# Predicting User Location Using Generative Models in RIS-Enabled 6G Network

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***Abstract*—The paper explores the utilization of Reconfigurable Intelligent Surfaces (RIS) as a novel approach in a 6G network. RIS is a powerful method that controls the propagation environment by adjusting incident signals and presents a cost-effective and energy-efficient alternative to complex and expensive Multiple Input Multiple Output (MIMO) systems. The work proposes a deep learning-based prediction framework that includes a Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM), and Transformer networks to predict user locations in real-time, enabling RIS to proactively enhance signal delivery. The choice of these specific models is rooted in their distinctive capabilities to process sequential data and their varying architectural strengths in capturing long and short-term dependencies. GRU and LSTM, both recurrent neural networks, offer nuanced approaches to temporal data processing. GRU simplifies the model architecture by using fewer gates compared to LSTM, making it more efficient for certain tasks, while LSTM's design allows for better handling of long-range dependencies at the cost of increased complexity. On the other hand, Transformers, eschewing recurrence entirely for a purely attention-based mechanism, demonstrate superior performance in parallelizing operations and managing long-range dependencies across sequences, a pivotal feature for real-time user location prediction in dynamic 6G environments. Our comparative analysis showcases the efficacy of Transformers in achieving a significantly lower Mean Absolute Error (MAE) in user location prediction, followed by GRU and LSTM. This study not only elucidates the distinct advantages of employing these models in a 6G context but also sets a foundation for future explorations into advanced deep learning architectures for wireless communication enhancements.**

***Index Terms*—6G, mmWave, THz networks, RIS, GRUs, Transformers, LSTM**

## I. Introduction

Recently, wireless network data traffic has increased significantly due to technological advancements such as autonomous driving, the Internet of Things (IoT) from 6G, and virtual/augmented reality (VR/AR). The integration of mmWave (Millimeter Waves) technology in 5G networks has addressed the spectrum scarcity prevalent in existing 4G cellular networks, which generally operate at frequencies below 6 GHz, yet new applications, yet to be developed, will require latency levels and data rates above what 5G networks already offer [1]. However, achieving substantial data rate improvements in mmWave communications presents significant challenges, which are primarily due to the increased vulnerability of mmWave signal propagation to obstructions and the significant training overhead required for fine-tuning the beamforming vectors of large mmWave arrays. To address this challenge and meet this demand, THz communication is considered a vital technology for wireless communication, addressing spectrum scarcity and capacity limits in present wireless systems [2]. THz band is a high frequency segment of the electromagnetic spectrum that ranges from around 100 GHz to 10 THz. This range is being evaluated for integration with 6G communication technology. [3]. Although 6G wireless networks have considerable advantages, they also come with some limitations such as path loss and attenuation due to molecular absorption [4]. Furthermore, the non-line-of-sight (NLoS) region has less coverage by THz signals [5]. Common solutions largely focus on enhancing network transmitter and receiver components to address this challenge, which includes measures such as deploying high gain antennas, applying beamforming structures, using cognitive modulation, and developing distance adaptive waveforms [6], but these are constrained by the progress in developing robust THz sources and detectors. Some methods used that mitigate these restrictions include highly directional antennas, multi-hop relaying, and adaptive beamforming [7]. The use of RIS in wireless systems has prominently addressed the coverage and spectrum scarcity issue [8]. It is an array of reflective elements that can reconfigure incident signals. Furthermore, the absence of Radio Frequency (RF) chains makes it more energy efficient and cost-effective [9]. It has been incorporated in many domains ranging from improving latency to power transfer (SWIPT) networks [10] to Mobile Edge Computing [11]. The authors in [12] on the optimization of parameters associated with RIS, encompassing aspects such as positioning, sub-channel allocation, and phase shifts. Furthermore, RIS can be integrated to enhance the communication capabilities of unmanned aerial vehicles (UAVs). Typically, UAVs face challenges with weak signal strength in cellular communication, as base station antennas are often down-tilted and optimized to serve ground users. Ding et al. [13] fine-tuned the phase shifts of the RIS to direct the reflected signal toward the UAV, aiming to maximize the incident signal power. In [14], the author presents a deep learning approach that uses historical drone location and beam trajectory data, this approach calculates the serving beam for each drone and serving base station/RIS.

The following are the main contributions;

- We employ GRU, LSTM, and transformer models to forecast user locations based on their real-time locations. This enables RIS to anticipate user positions and deliver signals in advance, ensuring seamless connectivity.
- Performance analysis and comparison of trained models on test dataset.

