Gefördert durch:

Bundesamt
für Sicherheit in der
Informationstechnik

Weather-Aware LoRaWAN Sensor Localization

RIoT RESILIENT

Towards a Data-Driven Network-as-a-Sensor Approach for Scalable Positioning in LoRaWAN Network

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Table of Content

1. Introduction

1.1 Motivation

- 3GPP 5G **Rel-16** guarantees up to **3 m horizontal accuracy**
- **20 cm** accuracy with **Rel-17**
- To support **emergency services**
- Foster **location-based applications** [7]
- Network-as-a-Sensor principle for position estimation **without additional data overhead**

1.2 Objectives

- A complementary positioning method based on LoRaWAN RAN measurements
- Performance comparison of different approaches
- Sensor location monitoring

1. Introduction

1.3 Localization Approaches

1. **Triangulation**
   - Using AoA (Angle of Arrival) at base-stations with **directional antennas**
   - Not achievable in general LoRaWAN infrastructure
2. **Trilateration**
   - Accurate ToF (Time of Flight) and ToA (Time of Arrival) required for **distance calculation**
   - Also not achievable as sensors are not synchronized to generate exact timestamps
3. **Multi-lateration**
   - **TDoA** (Time Difference of Arrival) at gateways
   - Position solving using Non-linear Least Square Estimation
4. **RSSI-based distance calculation**
   - From pathloss models and solving polynomial equations
5. **Fingerprinting**
   - Machine-learning-based location prediction from RSSI map

2. Range-based Position Estimation

Collecting signal metadata gateways

- Signal strength (RSSI)
- Frequency
- Height of MS and BS

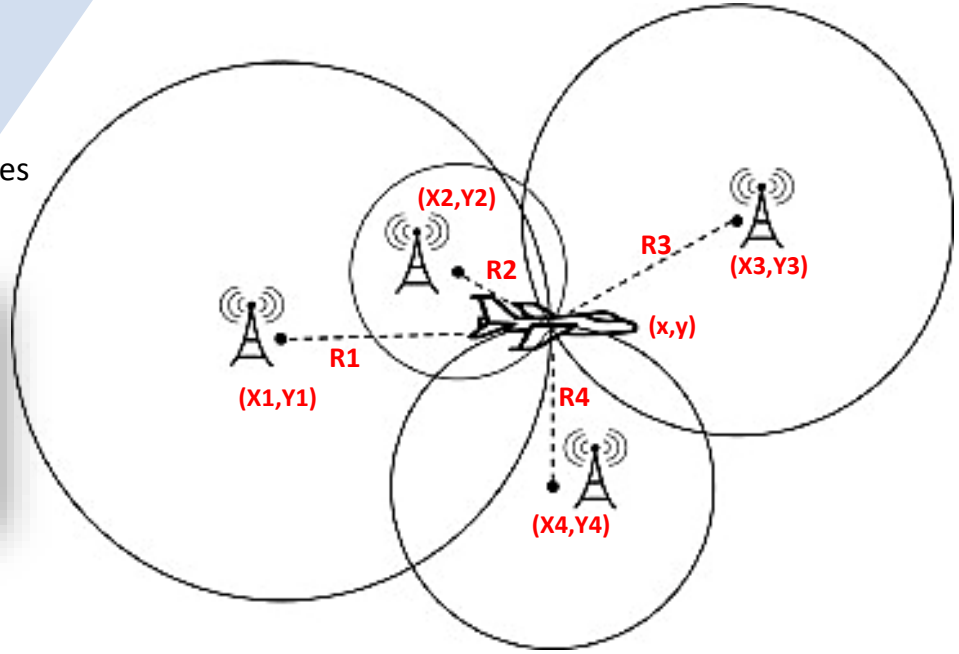
Distance calculation using empirical pathloss models

- i.e. Okumura-Hata, COST-231 Walfisch-Ikegami

Position solving

- From known **gateways coordinates (Xi, Yi)** and **distances** to the end devices **Ri**, calculate unknown **end device coordinates (x, y)**

$$R_1 = \sqrt{(X_1 - x)^2 + (Y_1 - y)^2}$$
$$R_2 = \sqrt{(X_2 - x)^2 + (Y_2 - y)^2}$$
$$R_3 = \sqrt{(X_3 - x)^2 + (Y_3 - y)^2}$$
$$\vdots$$
$$R_n = \sqrt{(X_n - x)^2 + (Y_n - y)^2}$$



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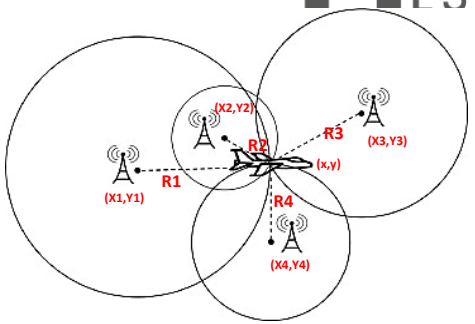

