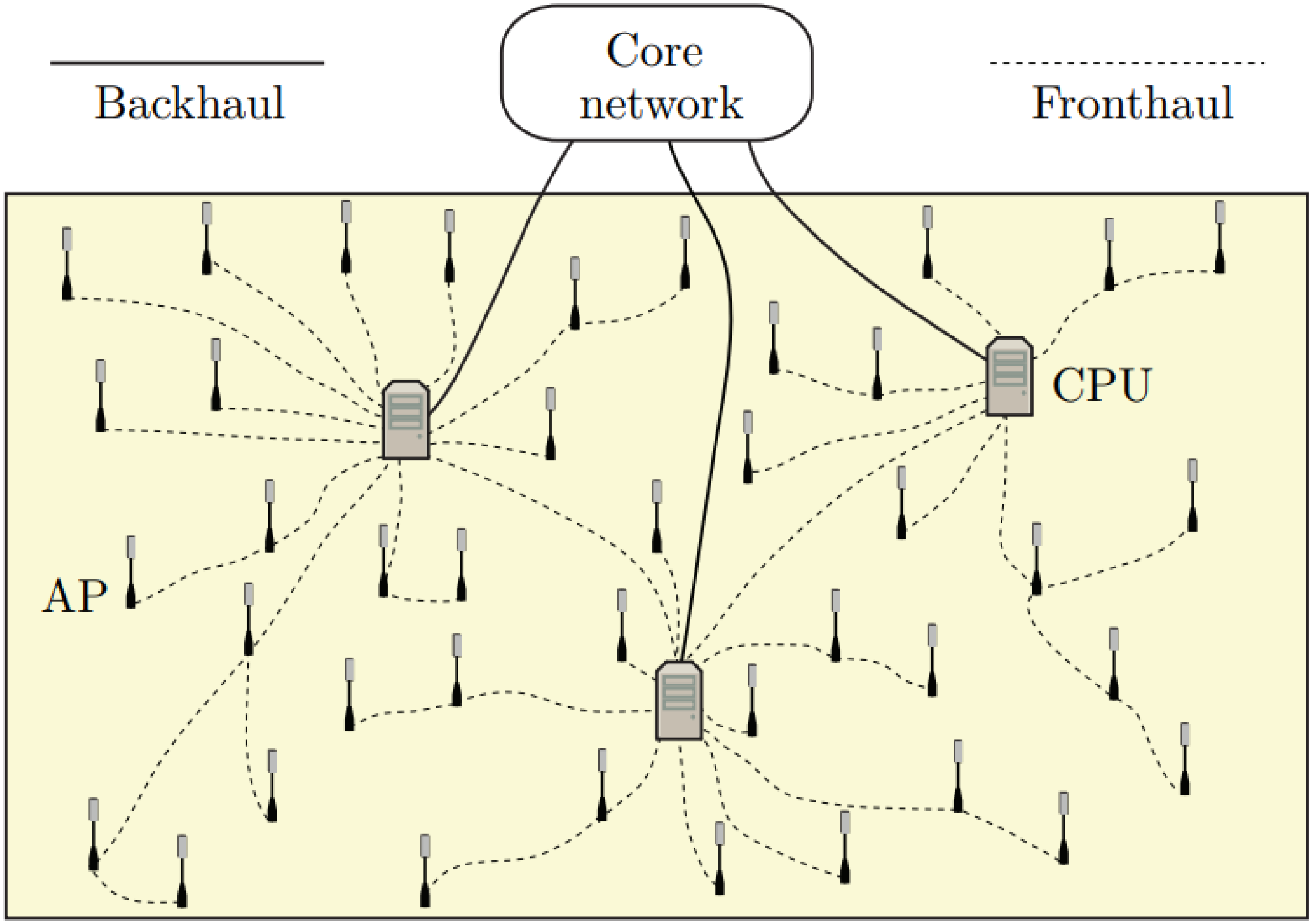
Dynamic Positioning in Outdoor Cellular Networks - A Hybrid Approach Integrating RSS Fingerprinting and RNN-Based Trajectory-Informed Positioning

Cell-free and Distributed MIMO

- Cell-free and distributed MIMO systems are futuristic cellular technologies
- Deployment of numerous access points (APs) across the network coverage area [18]
- Multiple APs serving a user equipment (UE) simultaneously
- Eliminates cell boundaries and serve a small number of users at the same frequency and time resources
- Offers a uniform SNR, higher throughput, interference management, power efficiency and macrodiversity

Cell Free Network



Possible Positioning Techniques

- Four main types of positioning [1]
    1. proximity-based
    2. angle-based
    3. range-based
    4. fingerprinting-based
- Proximity based positioning offer a rough estimate of the device's location based on its proximity to known base stations.
- Angle based techniques are prone to NLOS effects
- Range based positioning estimate UE position using trilateration
- Fingerprinting based positioning use measurements (called fingerprints) obtained at known positions within the deployment area

