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Jaspreet Kaur ; Satyam Bhatti ; Kang Tan ; Olaoluwa R. Popoola ; Muhammad Ali Imran ; Rami Ghannam ; Qammer H. Abbasi ; Hasan T. Abbas

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Jaspreet Kaur,[a] Satyam Bhatti,[b] Kang Tan,[c] Olaoluwa R. Popoola,[d] Muhammad Ali Imran,[e] Rami Ghannam,[f] Qammer H. Abbasi,[g] and Hasan T. Abbas[a]

AFFILIATIONS

James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, United Kingdom

[a]**Authors to whom correspondence should be addressed:** j.kaur.1@research.gla.ac.uk and Hasan.Abbas@glasgow.ac.uk
[b]s.bhatti.2@research.gla.ac.uk
[c]**Current address:** University of Electronic Science and Techonology of China. **Email address:** k.tan.3@research.gla.ac.uk
[d]Olaoluwa.Popoola@glasgow.ac.uk
[e]Muhammad.Imran@glasgow.ac.uk
[f]Rami.Ghannam@glasgow.ac.uk
[g]**Also at:** Artificial Intelligence Research Centre, Ajman University, Ajman, UAE. Qammer.Abbasi@glasgow.ac.uk

ABSTRACT

Beamforming, an integral component of modern mobile networks, enables spatial selectivity and improves network quality. However, many beamforming techniques are iterative, introducing unwanted latency to the system. In recent times, there has been a growing interest in leveraging mobile users' location information to expedite beamforming processes. This paper explores the concept of contextual beamforming, discussing its advantages, disadvantages, and implications. Notably, we demonstrate an impressive 53% improvement in the signal-to-interference-plus-noise ratio by implementing the adaptive beamforming maximum ratio transmission (MRT) algorithm compared to scenarios without beamforming. It further elucidates how MRT contributes to contextual beamforming. The importance of localization in implementing contextual beamforming is also examined. Additionally, the paper delves into the use of artificial intelligence (AI) schemes, including machine learning and deep learning, in implementing contextual beamforming techniques that leverage user location information. Based on the comprehensive review, the results suggest that the combination of MRT and zero-forcing techniques, alongside deep neural networks employing Bayesian optimization, represents the most promising approach for contextual beamforming. Furthermore, the study discusses the future potential of programmable switches, such as Tofino—an innovative switch developed by Barefoot Networks (now a part of Intel)—in enabling location-aware beamforming. This paper highlights the significance of contextual beamforming for improving wireless telecommunications performance. By capitalizing on location information and employing advanced AI techniques, the field can overcome challenges and unlock new possibilities for delivering reliable and efficient mobile networks.

I. INTRODUCTION

Every subsequent generation of cellular communication has brought advancements in data speeds and capabilities, with each generation offering significant improvements over its predecessor.[1] The first-generation (1G) introduced the concept of cell phones, while the second-generation (2G) enabled text messaging services. The advent of the third-generation (3G) brought about Internet streaming capabilities, and the fourth-generation (4G) revolutionized the mobile landscape with broadband Internet coverage. However, as user demands continue to escalate rapidly, 4G networks have reached their capacity limits, necessitating the need for more data to cater to the growing number of smartphones and smart devices.

The arrival of fifth-generation (5G) cellular technology promises to address these challenges by providing networks capable of carrying significantly higher traffic volumes than the currently available networks.[2] With 5G networks already under way, their evolution is outpacing the long-term development of 4G (LTE) by a factor of ten. This rapid advancement holds the promise of catalyzing breakthroughs in technologies like augmented reality (AR), autonomous vehicles, and the Internet of Things (IoT) citegohar2021role. At the core of 5G technology, there are five key advancements: full-duplex, massive multi-input multi-output (MIMO), millimeter wave (mmWave), smart cell, and BF. Smartphones and electronic devices operate within the radio frequency (RF) range, typically less than 6 GHz.[3–5] This spectral range is becoming increasingly congested due to the proliferation of communication technologies and multiple mobile carriers. The limited RF spectrum available in the industrial, scientific, and medical (ISM) band poses challenges for accommodating the growing demand for data transmission, resulting in slower services and more frequent lost connections.[6,7]