Limitations

- Due to long range/distance (up to 15km) and low power (RSSI~ -130 dBm), **minor path loss leads to large errors**
- Interference in the shared spectrum (e.g. ISM 868 MHz)
- Site specific requirements for model calibration
- **Weather** and **temporal** dynamics

3. TDoA-based Position Estimation

Pros

+ Independent of time synchronization of end device
+ Less sensitive to Tx/Rx power or signal level
+ Passive and scalable

Select Reference Gateway

- Preferably the 1st gateway to receive the packet

Calculate ToDA (Time Difference of Arrival) from ref Gateway

$$\tau_{TDoA} = \tau_1 - \tau_{ref}$$
$$\tau_{TDoA} * c = R_1 - R_{ref}$$
$$\tau_{TDoA} = \tau_2 - \tau_{ref}$$
$$\tau_{TDoA} * c = R_2 - R_{ref}$$
$$\tau_{TDoA} = \tau_3 - \tau_{ref}$$
$$\tau_{TDoA} * c = R_3 - R_{ref}$$

Formulate Position Solving Equations

- Distance eqution of end device from each gateway

$$R_1 = \sqrt{(X_1 - x)^2 + (Y_1 - y)^2}$$
$$R_2 = \sqrt{(X_2 - x)^2 + (Y_2 - y)^2}$$
$$R_3 = \sqrt{(X_3 - x)^2 + (Y_3 - y)^2}$$
$$R_{ref} = \sqrt{(X_{ref} - x)^2 + (Y_{ref} - y)^2}$$

Non-Linear Least Square Estimation

- For approximating the position

$$c * (\tau_1 - \tau_{ref}) = \sqrt{(X_1 - x)^2 + (Y_1 - y)^2} - \sqrt{(X_{ref} - x)^2 + (Y_{ref} - y)^2}$$
$$c * (\tau_2 - \tau_{ref}) = \sqrt{(X_2 - x)^2 + (Y_2 - y)^2} - \sqrt{(X_{ref} - x)^2 + (Y_{ref} - y)^2}$$
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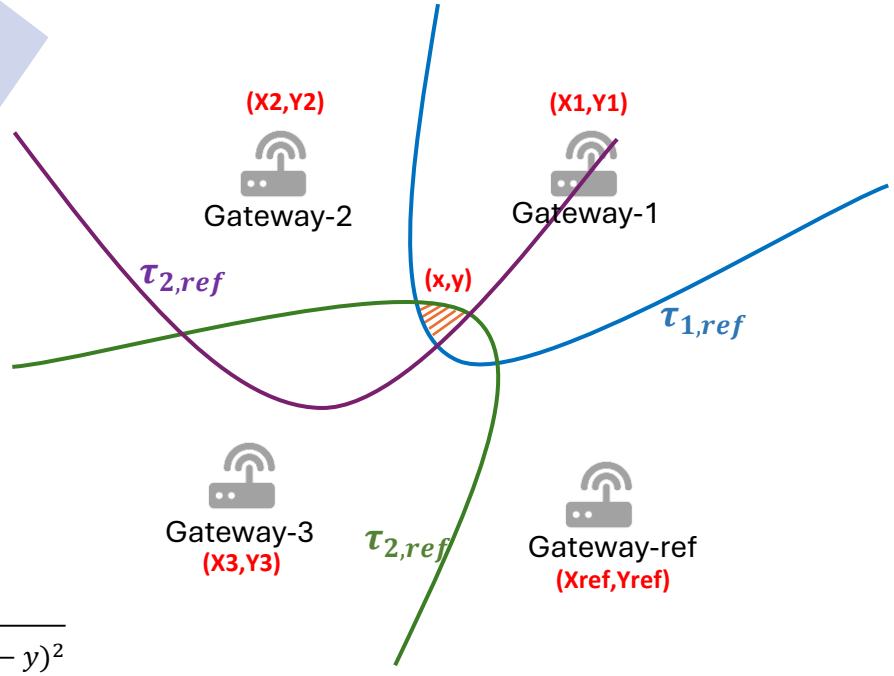

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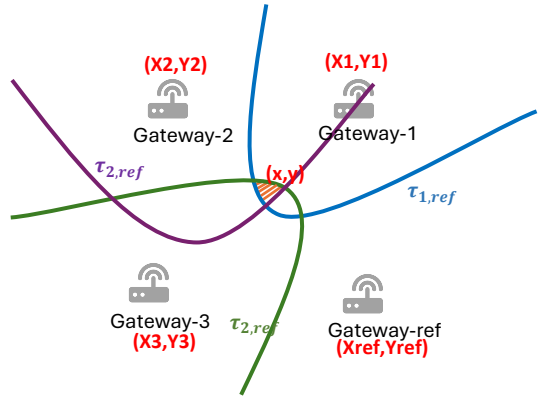
Non-Linear Least Square Estimation