Received Signal Strength Based Positioning

- RSS of the UE at a specific point in the coverage area can be calculated by each of the AP [1-3]
- Centralized repository of RSS data stored for known locations within the network area
- This repository of RSS data serves as a robust fingerprint for precise location estimation
- Comparison of RSS readings from all APs at an unknown location against stored fingerprints
- Most papers use KNN, Gaussian Process Regression, SVMs and Neural Networks for RSS based fingerprint positioning

Neural Network based positioning approaches

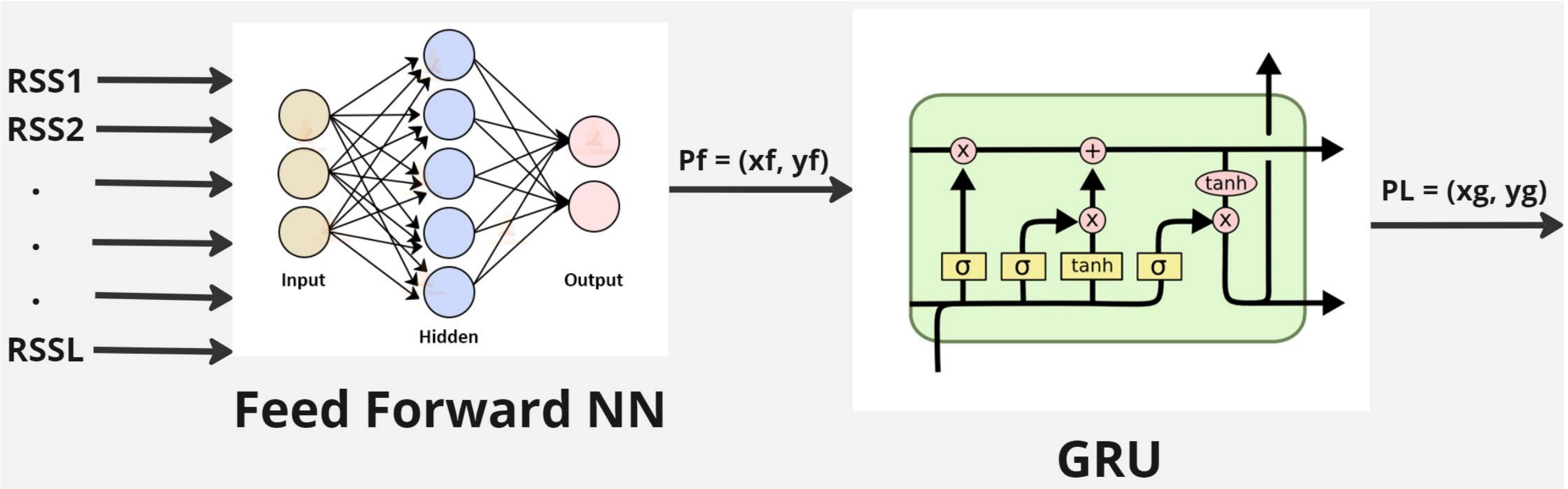
- Many models utilizing RNNs for predicting mobile users' positions over time have been proposed [5,6,11,14]
- [13] Enhances next location prediction by incorporating travel mode information using transformers
- [15] Utilizes Gated Recurrent Units (GRU) with RSS from a heterogeneous network for mobile positioning.
- [16] Predicts short-term travel time from GPS trace data using GRU.
- Many works focus exclusively on prediction with GPS data [8,10,16]
- An overview of various techniques, applications, and challenges in next location prediction can be obtained in [12]
- Many RNN based prediction approaches are based on variants of Long short-term Memory (LSTM) networks

Proposed RSS Fingerprinting Solution

- Current outdoor RSS fingerprinting solutions focus on static positioning
- They do not consider the UE's historical trajectory
- Propose a novel methodology leveraging past positional information.
- Aims to enhance positioning accuracy, especially for mobile UE scenarios.
- Two interconnected models:
    1. Traditional Feed Forward Neural Network (FFNN) model: Uses stored RSS fingerprints for static estimation
    2. Enhanced Recurrent Neural Network (RNN) model: Integrates past estimated locations for improved accuracy
- Incorporates tracking techniques using short-term historical data
- Addresses the dynamic nature of user mobility in outdoor cellular networks

Proposed RSS Fingerprinting Solution

- FFNN is dedicated to training with the RSS fingerprint
- It ultimately generates the static positioning coordinates (xf, yf) of the UE
- RNN processes user location information alongside timestamps of activities such as walking and driving
- The RNN refines the UE's current location based on past timestamps, handling the dynamic positioning aspect



Proposed RSS Fingerprinting Solution

- Gated Recurrent Unit (GRU) can capture the dynamics of the UE’s movement, including parameters such as speed, distance traveled, acceleration, and movement
- Role of GRU is to refine the initial estimates provided by the FFNN
- By analyzing how the FFNN output evolves over time, GRU continuously updates its estimation to provide a more accurate and reliable output
- This iterative process allows the system to adapt to changing movement patterns and environmental conditions

