly generate 5×9 blocks×20=900 jamming points

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| Method | Fixed rate | Successful rate (<60m) | Average latitude error | STD of latitude error | Average longitude error | STD of longitude error | Average horizontal error | STD of horizontal error |
|---|---|---|---|---|---|---|---|---|
| Classification + GSA | **100%** | **78.0%** | -0.28 m | 22.00 m | 0.56 m | 18.97 m | **24.55 m** | **15.51 m** |
| Pathloss model + Least squares | **20.7%** | **3.2%** | 6.19 m | 181.06 m | 84.56 m | 168.59 m | **214.52 m** | **148.87 m** |

Benchmark

Effectively jammed station < 3
or cannot converge accurately enough
(2D position + 1 public error)

Average C/N gap: 3.15 dB-Hz
STD of C/N gap: 2.02 dB-Hz
Break through the limitation of effective jamming zone

# THANK YOU!

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