Pros

+ Independent of time synchronization of end device
+ Less sensitive to Tx/Rx power or signal level
+ Passive and scalable

Limitations

- **Gateway Clock Synchronization:** up to nano-second level precision required
- **High Sensitivity**: An error of 1us results in error of 300m
- Multipath delays

4. Fingerprinting

A combination of RSSI fingerprinting map and Machine Learning

- Receiving Signal Strength (RSSI)
- Coordinates

Label

- Assign coordinates to each measurement

Pros

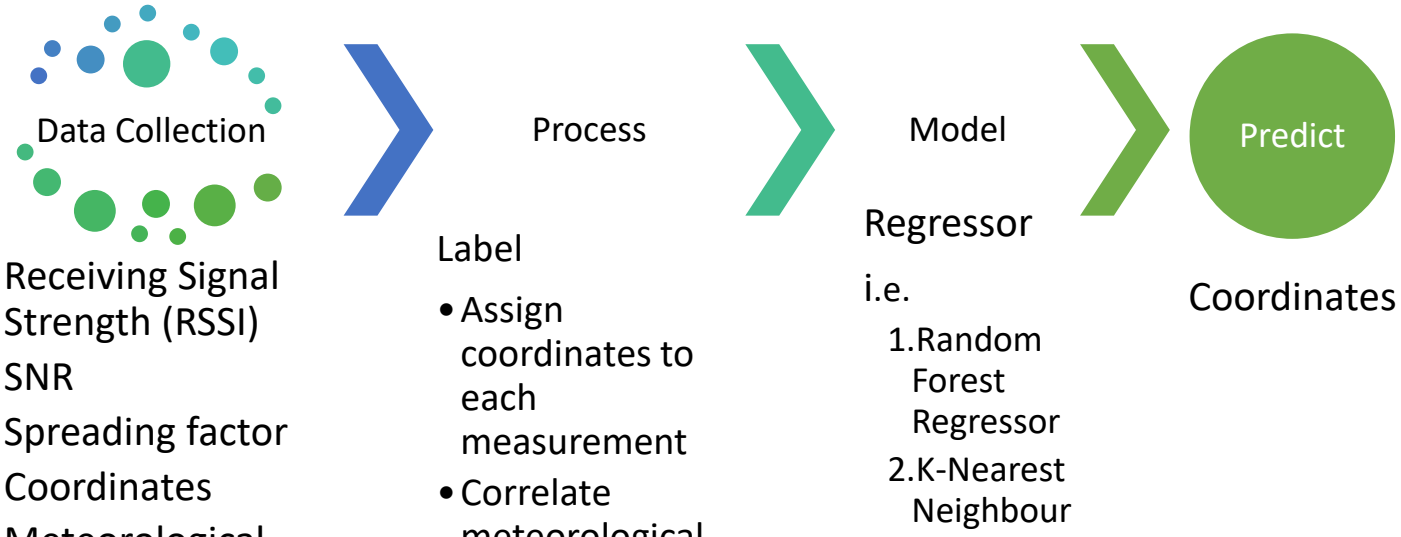
+ Scalable
+ **Generalized**: Robust against RSSI fluctuations
+ Low infrastructure dependency
    - No need for additional hardware (i.e. clock synchronizer)

Limitations

- Sensitive to environmental interference
    - i.e. obstacles, temperature, humidity, radiation, precipitation

4. Fingerprinting

4.1 **Proposed Solution**: Incorporating Meteorological Data



- Receiving Signal Strength (RSSI)
- SNR
- Spreading factor
- Coordinates
- Meteorological data from-
  - On-board sensors
  - External sources (e.g. OpenMeteo [6])

Label

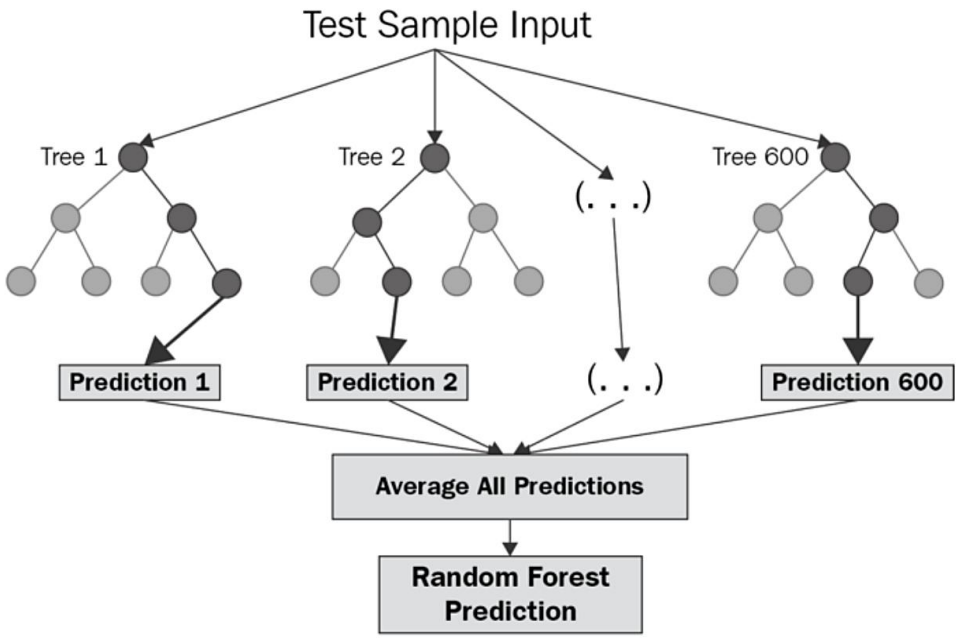
- Assign coordinates to each measurement
- Correlate meteorological data with samples