## II. Literature Review

The expected ability of 6G networks to support transmission speeds of up to one terabit per second (Tbps) is a crucial aspect of this evolution [15]. The anticipated sub-millisecond latency in 6G networks is essential for real-time communication applications, especially in autonomous vehicles [16]. Immediate data processing and decision-making are imperative for safety and operational efficiency as they help in making real-time decision-making [17]. This will facilitate the seamless integration of many vehicles and infrastructure devices, paving the way for a more cohesive and responsive transportation ecosystem [18]. While existing research has primarily focused on the performance of RIS-assisted systems in terms of data rate, coverage, and energy efficiency, there is still a significant knowledge gap in understanding these systems, particularly in their deployment and functioning within 6G networks [19]. In [20], the author introduces DeepIA, a deep learning solution designed to deliver speedy, and reliable initial access (IA) in mmWave networks in 5G systems. A further exploration of this research was presented, involving the application of DeepIA to 6G millimeter waves [21]. In both LoS and NLoS conditions, DeepIA demonstrates reduced IA time and improved beam prediction accuracy compared to conventional methods. To mitigate the issue of sensitivity in millimeter waves, a novel solution using machine learning in mmWave Multiple Input Multiple Output (MIMO) systems was proposed [22]. In this approach, base stations learn to predict potential link blockages by observing adopted beamforming vectors. In [23], the optimal linear precoder (OLP) achieves the minimum signal to interference noise ratio (SINR) within a certain limitation for various circumstances. The authors in [24] presented to achieve joint design through experimental interactions with the environment. The author in [25] assessed the use of the THz band for ISLs, computed the influence of misaligned fading on error performance. In [26], the authors introduce a sample network framework named Quan-Transformer for compressing and reconstructing Channel State Information (CSI). This enhances the performance of RIS-aided wireless communication systems. The author in [27] presents a RIS assisted sensing system based on transformer models namely WiRiS. By configuring the RIS, the system predicts the number of people and their locations. In conclusion, while the existing literature provides a robust foundation for understanding the role and potential of RIS in enhancing 6G vehicular networks, it is crucial to address the identified gaps. Doing so will not only contribute to the full potential of RIS capabilities in these advanced wireless systems. Still, it will also ensure that the transition to 6G vehicular networks is marked by enhanced performance, security, and user trust.

## III. Generalized System model

In the context of emergency response, the use of unmanned aerial systems (UAS), also known as drones, has become increasingly important for providing real-time data and improving situational awareness. Drones can be used in various scenarios, such as wildfire management, search and rescue operations, and post-fire assessment [28]. A flying Reflective Intelligent Surface (RIS) drone with reflectors can help maintain signal strength and provide reliable communication between the base station and the fire brigade navigating through challenging terrain with obstacles and weak signals [29] . The use of deep learning models can enhance the dynamicity of this process by predicting user locations [29].The advantages of using drones in emergency response and firefighting operations include improved efficiency, cost-effectiveness, and increased safety for responders. Drones can quickly reach challenging areas, gather real-time data on fire behavior, and provide valuable insights for resource allocation, evacuation, and firefighting strategies [30] . They can also facilitate communication and coordination among teams, especially in remote or disaster-stricken locations where communication infrastructure might be damaged or non-existent [30] . In terms of policy, it is crucial to regulate the use of drones near wildfires and other emergency situations to prevent interference with firefighting efforts and ensure the safety of both responders and the public. Policies in the United States, Canada, and Australia discourage the use of public drones near wildfires, and specific guidelines are in place for media personnel and other authorized users [28] . In conclusion, the proposed approaches using flying RIS drones with reflectors and deep learning models can be effective in various scenarios, including wildfire management and other emergency response situations. These methods can improve situational awareness, communication, and safety, ultimately leading to more efficient and effective firefighting operations.