System Model

- Consider a D-MIMO system, with L RRUs, each equipped with a single antenna
- all RRUs synchronize their operations to serve K UEs within the network’s coverage area
- Fingerprint constructed using a known UE positioned at M predefined locations, forming $(M \times L)$ matrix of RSS values
- RSS fingerprint dataset is stored in the CPU
- This fingerprint dataset is used to train a FFNN to learn the RSS-distance relation
- When the RSS from an unknown location is obtained, the trained FFNN estimates the location

System Model

- Signal $y_{kl} \in C$ corresponding to UE k at AP l is given by

$$y_{kl} = \sqrt{\rho_k} h_{kl} + n_{kl} \quad \rightarrow \quad (1)$$

- Here
  - $n_{kl} \sim N_C(0, {\sigma_n}^2)$
  - ρ_k is the transmit power of UE k
- h_{kl}, the channel coefficient, characterized using an uncorrelated Rayleigh fading model, i.e.

$$h_{kl} \sim N_C(0, R_{kl}) \quad \rightarrow \quad (2)$$

- $R_{kl} = \beta_{kl} \in R$ denotes the diagonal spatial correlation matrix
- RSS is calculated as

$$E\{\|y_{kl}\|^2\} = E\left\{\left\|\sqrt{\rho_k} h_{kl} + n_{kl}\right\|^2\right\} = \rho_k \, \beta_{kl} + {\sigma_n}^2 \quad \rightarrow \quad (3)$$

- Thus RSS is proportional (in log scale) to the path loss

System Model

- For β_{kl}, the large-scale fading coefficient, a log-distance path loss model is adopted i.e.

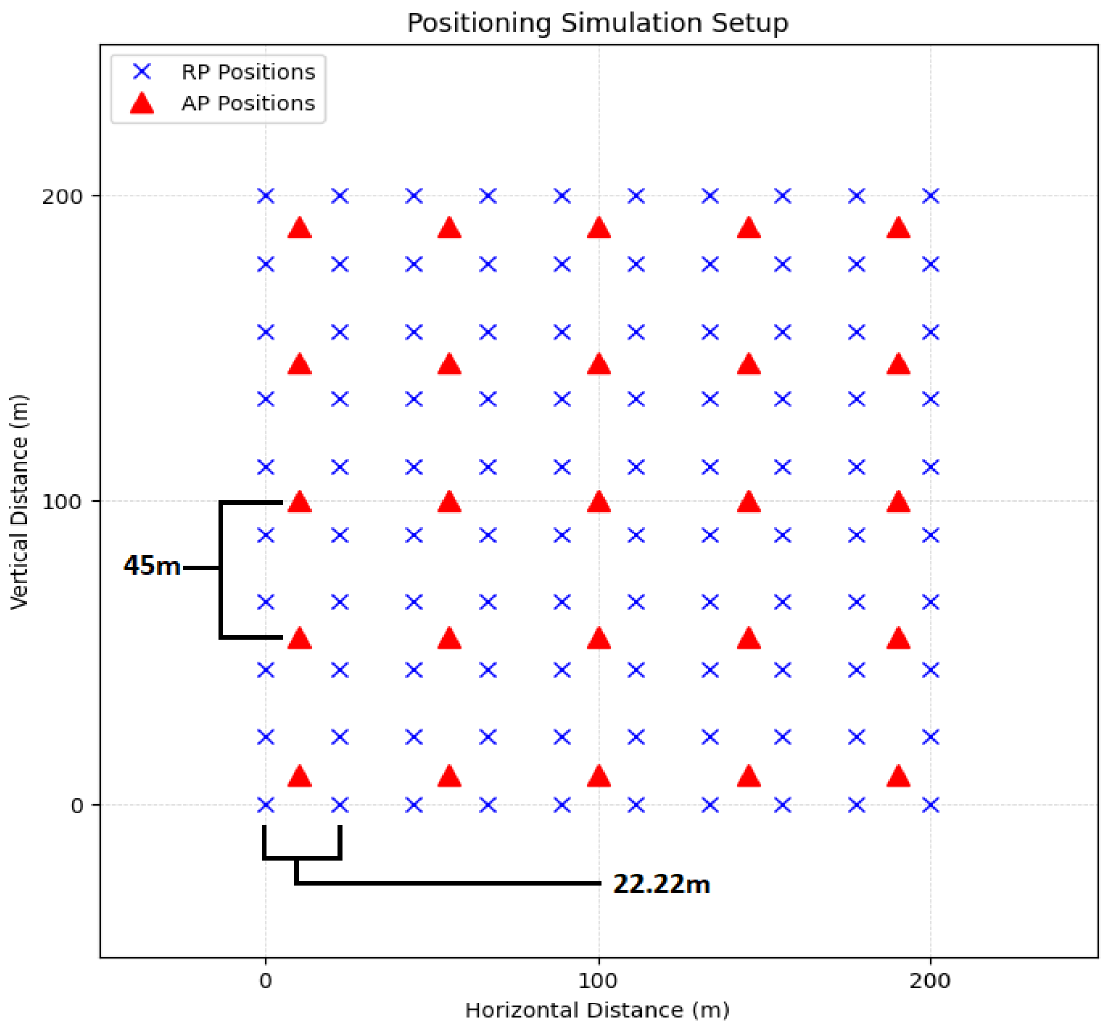
$$\beta_{kl} = -28.8 - 35.3 \log_{10}\left(\frac{d_{kl}}{1m}\right) + \vartheta \quad \rightarrow \quad (4)$$