Gains

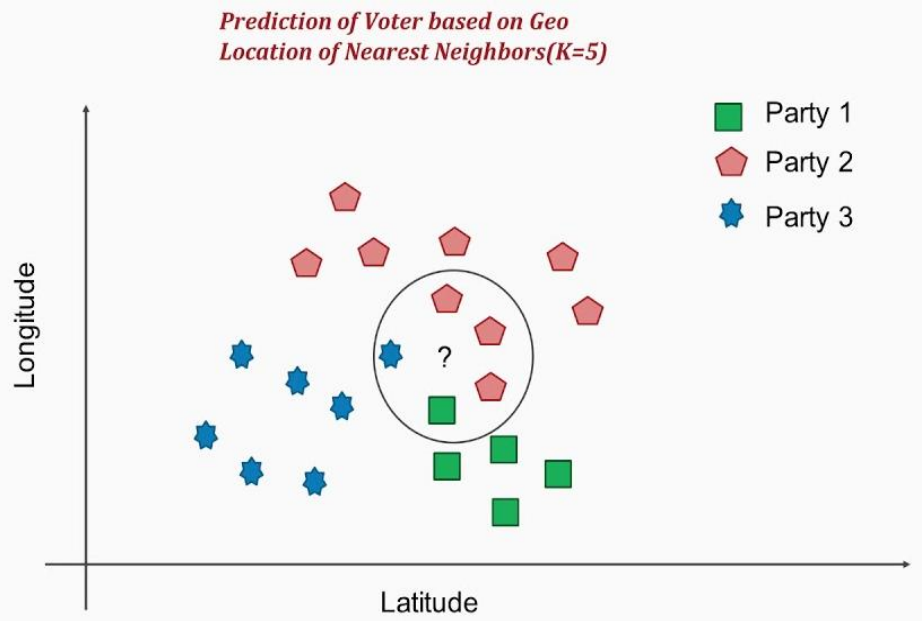
- Integration of weather data **addresses RSSI fluctuation problem** caused by environmental dynamics
- Additional data to enhance the
  - **Dimension of context**
  - **Differentiate** between **similar** inputs
  - Capture **hidden patterns**
  - **Compensate** for ambiguous data

