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AI FOR POSITIONING ACCURACY ENHANCEMENT IN THE IIOT

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ABSTRACT

The evolution of mobile networks, accelerated by the deployment of 5G and the upcoming shift toward 6G, has unlocked new possibilities for industrial applications. A key beneficiary of this progress is the Industrial Internet of Things (IIoT), which depends heavily on precise positioning to support automation, ensure operational safety, and enable real-time system monitoring. Despite these advancements, achieving reliable localization in complex indoor settings remains a persistent challenge for traditional techniques like Time Difference of Arrival (TDoA), which are vulnerable to signal reflections and obstructions caused by multipath propagation. To address these limitations, this study introduces an AI-powered localization method built on a deep learning framework using ResNet architecture. By integrating and analyzing data from multiple sources, the proposed solution overcomes the inherent weaknesses of conventional approaches, delivering enhanced accuracy and resilience in densely packed industrial environments. Comprehensive simulations in realistic indoor factory settings confirm the superiority of the AI-driven model over TDoA, with notable improvements in positioning accuracy. These results underscore the promise of deep learning for advancing IIoT localization, marking a significant step toward intelligent positioning systems in future 5G and 6G networks.

I. INTRODUCTION

The rapid evolution of mobile communication technologies has reached an advanced stage with the rollout of 5G and the ongoing research directed at 6G networks [1]. These next-generation systems are engineered not only to meet increasing demands for higher data throughput and ultra-low latency but also to accommodate a vast array of applications across industrial sectors. Among these, the Industrial Internet of Things (IIoT) is particularly reliant on accurate positioning to ensure efficient operations, improved safety, and real-time asset tracking within intricate environments like factories and warehouses [2]. While existing localization methods have achieved moderate success, the complexity of indoor IIoT environments continues to challenge their effectiveness. In this scenario, Artificial Intelligence (AI) presents a promising path toward enhancing localization accuracy in 5G and forthcoming 6G ecosystems [3].

Fifth-generation mobile networks have redefined benchmarks in speed, latency, and device connectivity. Offering peak data rates up to 10 Gbps, sub-millisecond latency, and support for massive machine-type communications, 5G enables revolutionary use cases, including smart infrastructure, autonomous systems, and telehealth services [4]. As research advances toward 6G, expectations include data transmission rates approaching 1 Tbps and latency shrinking to microsecond levels [5]. This next wave of mobile networks is poised to support sophisticated technologies such as immersive XR, real-time digital twins, and holographic communications, all of which demand exceptional reliability and sub-centimeter localization precision [6]. Consequently, there's an escalating demand for innovative localization approaches that can perform under the complex conditions found in modern industrial and urban environments [7].

As 5G and 6G architectures become increasingly intricate, AI has emerged as an important enabler for intelligent network management. Its capabilities in automating decision-making processes, minimizing operational overhead, and dynamically optimizing system performance make it well-suited for handling the challenges posed by high user densities, unpredictable traffic behavior, and diverse quality-of-service requirements [8]. Traditional static optimization methods struggle to keep up with such dynamic and complex environments.

In the realm of localization, AI-based methods offer distinct advantages over classical techniques. Conventional strategies like Time Difference of Arrival (TDoA) and Angle of Arrival (AoA) typically depend on direct line-of-sight (LOS) conditions and highly accurate signal timing or direction estimation [9]. However, in indoor industrial spaces, where obstructions, reflections, and interference are prevalent, these methods often experience significant degradation. In contrast, AI-powered models can learn from complex environmental data and adjust to varying conditions, leading to more robust and precise localization performance [10]. As accurate positioning becomes a cornerstone for IIoT and emerging applications, AI offers a viable and scalable solution.

This paper introduces an AI-driven localization framework aimed at enhancing positioning accuracy in indoor IIoT environments. Industrial facilities are particularly challenging due to obstacles like dense infrastructure, heavy machinery, and strong electromagnetic interference. High-precision positioning in such settings is essential for tasks such as automated navigation, asset localization, and safety enforcement. Our approach leverages a deep learning model, specifically, a ResNet-based architecture, to extract and learn from multi-source signal features and spatial patterns that are often overlooked by conventional algorithms.