To address this issue, researchers have been exploring higher frequency bands ranging from 30 to 300 GHz.[6,7] Although mmWave have been utilized in satellite communication for some time, their use in mobile communications is a fairly recent development. While offering a wider frequency spectrum, mmWave faces a major challenge due to its limited ability to penetrate obstacles such as built infrastructure. This characteristic leads to signal loss or absorption when mmWave encounters environmental obstacles.[8] Subsequently, smart cell networks provide a solution to overcome this problem. Unlike traditional cell connections that rely on large high-power cell towers that transmit signals over long distances, smart cell networks leverage thousands of small low-power access points (APs).[9,10] These APs are strategically placed in close proximity and grouped spatially to relay signals around obstructions. By eliminating reliance on the line of sight (LoS), smart cell networks ensure uninterrupted cellular service, even when users move behind obstacles. When user equipment (UE) travels behind an obstruction, it seamlessly switches to a new AP, maintaining a consistent connection.[11,12]

Another significant advancement in 5G technology is the use of massive MIMO (multi-input multi-output), which involves deploying a higher number of antennas compared to traditional MIMO systems. Massive MIMO leverages BF techniques to direct wireless signals toward their intended receivers and enables spatial multiplexing of multiple data streams over the same frequency band. BF is a signal processing technique that manipulates radio waves to focus them toward specific locations using electromagnetic beams. This eliminates the need for physical movements and reduces dependence on the physical structure of antennas. By utilizing BF, massive MIMO significantly enhances communication performance and can multiply the capacity of a mobile *ad hoc* network by a factor of 22 or more.[1,13] In a time-division multiplexing system, user equipment (UE) needs to alternate between transmitting and receiving, which can introduce delays and reduce communication efficiency. In traditional cellular base stations (BSs), antennas can only broadcast or receive signals at a given time. Multiplexing can improve performance, but transmitted and received signals are typically propagated at different frequencies.[14] Conventional cellular antennas broadcast signals in all directions simultaneously, leading to potential interference.[15] Advancements in signal processing techniques have made it possible to manipulate radio waves and focus them using electromagnetic beams. Figure 1 illustrates the BF process (broadcasting signals in a specific direction) in rural, semi-urban, urban, and highway areas.

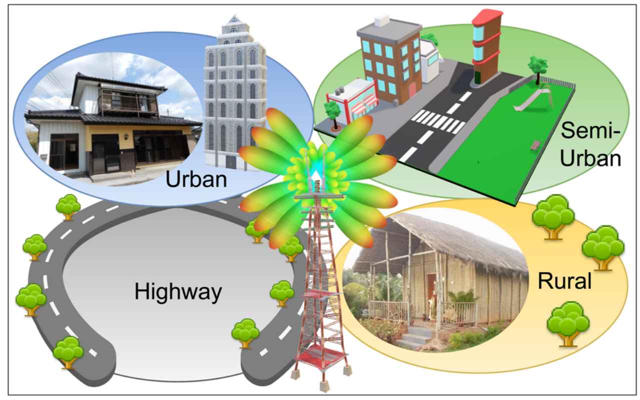

FIG. 1. Illustration of BF according to the scenario (rural, semi-urban, urban, highway).