Here

- d_{kl} is the three dimensional distance between UE k at AP l
- $\vartheta \sim N\left(0, {\sigma_{SF}}^2\right)$ is the shadowing noise

- The shadowing terms from an AP to distinct location points in the network area is correlated as
- $E\{\vartheta_{ml}\vartheta_{ij}\} = \begin{cases} {\sigma_{SF}}^2 * 2^{-\frac{d_{mi}}{d_{corr}}} & - \quad if\ l = j \\ 0 & - \quad otherwise \end{cases} \quad \rightarrow \quad (5)$
- Here
  - ϑ_{ml} is the shadowing from AP ℓ to location point m
    d_{mi} is the distance between locations i and m
  - d_{corr} is the decorrelation distance that is characteristic of the environment

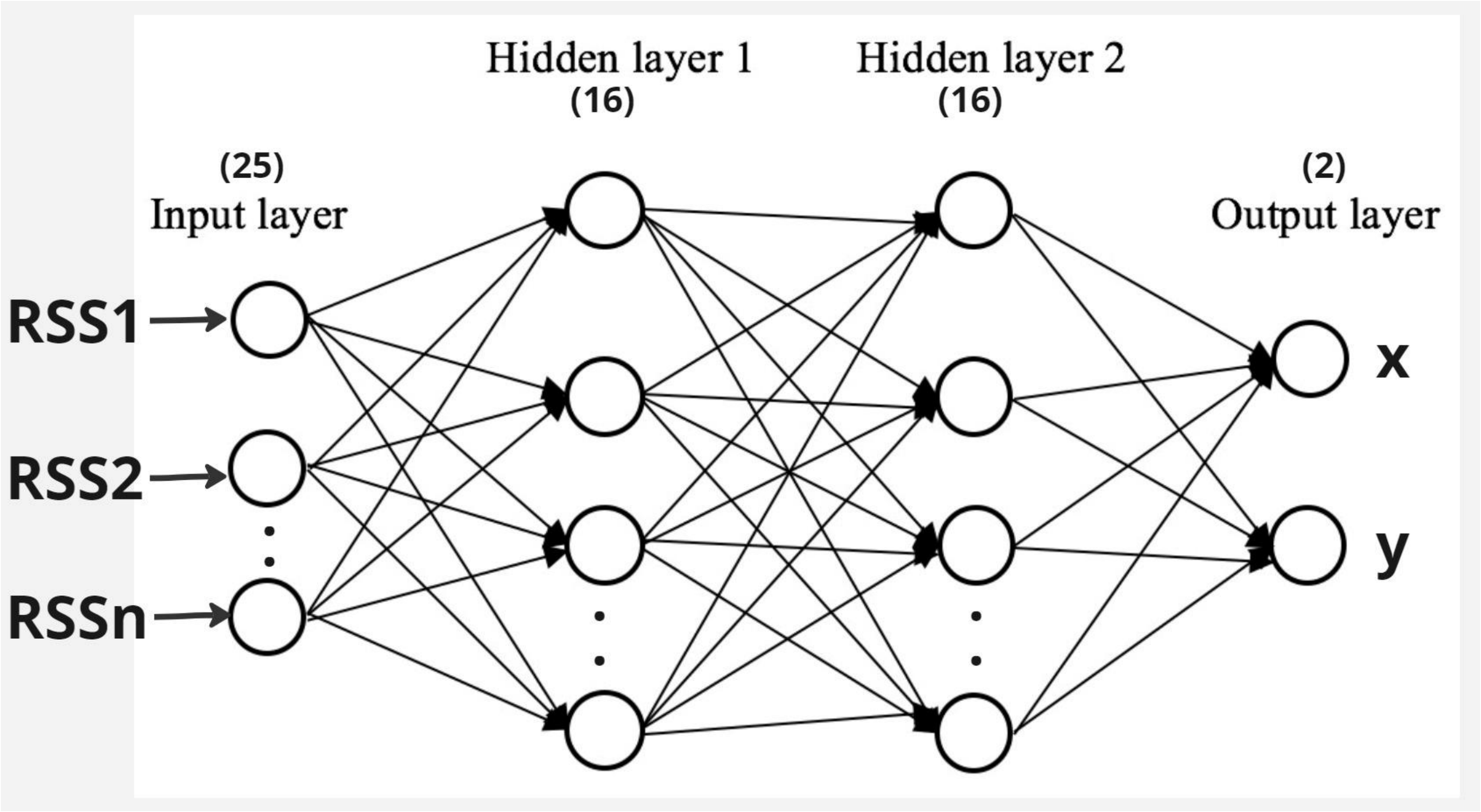
Simulation Setup



Feed Forward Neural Network (FFNN)