To validate our method, we benchmark its performance against the widely used TDoA localization technique, which estimates user equipment (UE) positions based on signal arrival time differences from various base stations. Although effective in open settings with accurate synchronization and unobstructed LOS, TDoA suffers from reduced accuracy in indoor environments due to multipath effects and signal blockage. In this study, both approaches are tested under identical simulation parameters that replicate a realistic industrial factory setup. Evaluation metrics such as cumulative error distributions and percentile-based accuracy comparisons demonstrate that our AI model consistently outperforms TDoA, offering superior precision and robustness. The AI-enhanced solution proves resilient to environmental changes and is thus a promising candidate for future high-precision IIoT positioning systems.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature; Section 3 explores the role of AI in mobile network communications; Section 4 outlines the proposed methodology and system model; Section 5 presents simulation results and analysis; and finally, Section 6 concludes the paper.

II. The LITERATURE REVIEW

Here we’ll have a look at the work done in the field of AI for Mobiles network Communications. Paper [11] examines the critical role of technology in managing the global COVID-19 outbreak, emphasizing the importance of IoT, AI, and 5G technologies in mitigating the virus's impact. The discussion highlights areas where these technologies have proven essential, including risk reduction, healthcare support, and facilitating public compliance with safety measures. The survey explores how IoT, AI, and 5G contribute to health improvements and ensure accuracy in drug and medicine delivery. By reviewing current applications, the paper also envisions the future potential of these technologies to enable more advanced and secure healthcare solutions. Paper [12] examines the integration of edge computing with deep learning to enhance mobile network services. The proposed "In-Edge AI" framework combines Deep Reinforcement Learning (DRL) and Federated Learning (FL) to optimize mobile edge computing, caching, and communication.

By leveraging device and edge node collaboration to exchange learning parameters, this framework aims to improve model training and inference, enabling dynamic optimization at both system and application levels while minimizing communication overhead. Evaluation results indicate that "In-Edge AI" achieves near-optimal performance with low learning overhead and adaptability to mobile systems, positioning it as a promising solution for future mobile communication challenges and advancements. Paper [13] explores the critical role of 5G networks as foundational infrastructure for various industries, including IoT, smart cities, and virtual reality.

Distinguishing 5G from previous generations, it incorporates advanced digital technologies like massive MIMO (mMIMO) and operates at higher radio frequencies, posing new challenges for network operators. Integrating Artificial Intelligence (AI) offers promising solutions to address these complexities, yet it also introduces security concerns that must be resolved for standardization. To enhance AI-enabled 5G networks, this work proposes integrating Blockchain technology, which facilitates secure information sharing across 5G nodes. The paper introduces "Block5GIntell," a comprehensive framework that leverages the convergence of Blockchain and AI to create intelligent, efficient, and secure 5G networks. Through a case study on energy savings, the proposed solution demonstrates a 20\% reduction in energy consumption at the RAN level, underscoring Blockchain's potential to support AI-driven 5G advancements. Paper [14] addresses the increasing demand for high-quality mobile services across various industries, as 5G incorporates technologies like machine learning and cloud computing into its ecosystem.

The 5Growth project seeks to advance these efforts by automating support for vertical use cases through several innovations: a portal connecting industry-specific applications to 5G platforms, a multi-domain service orchestrator, and a resource management layer. Additionally, the project emphasizes closed-loop, machine-learning-based SLA control and end-to-end optimization. Key 5Growth innovations include advancements in radio slicing, enhanced monitoring and analytics, and machine learning integration to streamline and elevate 5G capabilities for vertical industries. Paper [15] explores the transformative impact of smart tourism on the tourism industry, driven by advancements in communication and information technologies. It highlights the essential role of the Internet of Things (IoT) in smart tourism, despite challenges related to managing vast data and ensuring low-latency communication. To address these issues, the paper proposes 5G- and AI-enhanced IoT systems designed for efficient data transmission and intelligent processing. A case study on Points of Interest (POI) recommendation demonstrates the superior performance of this approach, showcasing its effectiveness and efficiency in enhancing IoT-based smart tourism applications.