4. Fingerprinting
4.1 ML Models

Random Forest Algorithm

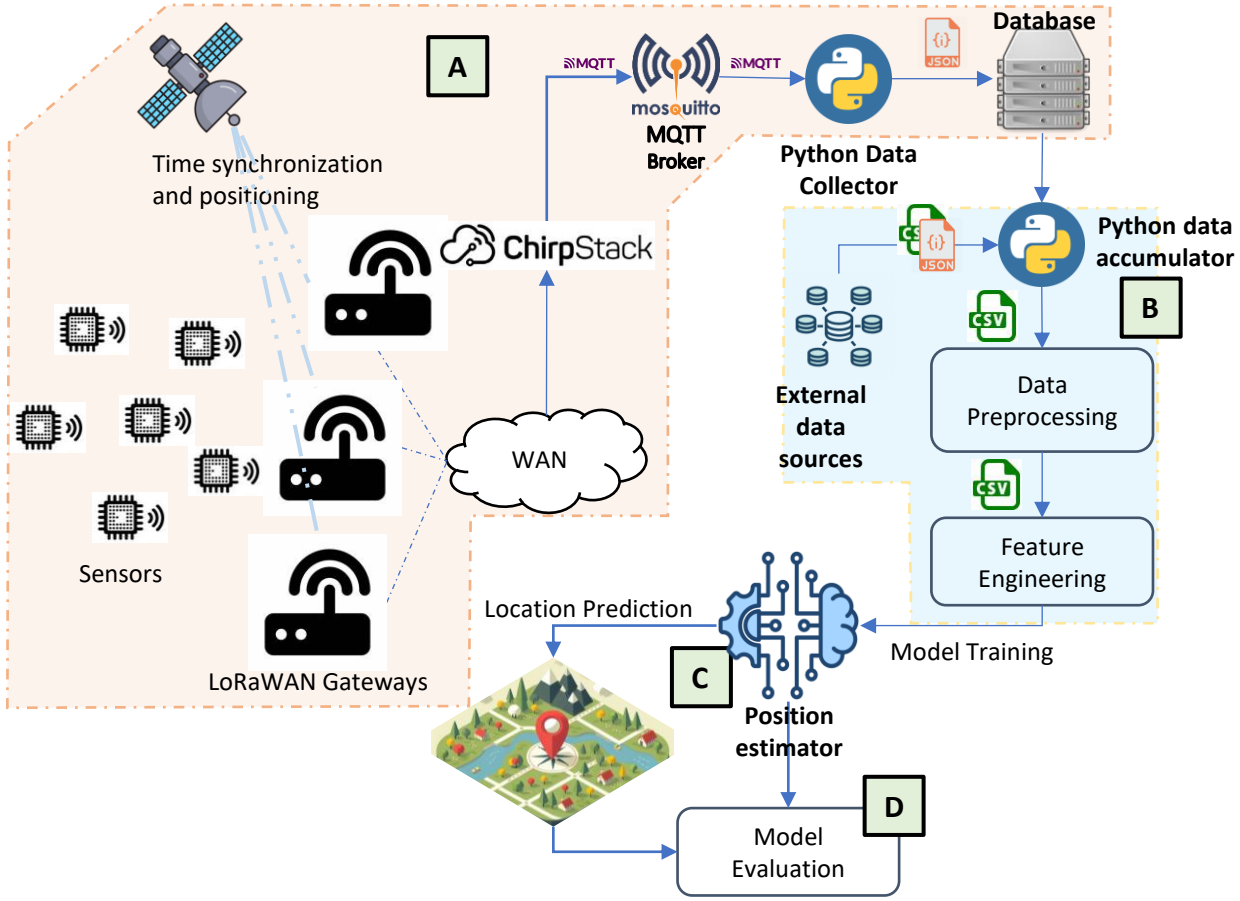


K Nearest Neighbour Algorithm



5. Lab Setup

A. Data Acquisition
B. Preprocessing
C. Position Estimation
D. Model Evaluation



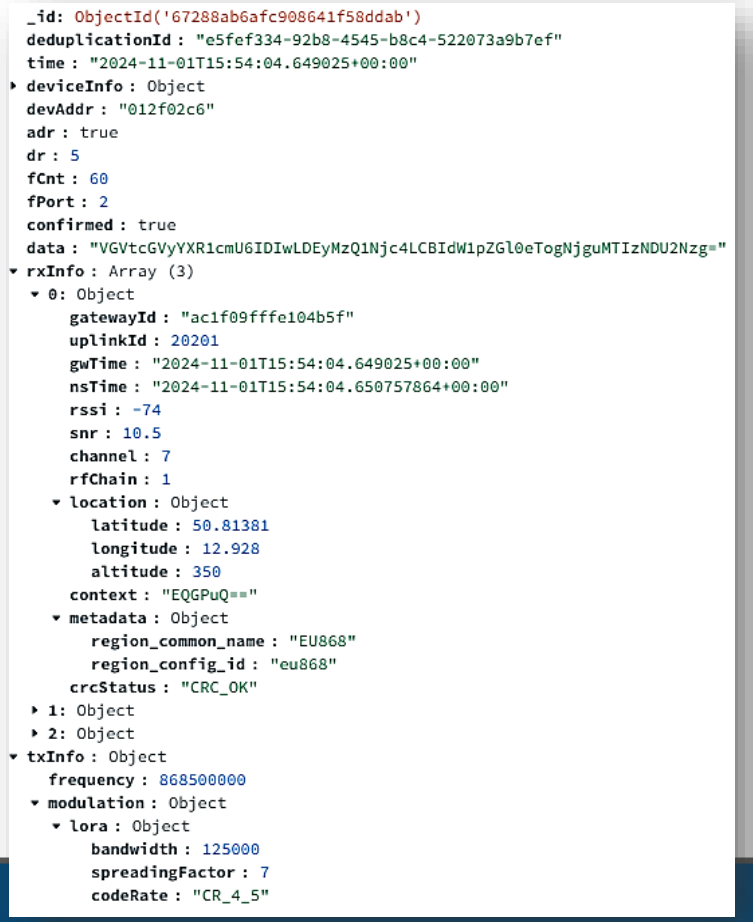
5. Lab Setup
5.1 Data Acquisition

Network as a Sensor

A network that both transmits information and actively monitors its own performance

LoRaWAN as a Sensor

- Meta-statistics collected form uplink messages
- Link budget parameters from meta-statistics and gateways