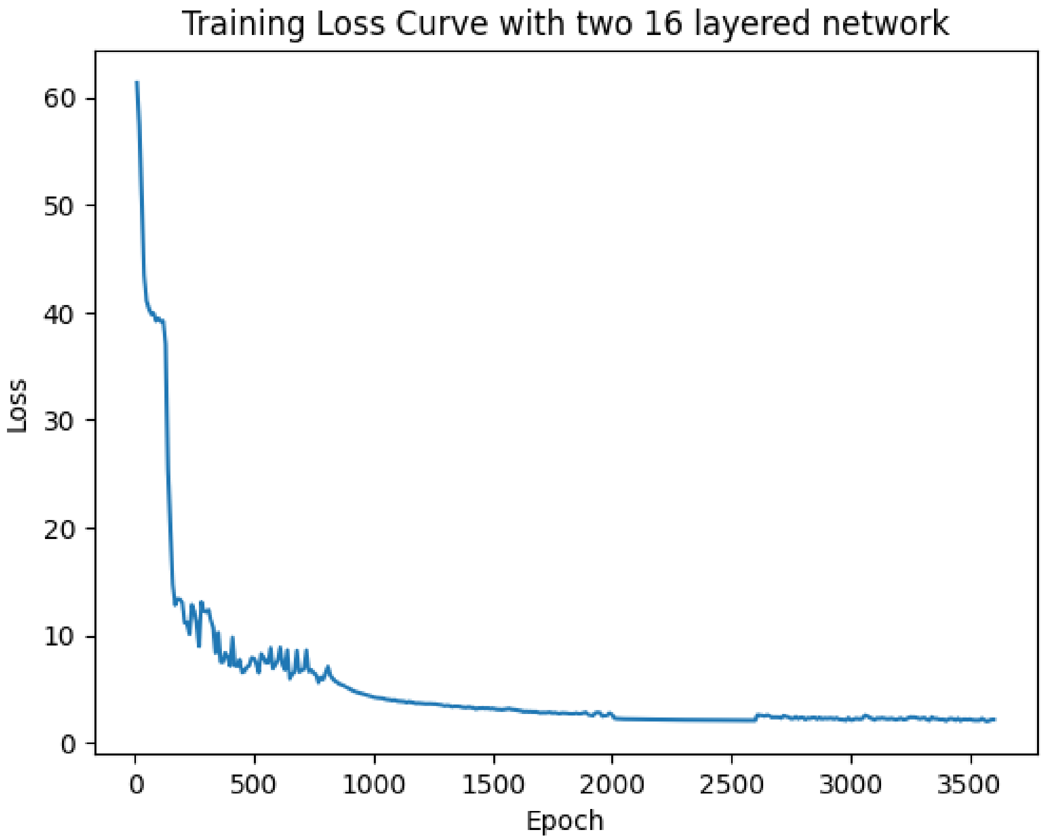
- M RSS vectors, each of size L, each associated with its corresponding position (x_i, y_i) = $f_\theta(RSS_i)$, i = {1, 2, ... ,M} collectively form the training dataset for the FFNN
- RSS_i is a (1xL) vector and θ represents the adjustable parameters of the network
- Through this training process, the neural network becomes learns to map RSS to their respective positions
- FFNN consists of an input layer, two hidden layers, and an output layer
- The input layer has 25 nodes, corresponding to RSS values from 25 Aps
- 2 hidden layers, each with 16 nodes were considered
- A Leaky ReLU activation function is applied after each linear transformation
- The output layer, is two nodes and corresponds to the predicted x and y coordinates of the target location