Paper [16] investigates the application of Artificial Intelligence (AI) beyond the wireless Physical Layer (PHY), focusing on Machine Learning (ML) techniques for the Medium Access Control (MAC) layer. Unlike the PHY, the MAC layer encompasses diverse features that require tailored ML approaches. This survey explores recent advancements in AI-driven MAC functions, including resource allocation, random access, Adaptive Modulation and Coding (AMC), power control, protocol learning, Channel State Information (CSI) reporting, Hybrid Automatic Repeat Request (HARQ), and Multi-RAT Spectrum Sharing (MRSS), highlighting their potential for optimizing wireless communication systems.

III. AI AND POSITIONING ACCURACY ENHANCEMENT

III.1 ARTIFICIAL INTELLIGENCEQPSK MODULATION

Artificial Intelligence (AI) has become a transformative technology, reshaping multiple aspects of modern life [17]. AI refers to the capability of machines to exhibit intelligence similar to that of humans, encompassing tasks such as learning, problem-solving, decision-making, and natural language processing. Recent advancements, particularly in machine learning (ML) and deep learning, have significantly enhanced AI's capabilities. The combination of vast datasets, increased computational power, and advanced algorithms has enabled AI systems to surpass human performance in certain fields, such as image recognition and speech processing.
AI development follows three primary trends:

- Machine Learning and Deep Learning: Machine learning, a fundamental subset of AI, has been the driving force behind many recent innovations. Within ML, deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have achieved state-of-the-art results in areas like image classification, natural language processing (NLP), and reinforcement learning. The strength of deep learning lies in its ability to learn hierarchical representations of data. For instance, in image recognition, lower CNN layers detect basic features like edges and textures, while deeper layers recognize complex structures, such as objects and faces. This hierarchical learning approach allows deep models to generalize well, provided they are trained on diverse and extensive datasets [18].
- Reinforcement Learning: Reinforcement learning (RL) has gained prominence for its ability to train AI agents to navigate dynamic environments with evolving rules and feedback mechanisms. One of the most well-known RL successes is AlphaGo, an AI system developed by DeepMind that surpassed human champions in the strategic game of Go—an achievement previously thought to be beyond AI's capabilities. RL operates by enabling an agent to interact with an environment, learn from feedback, and develop an optimal policy to maximize long-term rewards. This learning paradigm has been effectively applied in fields such as robotics, autonomous vehicle control, and game playing [19].
- Natural Language Processing: The field of natural language processing (NLP) has advanced significantly, particularly with the rise of transformer-based architectures such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer). These models have revolutionized tasks like translation, summarization, sentiment analysis, and creative writing. Unlike traditional sequence-based models, such as RNNs and LSTMs (Long Short-Term Memory networks), transformers excel at capturing long-range dependencies in text. The introduction of large-scale pre-training on extensive text corpora has enabled these models to be fine-tuned for specific NLP tasks, often achieving performance comparable to or even surpassing that of humans [20].

III.2 AI FOR POSITIONING ACCURACY ENHANCEMENT

In Release 18, the 3rd Generation Partnership Project (3GPP) explored the potential integration of Artificial Intelligence (AI) within the New Radio (NR) air interface, as detailed in Technical Report (TR) 38.843. This report identifies three key applications of AI in NR: improving channel state information (CSI) feedback, optimizing beam management, and enhancing positioning accuracy [21]. Traditional positioning techniques, such as Angle of Arrival (AoA) and Time Difference of Arrival (TDoA), depend on line-of-sight (LoS) propagation and often perform poorly in non-line-of-sight (NLoS) environments. Due to these limitations, conventional methods may fail to meet the stringent positioning requirements of 5G and future 6G networks. To address these challenges, AI and machine learning (AI/ML) techniques present innovative solutions for improving positioning accuracy in NR systems, particularly under complex propagation conditions [22]. AI/ML-based positioning can be implemented through two main approaches [23]:

- Direct AI/ML Positioning: As illustrated in Figure 1, this approach leverages AI/ML models to directly estimate the user equipment (UE) location through inference. By relying on data-driven learning, these models eliminate some of the inherent constraints of conventional positioning algorithms.