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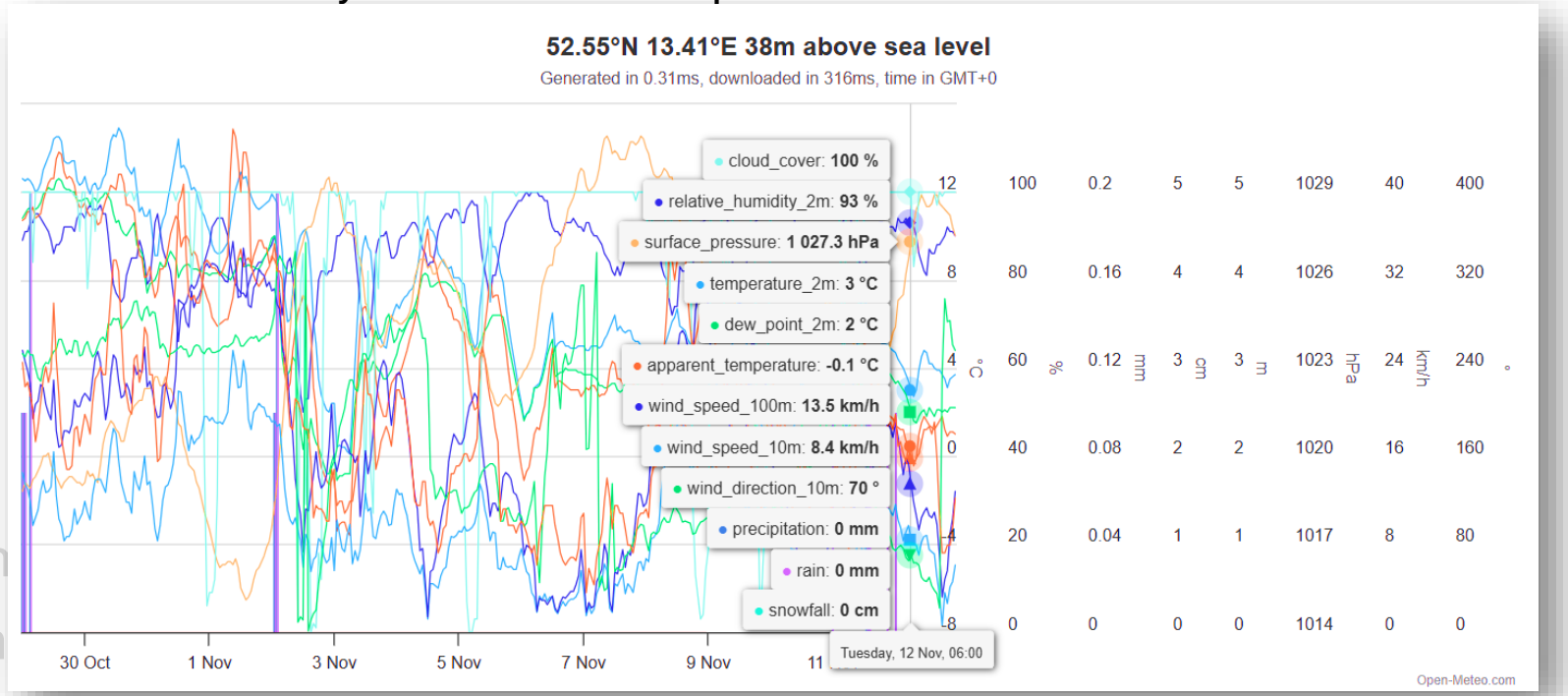


LoRaWAN as a Sensor

- Meta-statistics collected forn
- Link budget parameters from
- Weather data collection from mounted sensor (temperature, humidity, pressure…)
- Additional weather data from data sources (i.e. OpenMeteo [6])

5. Lab Setup

5.2 Preprocessing

- **Filtering**: Keep samples corresponding to packets that are ***received by at least four gateways***
- **Scaling**: Normalize data before training the machine learning models (i.e. mean-max scaler)

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

5.3 Model Evaluation

- **Error metrics**: Haversine distance between the estimated/predicted and the actual coordinates

$$d = 2r \arcsin\left(\sqrt{\text{hav}(\varphi_2 - \varphi_1) + \cos(\varphi_1)\cos(\varphi_2)\text{hav}(\lambda_2 - \lambda_1)}\right)$$

where:

- d is the distance between the two points,
- r is the radius of the sphere (e.g., Earth's radius: 6,371 km),
- φ_1, φ_2 are the latitudes of the two points in radians,
- λ_1, λ_2 are the longitudes of the two points in radians,
- $\text{hav}(\theta)$ is the haversine function, defined as:

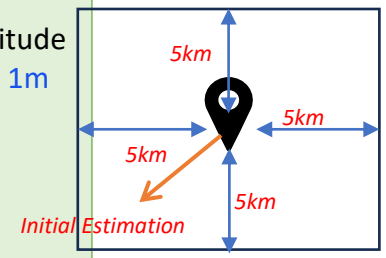
$$\text{hav}(\theta) = \sin^2\left(\frac{\theta}{2}\right)$$