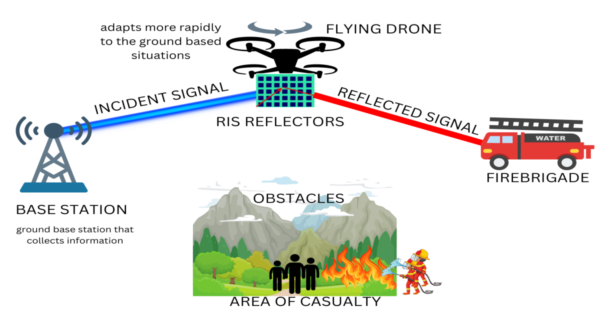


Fig. 1. Advanced RIS enhanced aerial communication relay for optimized signal propagation in emergency response scenarios in 6G network

**Algorithm 1** Location Prediction using Deep Learning

**Inputs:**

*Script to generate dataset*: A tool that makes a dataset.
*Number of training rounds*: How many times the model learns from the dataset.

**Main Steps:**

Run the script to make a dataset.
Look at the dataset, which has user coordinates (like latitude and longitude).
Divide the dataset into parts for training and testing.
Create a special type of computer program called a model.
**for** each round of training **do**
    Teach the model using the training part of the dataset.
    Check how well the model learns by testing it on a different part of the dataset.
**end for**
Use the model to guess where users are in the testing dataset.
Measure how close the guesses are to the real locations.
Show the guesses on a map or in a 3D view.

## IV. Methodology

In the following section, we provide a detailed discussion of the employed methodology, encompassing the dataset acquired from the deepmimo website [31]. We explore two distinct approaches as shown in Figure. 2. Additionally, we elaborate on the deep learning models implemented in our research.

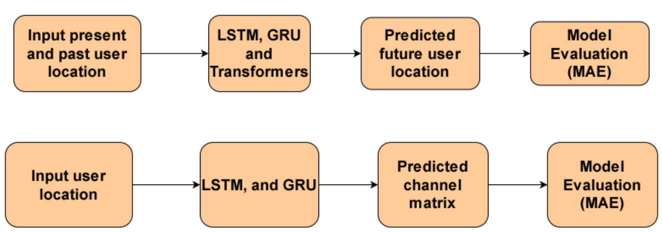


Fig. 2. Flow Diagram for user location prediction

### A. Dataset

We acquired the specialized THz drones with the flying RIS dataset from the DeepMIMO dataset repository, specifically targeting their THz drones with the Flying RIS scenario [31]. This dataset includes critical parameters such as locations, line of sight, path loss, and signal frequency for deep learning applications, these parameters fit our analytical models, laying the groundwork for our research. Based on these parameters we have designed our deep learning models to adapt to the dynamically changing aspects of data which is crucial for a deeper and more accurate prediction of wireless network behavior. Certain parameters were selected for dataset generation as depicted in Table. I.

TABLE I
DATASET GENERATION PARAMETERS.

| Parameter | Tower | RIS |
|---|---|---|
| Active BS | 1 | 1 |
| First User (active) | 1 | 1 |
| Last User (active) | 1 | 1 |
| Number of antennas (x,y,z) | (1, 8, 4) | (1, 4, 2) |
| Antenna spacing | 0.5 | 0.5 |
| Center Frequency | 0.05 GHz | 0.05 GHz |
| Bandwidth | 0.05 GHz | 0.05 GHz |
| Total OFDM subcarriers | 512 | 512 |
| OFDM limit | 64 | 64 |
| OFDM sampling factor | 1 | 1 |
| OFDM channels | 1 | 1 |
| Total paths | 5 | 5 |

### B. User Location Prediction

Let $\mathcal{L}$ represent the dataset comprising user location data in the form of sequential 3D coordinates $(x_t, y_t, z_t)$, where $t$ ranges from 1 to 544, indicating the time sequence. This dataset can be described as:

$$\mathcal{L} = \{(x_t, y_t, z_t) \mid t = 1, 2, \ldots, 544\} \tag{1}$$

For the prediction of the user location using LSTM, GRU, and Transformers. The future location $(x_{t+1}, y_{t+1}, z_{t+1})$ is predicted based on the current and past locations. This prediction can be represented by an equation as follows:

$$\hat{x}_{t+1}, y_{t+1}, z_{t+1} = f((x_t, y_t, z_t); \alpha) \tag{2}$$

Here, $\hat{y}_{t+1}$ denotes the predicted future location at time $t+1$, $f(\cdot)$ is the prediction function modeled using applied deep neural network with learned parameters $\alpha$, and $(x_t, y_t, z_t)$ is the actual location input at time $t$.