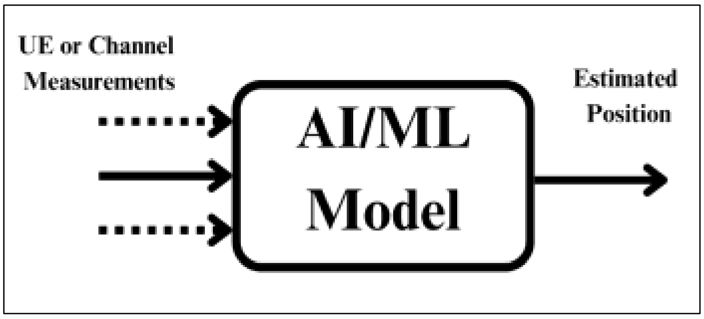

Figure 1: Direct Positioning.
Source: Authors, (2025).

- AI/ML-Assisted Positioning: Shown in Figure 2, this method employs AI/ML models to generate intermediate estimates, such as identifying LoS/NLoS conditions or extracting angular and timing information. These outputs can then be integrated with either traditional positioning techniques or additional AI/ML models to achieve more accurate and resilient UE positioning.

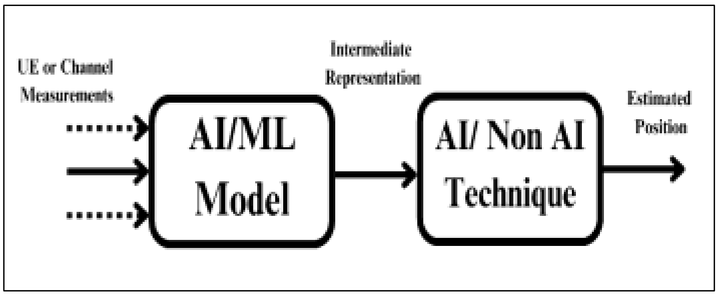

Figure 2: AI/ML-Assisted Positioning.
Source: Authors, (2025).

IV. METHODOLOGY AND SYSTEM MODEL

In this section we present the construction and training process of a Residual Network (ResNet) for enhanced user equipment (UE) positioning accuracy, particularly in non-line-of-sight (NLoS) conditions. The proposed approach leverages uplink (UL) sounding reference signal (SRS) channel estimation in simulation mode to determine UE locations. To achieve this, a deep convolutional neural network (DCNN) based on the ResNet architecture is implemented. Following the architectural configuration, the network undergoes training in a supervised learning framework or utilizes UL SRS-based channel estimation to infer UE positions in a simulated environment [24].

Deep neural networks have demonstrated significant capability in feature extraction and learning from high-dimensional data. However, increasing the network depth indiscriminately may lead to accuracy saturation and training inefficiencies, commonly referred to as the degradation problem. The ResNet architecture mitigates this issue by incorporating skip connections, which facilitate gradient propagation and improve convergence. These shortcut connections enable the direct transfer of information across layers, thereby enhancing network stability and learning efficiency.

In AI/ML-based positioning systems, channel measurements collected at the transmission and reception points serve as input features, while the output corresponds to the estimated two-dimensional (2D) coordinates of the UE. This formulation characterizes the positioning task as a regression problem. Unlike traditional image classification tasks, where patterns are visually interpretable, channel measurement-based data representations are often non-intuitive. This underscores the significance of deep learning models in extracting hidden features that correlate with UE positioning.

Due to its capacity for constructing deep yet computationally efficient models, ResNet has been widely adopted in localization applications [25]. To evaluate positioning performance, the ResNet model is tested in simulation mode using a pretrained network and a generated test dataset comprising samples. Conversely, in training mode, a customized ResNet architecture is designed, and training is performed using TrainRatio of the total dataset, with the remaining samples reserved for validation. The validation set plays an essential role in monitoring model performance and mitigating overfitting [26].

The final pretrained ResNet model, consisting of eight layers, is stored within the working directory. As part of the preprocessing step, the channel state information (CSI) images are resized to dimensions $32 \times 32 \times 18$ and normalized to a range of [0,1] before being fed into the network. In this study, we focus on an Industrial Internet of Things (IIoT) scenario to assess the performance of AI/ML-based positioning methods. The process implemented in our model is illustrated in Figure 3.