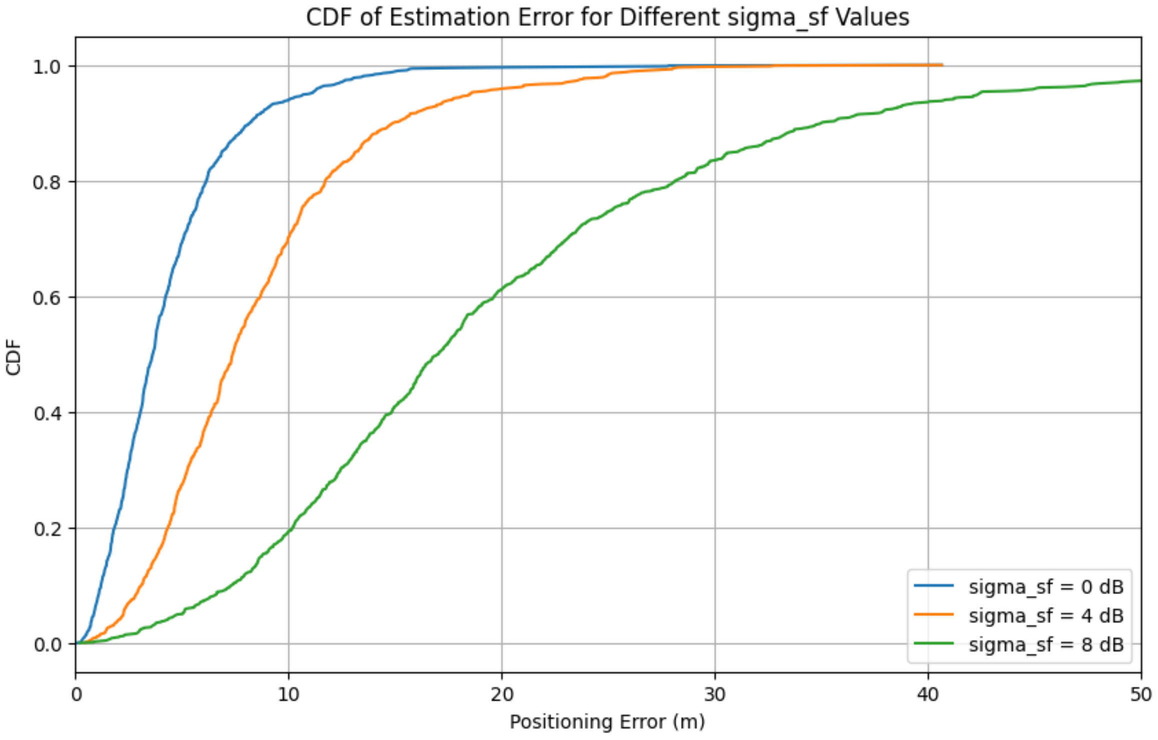
FFNN Architecture



FFNN Training

- Euclidian distance is used as loss function
- The Adam optimizer is chosen to optimize the parameters of the neural network
- Adam is a popular choice due to its adaptive learning rate capabilities
- The learning rate α = 0.001, first moment β_1 = 0.9 and second moment β_2 = 0.999 (hyperparameters)
- Within each epoch, the loop iterates over the training data batches, computes the loss, performs backpropagation, and updates the model parameters