6. Experimental Analysis
6.1 Baseline Approaches

- **Range-Based Position Estimators**
  - Range/distance equations using
    - Okumura-Hata pathloss model
    - COST-231 Walfisch-Ikegami model
- **TDoA Based Multilateration**
- **Fingerprinting**
  - Machine Learning Models
    - **Random Forest**
    - **K-Nearest Neighbour [4]**
  - Alternative Datasets
    - Only RSSI fingerprints /map
    - Combination of
      - **Signal metadata**
        - **RSSI, SNR, Spreading Factor**
      - **Weather info**
        - **Temperature, Humidity, precipitation, radiation**

Assumptions
1. All the gateways has 30m altitude
2. Height of the target sensor = 1m
3. P_tx = 14 dBm
4. G_rx = 3dBm
5. G_tx = 2dBm

Estimation Boundaries
- $25\ km^2$ square boundary to filter far-off outliers



6. Experimental Analysis

6.2 Baseline Dataset

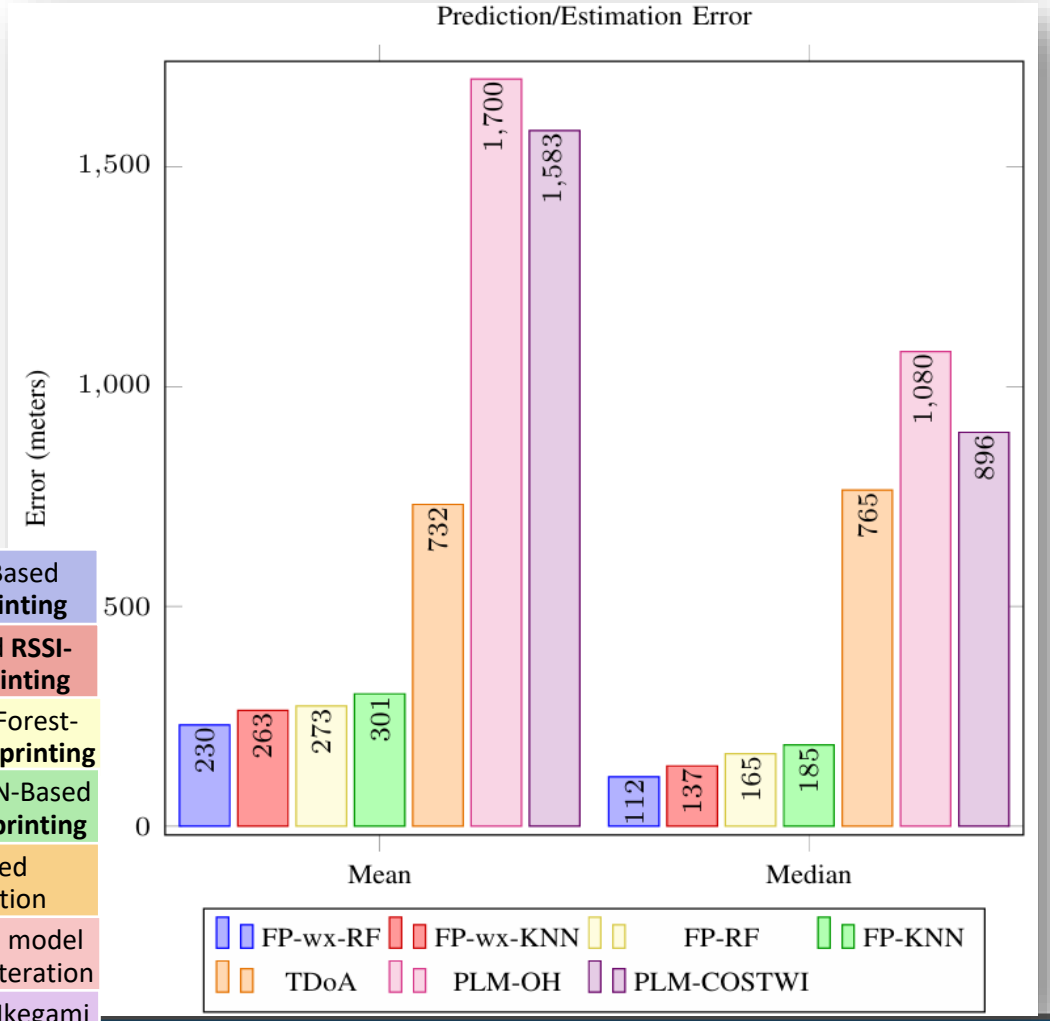
Antwerp LoRaWAN dataset [4] [5]

- RSSI from 72 different GWs located all over Antwerp
- Features: RSSI, Rx Time, Lat-Long, HDOP, SF