In this context, achieving accurate positioning relies on synchronized timing and channel estimation, facilitated by uplink (UL) sounding reference signals (SRS). By simulating UL SRS transmissions, we extract channel parameters to build a labeled dataset containing 2D user equipment (UE) locations, which are then used for AI/ML model training. The 3GPP Technical Report 38.901 standard [27] defines various indoor factory (InF) environments, each designed to represent different levels of clutter and variations in transmitter (Tx) and receiver (Rx) antenna heights. These environments are categorized as follows:

- InF-SL: Represents a sparsely cluttered indoor factory with a low base station height, where both Tx and Rx are positioned below the average clutter height.
- InF-DL: Depicts an indoor factory with dense clutter and a low base station height, where Tx and Rx remain below the clutter level.
- InF-SH: Models a setting with sparse clutter but a high base station height, where either the Tx or Rx is elevated above the surrounding obstacles.
- InF-DH: Represents a densely cluttered indoor factory with a high base station height, featuring an elevated Tx or Rx positioned above the clutter.
- InF-HH: A scenario where both Tx and Rx are elevated, positioned higher than the surrounding clutter elements.

Our uplink simulation operates through multiple stages like presented in figure 3:

- Scenario Configuration: Defines environmental characteristics, channel parameters, and Tx/Rx deployment settings.
- OFDM Transmission: Sends SRS through the predefined channel.
- Channel Processing: Applies channel-specific filtering and incorporates additive white Gaussian noise (AWGN).
- OFDM Demodulation: Conducts timing synchronization and estimates the channel response.
- Position Estimation: Integrates AI/ML techniques with Time Difference of Arrival (TDoA) algorithms to determine UE location.

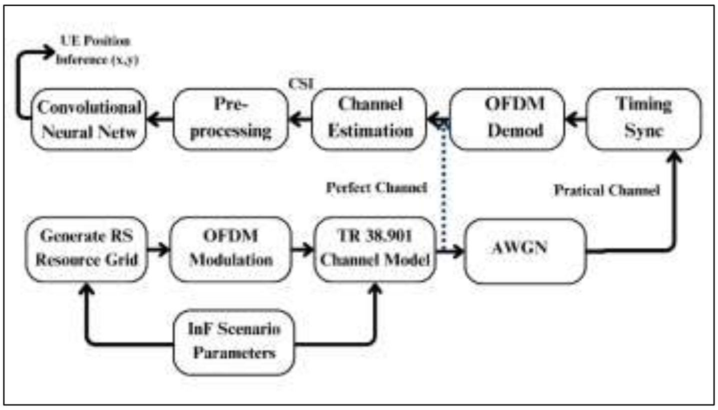

Figure 3: The implemented processing chain.
Source: Authors, (2025).

V. SIMULATION RESULTS AND DISCUSSIONS

To assess the effectiveness of the ResNet-based AI approach in enhancing positioning accuracy, we conducted simulations using MATLAB. These simulations aimed to replicate a realistic indoor environment by modeling multiple User Equipment (UE) positions and signal propagation characteristics. For the indoor environment, we adopted the factory scenarios defined in 3GPP TR 38.901. Specifically, we simulated a hall measuring 120 × 60 × 20 meters, incorporating clutter elements with a density of 0.6 and an average size of 2 meters. To introduce complexity in signal propagation, the clutter height was set at 6 meters, creating challenging conditions for positioning accuracy due to multipath effects and signal obstructions. The key parameters of the simulation were as follows:

- Base Station (BS): Deployed at intervals of 20×20 meters, featuring antennas positioned at an 8-meter height and a noise figure of 5 dB.
- User Equipment (UE): A total of 20 UEs were randomly distributed within the environment, each equipped with antennas at a height of 1.5 meters.
- Carrier and SRS Configuration: The subcarrier spacing was fixed at 30 kHz, with a carrier grid size of 270. The Sounding Reference Signal (SRS) was optimized using 12 OFDM symbols and a comb number of 8 to enhance positioning precision.