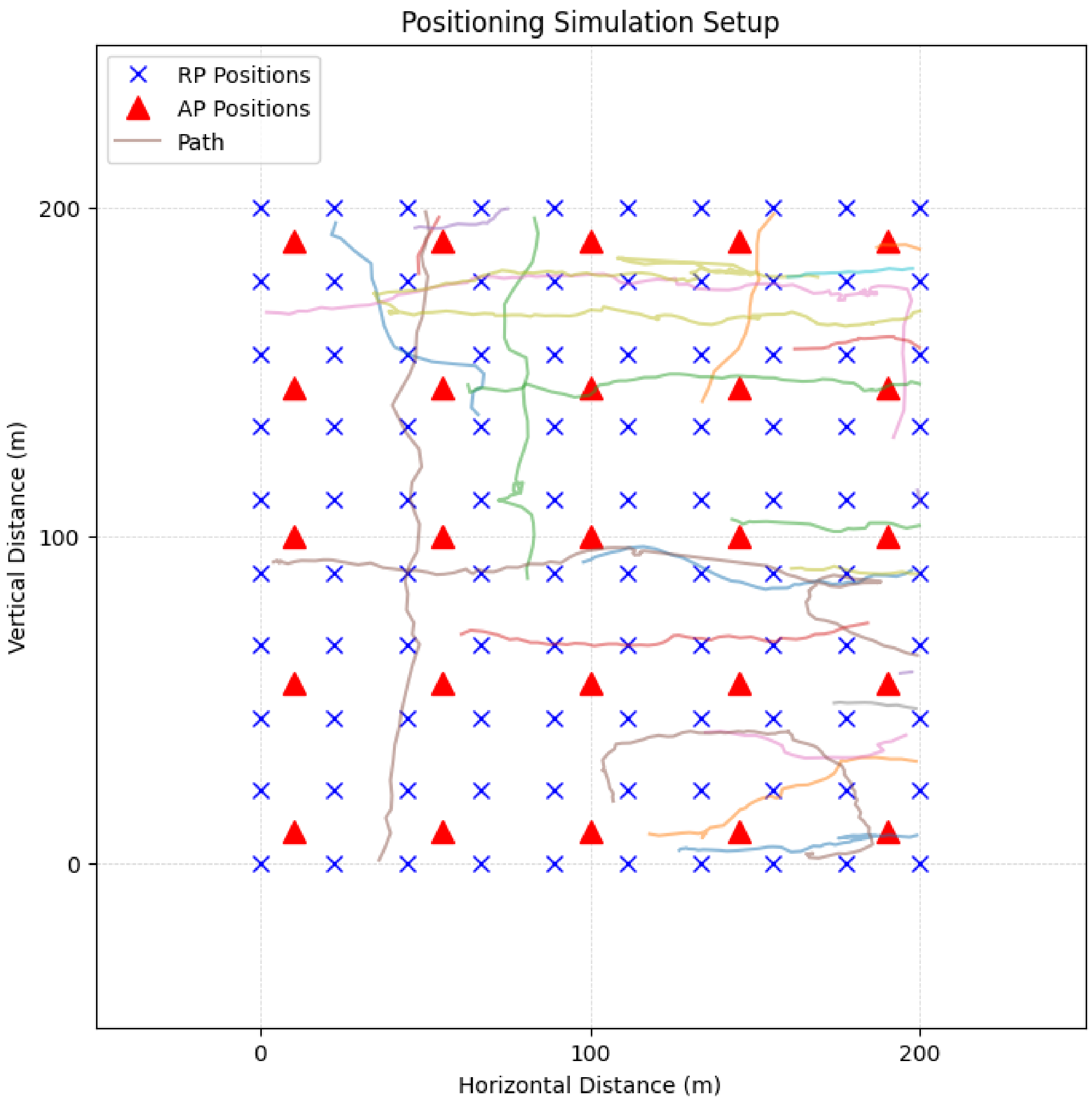

Training Loss Curve with two 16 layered network
Loss
Epoch
0
10
20
30
40
50
60
0
500
1000
1500
2000
2500
3000
3500


CDF of Estimation Error for Different sigma_sf Values
CDF
Positioning Error (m)
sigma_sf = 0 dB
sigma_sf = 4 dB
sigma_sf = 8 dB
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40
50

Geolife GPS trajectory dataset

- RNN (GRU) was trained with the Geolife GPS trajectory dataset [4]
- Geolife GPS trajectory dataset is provided by Microsoft
- A GPS trajectory is represented by a sequence of time-stamped points, containing the information of latitude, longitude and altitude
- Contains 17,621 trajectories with a total distance of about 1.2 million kilometers
- These trajectories were recorded by different GPS loggers and GPS-phones
- This dataset recoded a broad range of users' outdoor movements
- About 1000 paths of two activities walking (~350) and biking were collected (~700) and overlaid onto the simulation area