BF offers several advantages in cellular communication. It enables more reliable and faster data transmission by establishing a more direct connection between transmitters and receivers. BF has become an essential technology in various applications, including the 5G standard for cellular networks and radar-detection systems.[16] However, implementing BF requires significant processing resources, which can pose challenges related to cost, hardware, and energy consumption. In the past, radar systems relied on mechanically moving and steering antennas to direct signals.[17]

The development of antenna systems for 5G networks must meet the requirements of compact size and low power consumption. To enhance spectrum efficiency and throughput, antenna arrays with larger dimensions, such as 64×64 MIMO and beyond, are being utilized. However, the accuracy of these antenna arrays significantly affects the performance of BF. As wavelengths decrease, component sizes, including those of RF transceivers with features like analog-to-digital converters (ADCs), also decrease. Exploring new materials, such as 40 nm Complementary Metal-Oxide-Semiconductor (CMOS), is helping to reduce the size and power consumption of essential components in 5G networks. Traditional RF power amplifiers made with materials like gallium arsenide (GaAs) and other III–V semiconductors are not power-efficient and do not integrate well with other capabilities. This is where advancements in 40 nm CMOS technology can play a role in further reducing the size and power consumption of these critical components. Moreover, as the number of beams created by individual next-generation node B (gNB) increases, more advanced signal processing techniques are required. This pushes power budgets and space restrictions even further. Despite these challenges, BF holds a promising future in various application areas.[18]

Cont-BF is a promising technique for enhancing the performance of 5G communication systems. It enables the use of mmWave frequencies and massive MIMO technologies to achieve high data rates and low latency. Cont-BF adapts BF parameters in real time based on environmental conditions and user requirements. This is achieved through feedback from the network and user devices, as well as the utilization of machine learning (ML) algorithms to optimize the BF process. Cont-BF has applications in mobile edge computing (MEC), where low-latency computing and networking services are provided to mobile users. By dynamically adjusting the BF parameters based on the location, movement, and traffic conditions of the users, the quality of wireless links between user devices and MEC servers can be improved. In VR/AR, cont-BF can improve the quality of audio and video streams used in VR/AR applications by selectively enhancing relevant signals and suppressing irrelevant or distracting ones.

Moreover, in this line, location-assisted BF is a BF technique that takes advantage of spatial information about the positions of user devices or antennas to enhance wireless communication performance. Unlike conventional BF, which typically relies on predefined patterns or fixed configurations, location-assisted BF uses the knowledge of user locations to dynamically adjust the directionality of transmitted signals. This adjustment aims to optimize signal reception at the intended devices while minimizing interference and improving the overall signal quality. In comparison to cont-BF, which considers various factors beyond just user locations (such as environmental conditions, interference sources, and network load), location-assisted BF specifically emphasizes the role of physical positioning. It focuses on leveraging the geometric arrangement of user devices and antennas to improve communication efficiency. In other words, location-assisted BF is a subset of cont-BF placing particular emphasis on utilizing user location information to enhance the efficiency of wireless communication systems. It utilizes the geometric arrangement of devices to optimize signal transmission, ultimately improving user experience and network performance.

Apart from this, artificial intelligence (AI) is used in 5G technology to optimize BF.[19] AI and ML are terms that refer to the simulation of human intelligence processes by machines, particularly computer systems. AI encompasses a wide range of technologies that enable machines to perform tasks that typically require human intelligence, such as problem-solving, learning from experience, speech recognition, and decision-making. ML, a subset of AI, involves the development of algorithms and statistical models that allow computers to learn from and make predictions or decisions based on data. Deep learning (DL) is a specific subfield of ML that involves neural networks with multiple layers, enabling them to automatically learn patterns from data.

Conventional BF techniques in cellular communication involve using predefined models or fixed configurations to direct signals from antennas in specific directions. These techniques are often based on mathematical formulas and linear optimization methods. While they can provide satisfactory performance in certain scenarios, they might struggle to adapt to complex and dynamic wireless environments with multiple users and interference sources.

In contrast, AI-, ML-, and DL-assisted BF involves integrating advanced AI and ML techniques into the BF process. AI-, ML- and DL-assisted BF leverages the capabilities of AI and ML to improve the efficiency, adaptability, and performance of BF processes in wireless communication systems, especially in dynamic and complex scenarios. This is in contrast to conventional techniques that are often more static and less adaptable.