The trained model is tested and the performance of the LSTM, GRU, and Transformer models is evaluated using the Mean Absolute Error (MAE) [32], which shows the average values of errors in a series of predictions. The MAE is defined as:

$$\text{MAE} = \frac{1}{N} \sum_{t=1}^{N} |\hat{y}_{t+1} - y_{t+1}| \tag{3}$$

Total number of predictions denoted by $N$, $\hat{y}t + 1$ is the predicted future location, and $yt + 1$ is the actual future location for the $t + 1$-th time step. A lower MAE value indicates better predictive performance, as it reflects a smaller average error in the location predictions.

The dataset can be written as:

$$\mathcal{D} = \{C_k, (x_k, y_k, z_k) \mid k = 1, 2, \ldots, 544\} \tag{4}$$

where $C_k$ is the channel matrix of the $k$-th sample.

In our prediction model, we have only considered the real part of each channel matrix, denoted as $\Re(C_k)$ as labels, along with the user location coordinates $(x_k, y_k, z_k)$. The predictive function for both LSTM and GRU models at sample $k$ can be expressed as:

$$\hat{\Re}(C_k) = f(;x_k, y_k, z_k\beta) \tag{5}$$

where $\Re(C_k)$ is the predicted channel matrix for the $k$-th sample, $f(\cdot)$ is the predictive function modeled by either an applied deep neural network with parameters $\beta$.

### C. Deep Learning Models

Our methodology comprises the implementation of the following deep-learning models. The hyper-parameter set for the models is shown in Table. II.

*1) Gated Recurrent Unit (GRU):* GRUs are a gating mechanism used in recurrent neural networks introduced by Cho et al. [33] in 2014. In our wireless communication context, the GRU is specifically tasked with managing the dynamic aspects of the data, such as the immediate correlation between location changes and channel conditions.

*2) Long Short-Term Memory (LSTM):* The vanishing gradient problem was solved by LSTM Network which is a type of RNN. Hochreiter and Schmidhuber [34] initially introduced it in 1997. Unlike a traditional recurrent unit that replaces its content with each time step, an LSTM unit can decide whether to retain current memory by incorporating gates. This enables it to excel at identifying potential long-distance dependencies.

*3) Transformers:* Transformers are sequence-to-sequence deep learning architecture introduced in 2017 in the paper ”Attention is all you need” [35]. It has a multi-head attention mechanism with no recurrent unit which results in faster training than existing recurrent neural architectures such as LSTM and GRU. It operates based on the tokenization of input data principle, in which each token is contextualised through the use of the multi-head attention feature.

TABLE II
HYPERPARAMETERS OF GRU, LSTM, AND TRANSFORMER MODELS

| **Hyperparameter** | **GRU** | **LSTM** | **Transformer** |
|---|---|---|---|
| Number of RNN Layers | 2 | 2 | - |
| Units in First Layer | 20 | 20 | - |
| Units in Second Layer | 20 | 20 | - |
| Dropout Rate | 0.2 | 0.2 | 0.1 |
| Recurrent Dropout Rate | 0.2 | 0.2 | - |
| Dense Layer Units | 256 | 256 | 256 |
| Activation (Dense Layer) | ReLU | ReLU | ReLU |
| Output Units | 3 | 3 | 3 |
| Output Activation | Linear | Linear | Linear |
| Optimizer | Adam | Adam | Adam |
| Training Epochs | 280 | 250 | 220 |
| Batch Size | 32 | 32 | 32 |
| Validation Split | 10% | 10% | 10% |
| Test Split | 30% | 30% | 30% |
| Random State | 42 | 42 | 42 |
| Embedding Dimension | - | - | 32 |
| Number of Attention Heads | - | - | 2 |
| Feed Forward Network Dimension | - | - | 32 |

### D. Model Performance Metrics

## V. RESULTS

This section presents the key outcomes from our research. After the training of GRU, LSTM and Transformer models, the training and validation loss and MAE are plotted as depicted in Figure 3. **Comparative Analysis**

TABLE III
PERFORMANCE METRICS OF DIFFERENT MODELS

| blue!20**Metrics** | **GRU** | **LSTM** | **Transformers** |
|---|---|---|---|
| Time taken for training | 34.28 seconds | 35.63 seconds | 27.62 seconds |
| Time taken for prediction | 1.07 seconds | 0.87 seconds | 0.62 seconds |
| Memory usage in training | 605.07 MB | 521.58 MB | 495.48 MB |
| Memory usage in prediction | 607.69 MB | 526.43 MB | 495.89 MB |
| Mean Absolute Error | 0.79 | 0.79 | 0.32 |

1) **Time Efficiency:** The Transformers model outperforms both GRU and LSTM models in terms of training and prediction time, being the fastest among the three.
2) **Memory Usage:** The Transformers model also shows lower memory usage during both training and prediction compared to GRU and LSTM models, indicating better memory efficiency.
3) **Model Accuracy:** The Transformers model exhibits a significantly lower Mean Absolute Error (MAE) of 0.32, suggesting better predictive accuracy compared to GRU and LSTM models with an MAE of 0.79.