	'BS 1'	'BS 2'	'BS 3'	'BS 4'	'BS 5'	'BS 6'	'BS 7'	'BS 8'	'BS 9'	'BS 10'	...	'BS 64'	'BS 65'	'BS 66'	'BS 67'	'BS 68'	'RX Time'	'SF'	'HDOP'	'Latitude'	'Longitude'
0	-200	-200	-200	-200	-200	-200	-200	-200	-114	-200	...	-200	-200	-200	-200	-200	'2017-12-28T16:14:07.247000+00:00'	12	1.02	51.216736	4.412130
1	-200	-200	-200	-200	-200	-200	-200	-200	-200	-200	...	-200	-200	-200	-200	-200	'2017-11-28T12:01:02.380000+00:00'	7	0.57	51.232037	4.405185
2	-200	-200	-200	-200	-200	-200	-200	-200	-200	-200	...	-200	-200	-200	-200	-200	'2017-12-14T09:05:22.832000+00:00'	9	1.00	51.202763	4.390477
3	-200	-100	-200	-200	-200	-200	-200	-200	-200	-113	...	-200	-200	-200	-200	-200	'2018-01-17T09:11:49.222000+00:00'	12	0.62	51.194584	4.417887
4	-200	-106	-107	-200	-200	-200	-200	-200	-200	-200	...	-200	-200	-200	-200	-200	'2018-01-10T14:47:01.379000+00:00'	12	1.00	51.207203	4.403470
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
123523	-200	-103	-106	-200	-200	-200	-200	-200	-200	-200	...	-200	-200	-200	-200	-200	'2018-01-04T10:57:15.856000+00:00'	12	0.61	51.201839	4.414310
123524	-200	-200	-200	-200	-200	-200	-200	-200	-200	-200	...	-200	-200	-200	-200	-200	'2018-01-03T23:17:34.799000+00:00'	8	1.10	51.233677	4.416892
123525	-200	-200	-200	-200	-200	-200	-200	-200	-200	-200	...	-200	-200	-200	-200	-200	'2017-12-15T10:13:56.383000+00:00'	12	0.82	51.215370	4.412519
123526	-200	-97	-200	-200	-200	-200	-200	-200	-200	-92	...	-200	-200	-200	-200	-200	'2018-01-12T23:33:09.229000+00:00'	12	0.61	51.194252	4.418354
123527	-82	-200	-100	-200	-200	-200	-200	-109	-200	-200	...	-200	-200	-200	-200	-200	'2018-01-15T16:40:56.912000+00:00'	10	0.57	51.190994	4.449602

6. Experimental Analysis
6.3 Localization Error Comparison

	Prediction Errors (m)	
Localization Approach	Mean	Median
Random-Forest-based **RSSI-Weather data** Fingerprinting	**230**	**112**
KNN-based **RSSI-Weather data** Fingerprinting	263	137
Random-Forest-based **RSSI** Fingerprinting	273	165
KNN-based **RSSI** Fingerprinting [4]	301	185
TDoA-based Multilateration	732	765
Okumura-Hata model and **Range**-based Multilateration	1700	1080
COST-231 WI model and **Range**-based Multilateration	1583	896



FP-wx-RF: Random-Forest-Based **RSSI-Weather** data **Fingerprinting**

FP-wx-KNN: KNN-Based **RSSI-Weather** data **Fingerprinting**

FP-RF: Random-Forest-Based **RSSI Fingerprinting**

FP-KNN: KNN-Based **RSSI Fingerprinting**

TDoA Based Multilateration

PLM-OH: Okumura-Hata model and Range-based Multilateration

PLM-COSTWI: COST-231 Walfisch-Ikegami model and Range-based Multilateration

7. Summary

- Incorporation of meteorological data and use of random forest algorithm improves the RSSI fingerprinting results by **23%** (mean error from 301m to 230m)

- Better results can be expected in a denser networks
  - LoRaWAN networks are usually sparce (e.g. 72 gateway in 204km²: **One gateway per ~3km²** in the experimental network)
  - **2-5 per km²** urban full network rollout recommendation

- Sets up the ground to build our own campus LoRaWAN network for-
  - Granular and precise data collection and measurements
  - Make an opensource data model

8. References

[1] Indoor Positioning Systems: https://www.youtube.com/playlist?list=PLNgzB9uJ0Ss7jRwvl37mVCySnPo4HUtv7

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[3] Fargas, Bernat Carbonés, and Martin Nordal Petersen. "GPS-free geolocation using LoRa in low-power WANs." *2017 global internet of things summit (Giots)*. IEEE, 2017.

[4] Aernouts, Michiel, et al. "Sigfox and LoRaWAN datasets for fingerprint localization in large urban and rural areas." *Data* 3.2 (2018): 13.

[5] Sigfox and LoRaWAN Datasets for Fingerprint Localization in Large Urban and Rural Areas (zenodo.org)

[6] Open-Meteo, Available: https://open-meteo.com/en/docs/historical-weather-api

[7] "A Tutorial on 5G Positioning," in IEEE Communications Surveys \& Tutorials, doi: 10.1109/COMST.2024.3449031.

Q&A

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