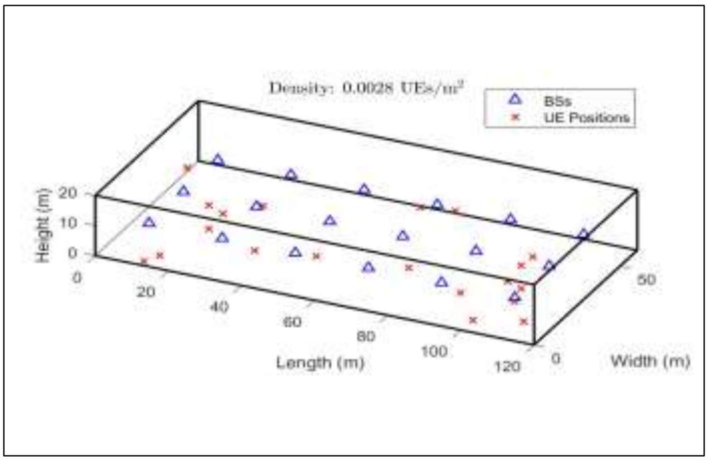

Figure 4: 3D representation of an indoor factory hall scenario with 20 UEs.
Source: Authors, (2025).

Figure 4, shows a 3D representation of an indoor factory hall scenario or 20 UE, used for positioning analysis. Here's a breakdown of the key elements:

- Hall Dimensions: The plot shows a hall with the dimensions set to approximately 120 meters in length, 60 meters in width, and 20 meters in height, which is typical for a dense indoor factory setting. This scale is realistic for testing positioning accuracy in large indoor spaces.
- UE (User Equipment) Density: The density of UEs is noted as 0.0028 UEs/m², indicating a sparse distribution of users within the hall. This density helps in examining how well the system performs with limited user clustering and interference.
- BS (Base Station) Positions: The blue triangles represent the locations of the base stations (BSs) placed throughout the hall at strategic heights. These BSs are crucial in providing signal coverage for positioning and represent points where data is transmitted or received for determining user positions.
- UE Positions: The red crosses mark the positions of the UEs within the hall. The random placement of these UEs reflects a realistic distribution of users in a factory setting where workers or equipment might be spread across the area.

We estimate UE positions with a positioning simulation that includes both the proposed AI and TDoA approaches. The estimate procedure consists of producing the resource grid, synthesizing the waveform, modeling the noisy channel, and conducting synchronization and channel estimation. For AI-based positioning, we use perfect channel estimations to determine the UE's position with a pretrained network. In TDoA-based positioning, TRPs calculate timing offsets from received SRSs and use these estimates to identify the UE, with the option of employing perfect or realistic timing approximations. By default, we assume perfect timing estimation.

Table 1: Neural Network Summary.

Parameter	Value
Number of layers	8
Complexity	$1.2816\ million$
Input size	$[32, 32, 18]$
Output size	$[2]$

Source: Authors, (2025).

The table 1 provides a concise overview of the ResNet architecture used for AI/ML-based positioning. The key details include:

- Number of layers: The network consists of 8 layers, making it relatively deep while maintaining efficiency.
- Complexity: The model has **1.2816 million parameters**, indicating its capacity to learn complex spatial relationships in positioning.
- Input size: The input dimensions are [32, 32, 18], representing the structure of the input feature maps, likely derived from channel state information (CSI) or other positioning-related data.
- Output size: The network predicts (2) values, which likely correspond to the x and y coordinates of the User Equipment (UE) position.

The figure 5 illustrates the structure of the custom ResNet model used for UE positioning. The key elements include:

- Input Layer: Takes in the CSI-based input representation.
- Convolutional Layers (conv, bn, relu): Feature extraction is performed using convolutional layers, batch normalization (bn), and activation functions (ReLU).
- Residual Connections (shortcut, add): These help in maintaining gradient flow and preventing vanishing gradient issues, making deep networks trainable.
- Global Average Pooling (globavgpool) and Fully Connected Layer (fc): These layers transform extracted features into final positioning predictions.