Based on the comparative analysis, the Transformers model emerges as the most efficient and accurate model among GRU, LSTM, and Transformers. It demonstrates superior performance in terms of time efficiency, memory usage, and predictive accuracy.

To predict the future user location we have utilized the deep learning models Transformers, LSTM, and GRU. We have extracted the values (x, y, z ), since the model accepts sequential data, we have concatenated the values of y and z. we have a total of 544 samples under which the data is split. To carry out the prediction we split the dataset into two parts the first part which is 70% of the data is our training data on which the model trains itself, the remaining 30% is our testing data. After the training of GRU, LSTM, and transformer models, the training and validation loss and MAE are plotted as depicted in Figure 3. It shows how both losses evolve through training, aiming for a decrease in both, particularly the validation loss, which indicates the model's performance on unseen data. The validation loss shows some fluctuations but generally aligns with the decreasing trend of the training loss, which shows that there is no overfitting of the model. The training MAE for Transformer starts at around 0.14 and decreases to about 0.07, while the validation MAE starts slightly higher but decreases following a similar trend to the training MAE. This downward trend in MAE suggests that the model's predictions are becoming closer to the true values as training progresses. All the models performed considerably well, but among the three models, the transformer has the lowest MAE as shown in Table. IVshowcasing its ability to accurately predict future user location using the present user location.

Fig. 4 displays a 3D scatter plot comparing the performance of three different deep learning models: GRU, LSTM, and Transformers, in predicting user locations. The actual locations