A. Contribution to the literature

In our paper, we analyzed the role of BF in the field of mobile communication. We conducted a review of the applications of BF in the algorithms, antenna fabrication, and the discovery of new AI approaches. Our article is an effort to provide a review of cont-BF. The following are the major contributions of this article:

1. We shortlisted research articles related to BF techniques that can help in cont-BF.
2. We reviewed the literature on BF types, both standard and using ML and AI techniques.
3. We presented various ML techniques that facilitated the estimation of user location and beam management in the study.
4. We investigated the techniques used for the optimization of BF with the help of ML.
5. We highlighted the challenges associated with using ML techniques for cont-BF.

B. State of the art

The field of cont-BF in 5G technology is in a constant state of evolution, with ongoing research and development efforts aimed at improving its efficiency and effectiveness. Pioneering work in this domain can be traced back to the seminal paper by the authors of the work of Islam *et al.*, which laid the foundation for subsequent investigations.[20] Recent advancements are highlighted in the work of Chen *et al.*, whose paper provides insight into the latest breakthroughs.[21]

In recent years, there has been a surge in the use of conventional, ML, and AI techniques for BF. Notable contributions include the study of ElHalawany *et al.*, demonstrating the growing interest and applicability of these approaches in the context of cont-BF.[22]

By considering location-unaware systems with benchmarking techniques,[23] a location-aware system can be developed and make location estimation more accurate. Additionally, opportunistic BF, as used in this context, refers to a technique where smart antennas utilize channel delay information to optimize their BF strategies based on the prevailing conditions. The study of Cheng *et al.* explores leveraging channel delay information as feedback to enhance the effectiveness of smart antennas dynamically and adaptively.[24]

In Ref. 25, the authors proposed a recursive matrix shrinkage method to estimate the interference-plus-noise covariance matrix along with the desired signal steering vector mismatch. A two-stage design approach was utilized in Ref. 26, with the first stage dealing with BF, and the second with adaptive power allocation and modulation. Another recent study by Ref. 27 proposed a novel and general approach for deriving the statistical distribution of the signal-to-noise ratio (SNR) by exploiting the array structure, BF type, and slow fading channel coefficients. This approach was used to design power and modulation adaptation strategies. Reference 28 presented the scheme that uses coordinated beam search from a small beam dataset within the error offset, and then the selected beams are used to guide the search for beam prediction.

Additionally, Ref. 29 proposes an end-to-end DL technique to design a structured compressed sensing (CS) matrix that is well-suited for the underlying channel distribution. This technique leverages sparsity and the spatial structure that appears in vehicular channels. In contrast, in Ref. 30, it was noted that current mmWave beam training and channel estimation techniques do not typically make use of prior beam training or channel estimation observations. Moreover, Ref. 31 shows that determining the optimal BF vectors in large antenna array mmWave systems necessitates significant training overhead, which can have a significant impact on the efficiency of these mobile systems.

As various ML techniques have been adopted for BF, this paper aims to provide a detailed review of different ML-based BF techniques. These ML techniques include the procedure to preprocess the input data and various ML algorithms in any environment. Our study goes beyond existing literature, showcasing how various ML techniques can be used to screen large numbers of BF approaches for potential location estimation applications and to optimize the approaches using high computational power. Accordingly, the following sections will describe the in-depth analysis of currently popular BF techniques and how AI can improve their overall performance by mitigating their limitations.

C. Organization of the study

The rest of this paper is organized depending on finding the gap from the state of the art in the recent literature review and is described as follows: The adopted methodology is presented in Sec. II, followed by the discussion of results and analysis of the study in Sec. III. In addition, Sec. IV elaborates on the challenges associated with using the recent AI, ML, and DL techniques for cont-BF. Moreover, Sec. V incorporates the potential applications of cont-BF. Subsequently, Sec. VI concludes the article.