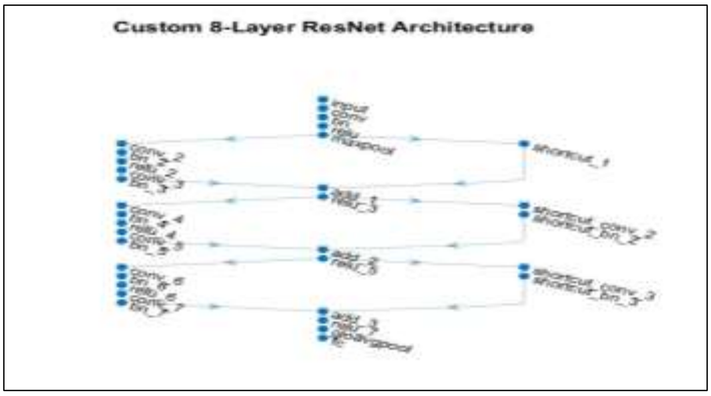

Figure 5: The structure of the custom ResNet mode.

Source: Authors, (2025).

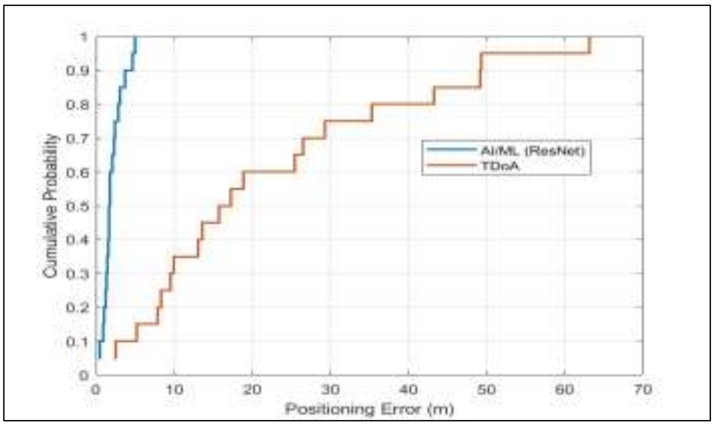

Figure 6: The CDF of positioning error for InF-DH environments with 20 UEs.

Source: Authors, (2025).

Figure 6, illustrates the Cumulative Distribution Function (CDF) of positioning error with 20 UE, for two positioning methods: the proposed AI method and TDoA method for each indoor factory (InF) environments.

- X-axis (Positioning Error in Meters): The x-axis represents the positioning error in meters, showing the accuracy of each method. Lower values indicate better positioning accuracy.
- Y-axis (Cumulative Probability): The y-axis shows the cumulative probability, indicating the proportion of samples with positioning error up to the value on the x-axis. A steeper curve indicates higher accuracy.

The blue line represents the AI based method. It shows a steep curve with most errors concentrated below 10 meters. This suggests that the AI model achieves high positioning accuracy, as a large portion of the cumulative probability reaches close to 1 (or 100%) with minimal error. The orange line represents the traditional TDoA method, which has a more gradual slope and reaches higher positioning errors. This method performs less accurately, with positioning errors extending up to around 60 meters before reaching 100% cumulative probability. The table 2 present the Positioning Errors at Different Percentiles.

Table 2: Comparison of AI/ML (ResNet) and TDoA Positioning Errors at Different Percentiles for 20 UE.

Percentile	AI/ML (ResNet) Positioning Error (m)	TDoA Positioning Error (m)
10th	0.6847	3.8438
50th	1.7341	16.508
90th	4.2152	49.243

Source: Authors, (2025).

Now we increase the number of UEs, to understand how positioning accuracy scales with crowding.
The figure 7, shows a 3D representation of an indoor factory hall scenario InF-DH with 200 UE, used for positioning analysis.