GPS Trajectory Data Overlaid onto the Simulation Setup

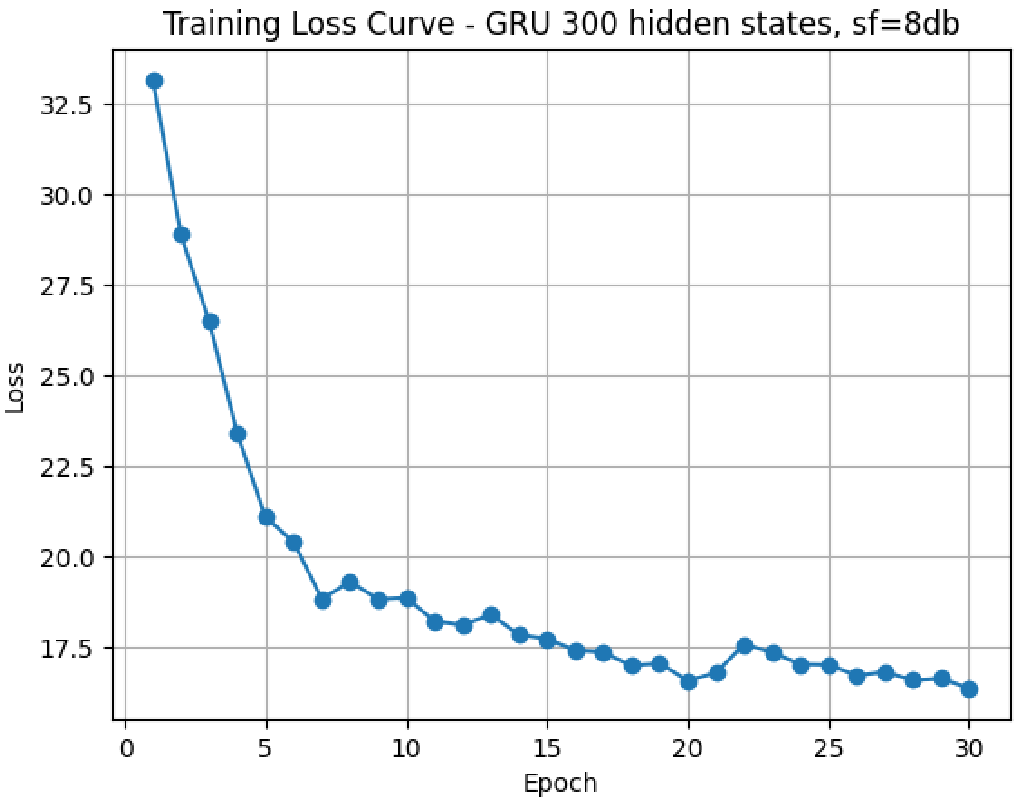


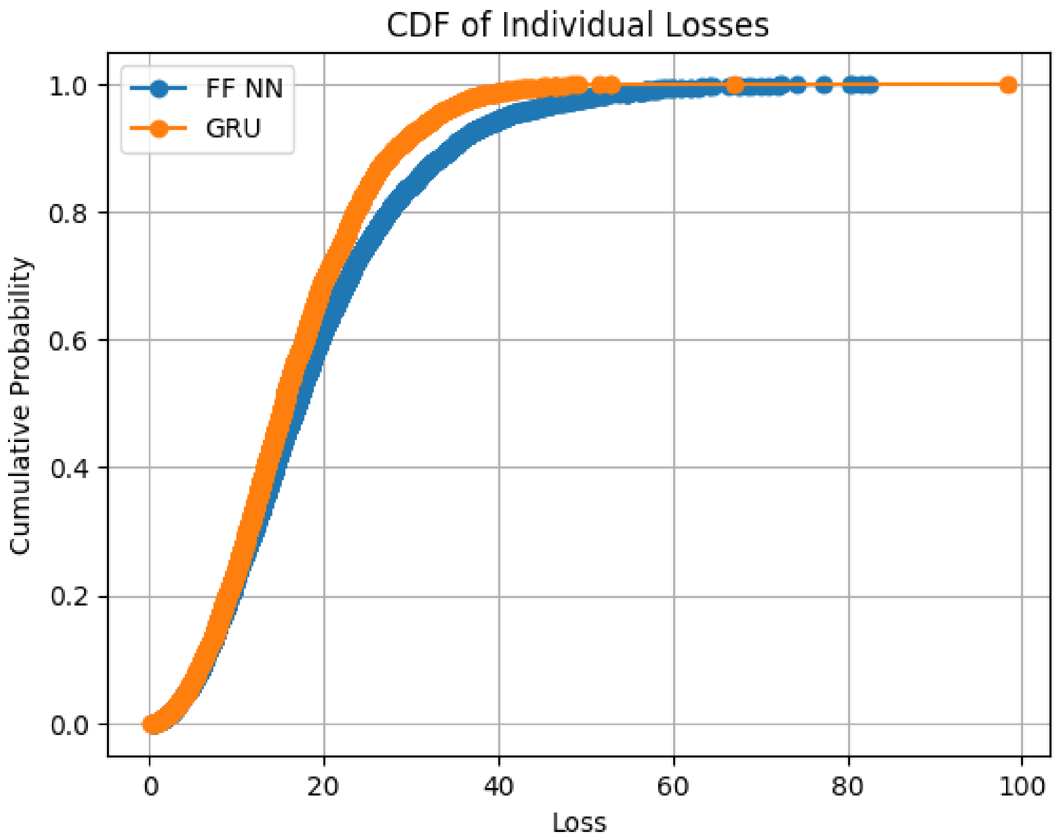
Gated Recurrent Unit

- GRU is a type of RNN that is designed to address the vanishing gradient problem and long-term dependency issue in traditional RNNs
- It consists of a series of repeating units, each with a hidden state
- The key components of a GRU unit include a reset gate and an update gate
- Gates allow selective update of information
- GRU is trained using backpropagation through time (BPTT)
- GRU has been widely used in various natural language processing (NLP) tasks, time series prediction, speech recognition, and other sequential data tasks

Gated Recurrent Unit

- GRU architecture comprising 5 input layers and 300 hidden states was utilized (~300K parameters)
- The GRU output is fed into a fully connected layer, producing a 2-node output
- These 2 nodes represent the corrected estimates of the x and y coordinates from the FFNN output
- The training dataset was constructed with a window size of 5
- Each dataset entry includes 5 pairs of estimated (x, y) coordinates from the preceding FFNN as input
- The target labels (Y) correspond to the actual (x, y) coordinates from the overlaid path
- Higher shadowing (8dB) demonstrated superior performance with the GRU model
- Lower shadowing (4dB) exhibited reduced average test error compared to the FFNN model


Training Loss Curve - GRU 300 hidden states, sf=8db
Loss
Epoch
32.5
30.0
27.5
25.0
22.5
20.0
17.5
0
5
10
15
20
25
30


CDF of Individual Losses
Cumulative Probability
Loss
FF NN
GRU
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100

Future Directions and Challenges

- Exploration of other models such as LSTMs, Transformers, or hybrid architectures to compare their performance with the GRU model
- Extension of the task to classification, where the goal is to predict the type of motion of the UE based on its trajectory
- Implementation of predictive modeling to forecast the UE's location at future time instances
- Predictive modeling enables the provision of location-based services and facilitating handoff preparations in cellular networks.
- Addressing challenges associated with scaling up the simulation area and overlaying data collected over millions of kilometers onto a smaller simulation area
- This may involve techniques for data preprocessing, dimensionality reduction, or data augmentation

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