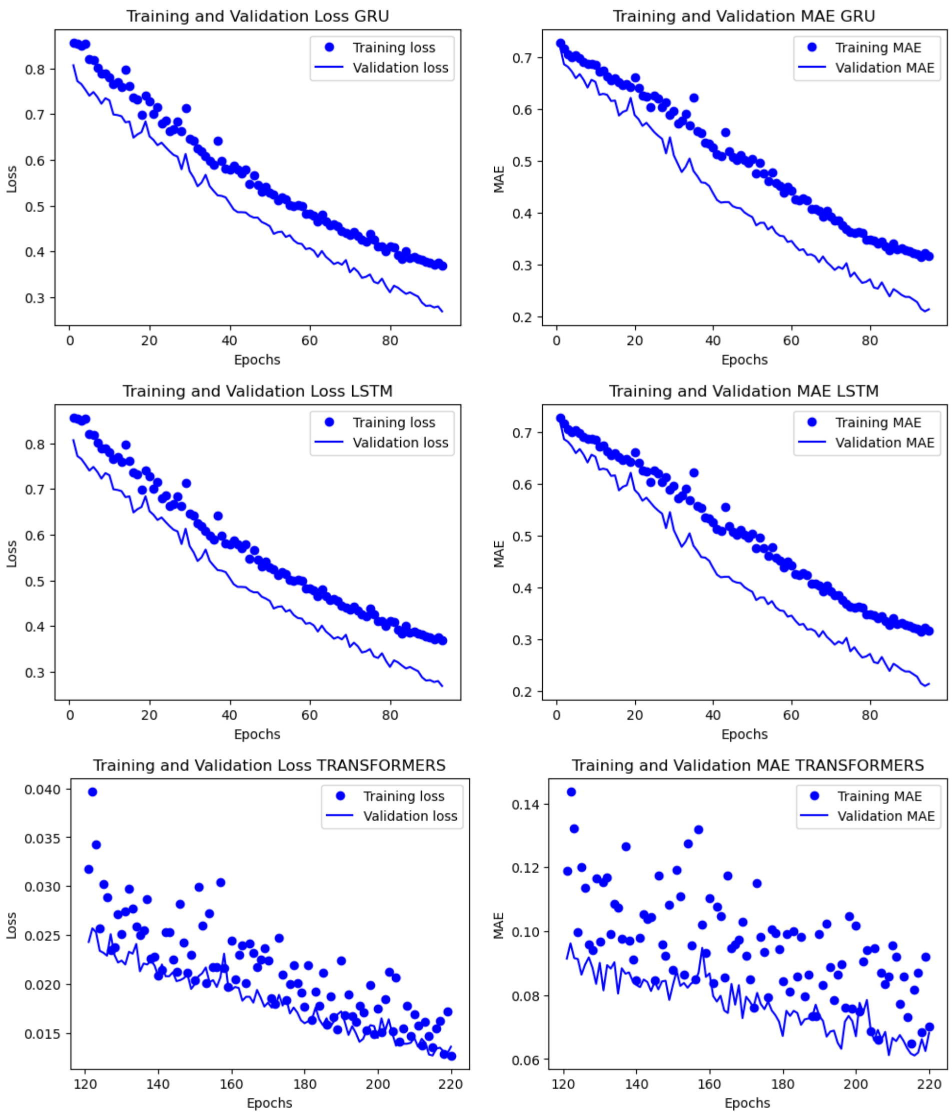


Fig. 3. Training and Validation Loss, MAE for Deep Learning models

TABLE IV
PERFORMANCE METRICS OF GRU, LSTM, AND TRANSFORMER MODELS FOR USER LOCATION PREDICTION

| Model | Training Loss | Validation Loss | Test MAE |
|---|---|---|---|
| GRU | 0.3857 | 0.4026 | 0.29 |
| LSTM | 1.2943 | 0.5794 | 0.35 |
| Transformer | 0.013 | 0.012 | 0.07 |

are marked distinctly, allowing a direct visual comparison of the prediction accuracy of each model. The GRU and LSTM models show a closely aligned trajectory with the actual locations, suggesting competent predictive capabilities. However, the Transformer model exhibits a tighter clustering around the true user locations, indicating a higher prediction accuracy. Overall, the Transformer model appears to outperform GRU and LSTM in terms of proximity to the actual data points

## CONCLUSION AND FUTURE WORK

In our research, we have implemented GRU, LSTM, and transformers models to determine user locations accurately, this shows that these deep learning models can handle complex spatial patterns from location data. Location prediction is important for planning and optimizing effective navigation and resource allocation in wireless networks. Because RIS can dynamically modify signal phases to reduce interference and improve overall coverage, it is utilized for this purpose. . This is particularly important in vehicular networks, where RIS can intelligently direct communication signals, improving efficiency and reliability. RIS makes use of our deep learning models; GRU, LSTM, and Transformer to get higher predictive accuracy which is a critical aspect in optimizing communication protocols for drones. Integrating RIS in vehicular networks enhances signal quality by reducing interference, and ensuring seamless communication in dynamic and challenging

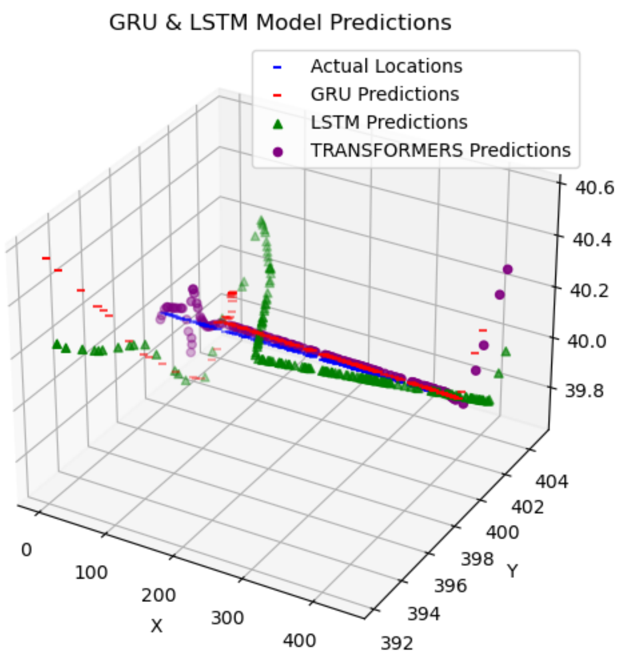


Fig. 4. 3D visualizations of location-to-location predictions using GRU, LSTM, and Transformers.

environments.Results when tested for user location prediction show that the transformer has the lowest MAE among the other trained models going as low as 0.07. As we look toward the future, we aim to incorporate a beam-forming side lobe canceler. This approach promises to further reduce interference and elevate signal quality in the realms of 5G and 6G networks.

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