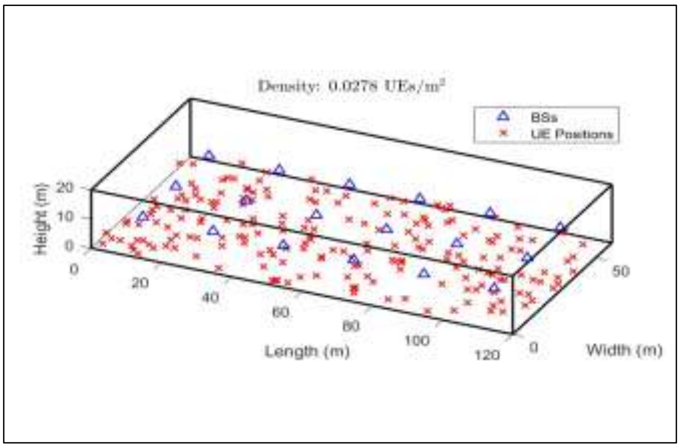

Figure 7: 3D representation of an indoor factory hall scenario with 200 UEs.
Source: Authors, (2025).

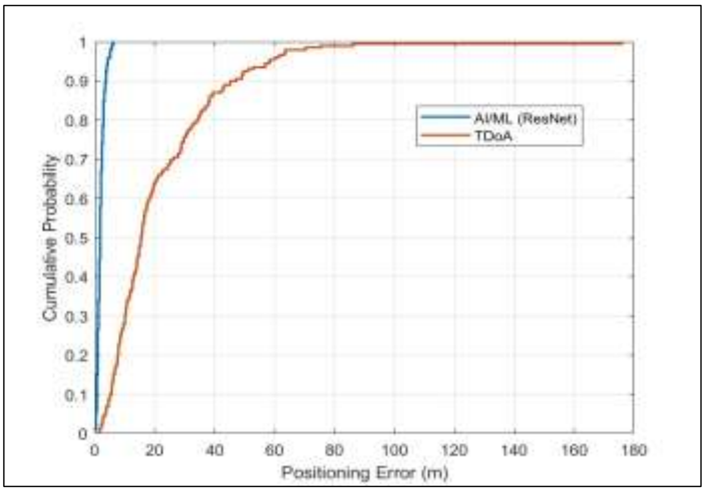

Figure 8: The CDF of positioning error for InF-DH environments with 200 UEs.
Source: Authors, (2025).

Figures 8, illustrates the CDF of positioning error for InF-DH environments with increasing the number of UEs to 200. The AI based method shows a steep curve with most errors concentrated around 5 meters. This suggests that the AI model achieves high positioning accuracy, as a large portion of the cumulative probability reaches close to 1 (or 100 %) with minimal error. The traditional TDoA method, which has a more gradual slope and reaches higher positioning errors. This method performs less accurately, with positioning errors extending up to around 100 meters before reaching 100 % cumulative probability.

The table 3 present the Positioning Errors at Different Percentiles for 200 UE.

Table 3: Comparison of AI/ML (ResNet) and TDoA Positioning Errors at Different Percentiles for 200 UE.

Percentile	AI/ML (ResNet) Positioning Error (m)	TDoA Positioning Error (m)
10th	0.66627	5.3964
50th	1.7679	15.47
90th	3.6627	46.126

Source: Authors, (2025).

In all cases, the AI approach outperforms TDoA by achieving a significantly lower error range, which means it provides more precise location estimates. The quick rise to near 100 % cumulative probability within a small positioning error range indicates that the AI method is more robust and reliable for positioning in complex indoor environments.

VI. CONCLUSIONS

This study highlights the potential of AI-driven positioning techniques in enhancing localization accuracy within complex industrial environments under 5G and emerging 6G networks. By leveraging a ResNet-based deep learning model, our approach consistently outperformed the traditional TDoA method across various indoor factory scenarios. The AI model demonstrated strong resilience to multipath interference and signal obstruction, maintaining high accuracy even in densely cluttered environments with diverse equipment positioning.

These findings confirm the effectiveness of deep neural networks in improving positioning accuracy, an essential factor for IIoT applications requiring precise monitoring, automation, and safety compliance. As mobile networks continue to evolve, integrating AI-based positioning solutions will be essential to meet the increasing demands of future industrial environments.

Future research could explore real-time AI implementations and hybrid approaches that combine multiple positioning techniques to further enhance the robustness and scalability of localization systems in 5G/6G industrial scenarios.

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