II. REVIEW METHODOLOGY

This section presents our methodology depending on the defined research objectives and questions that were used for shortlisting the relevant research articles on ML algorithms for cont-BF techniques.

A. Research objectives

The four key objectives of our article are as follows:

O1: To review the range of BF techniques and ML-based BF using priori user data.
O2: To identify the ML techniques used specifically for cont-BF.
O3: From a practical perspective, identify the specific ML and optimization techniques used for real-time implementation.
O4: To identify ML algorithms specifically used for the BF for low latency, high throughput, and signal-to-interference-plus-noise ratio (SINR).

B. Research questions

Our study aims to answer the following four research questions:

RQ1: What are the main BF techniques that use location information?
RQ2: What are the different types of ML and AI techniques used for cont-BF?
RQ3: What are the datasets required for classifying the cont-BF?
RQ4: How can the cont-BF models be optimized for real-time processing?

C. Review protocol

For structuring our study, we instigated a review protocol, and the following are the perquisites of the adopted analogy. In this section, we discuss the search strategy, inclusion criteria, exclusion criteria, analysis, and screening mechanisms for selecting relevant research papers.

1. Search strategy

The most recent research papers from renowned publishing houses like IET, Science Direct, Nature, AIP, Wiley, IEEE Xplore, IoP Science, ACS publications, and MDPI were taken into account during our study. We also included preprint papers from arXiv in our search. As a result, we evaluated and critically analyzed the gray literature (research and publications produced by organizations not usually linked with academic or commercial publishing organizations) using the AACODS (Authority, Accuracy, Coverage, Objectivity, Date, Significance) criteria.[32]

We commence by querying every database that contains various study items. To compile our study articles, we defined keywords like "ML," "DL," "BF," "location," "context information," "5G," and "vehicular communication." Based on the article's title and abstract, as well as a full-text read of the papers, the articles were scanned. To link these keywords, we also created search strings using the Boolean operators AND and OR.

2. Inclusion criteria

The following are the parameters used in the inclusion criteria:

1. We included only English-language articles involving the data-driven approaches of BF using conventional and ML techniques that were pertinent to the study issues, such as poor data quantity and data quality.
2. We included the pertinent articles facilitating the discovery of only low-latency BF algorithms using ML methods before determining their eligibility.
3. We included comparative studies involving the optimization and robustness of BF techniques designed from ML services.
4. We targeted only articles that discussed ML for BF, location information, and publications on ML integration on cont-BF.

3. Exclusion criteria

The following is a list of the exclusion criteria for shortlisting research papers based on our research objectives and targeted research questions.

1. English-language research articles released in other languages.
2. Research papers without a complete text version.
3. Editorials, review articles of surveys, abstracts, and short papers concerning secondary studies are not accepted.
4. Articles that did not discuss how to combine ML techniques with BF.

4. Screening phase

The articles underwent a two-phase screening process. Initially, we assessed the title and abstract of each research article to determine whether they met our inclusion criteria. In the subsequent phase, we refined our selection based on the full text of the articles. It is noteworthy that identical content often appeared in different publications, such as conference papers also being present in journals. Throughout screening stage two, we considered the original writing of each item. Survey and review papers were excluded from our study. Ultimately, each article underwent thorough thematic classification and evaluation.

III. RESULTS AND ANALYSIS OF THE REVIEW

This section of the paper summarizes the research articles that are shortlisted using the defined research objectives as well as aims to answer the predefined research questions.

A. What are the main BF techniques that use location information [RQ:1]

With an extensive utilization of global navigation satellite systems (GNSSs), such as global positioning systems (GPS), Galileo, and BeiDou, various BF techniques that use user location are becoming exponentially important. Adaptive BF, cont-BF, and location-assisted BF are techniques used in signal processing to improve the quality of transmitted or received signals. Adaptive BF refers to using real-time feedback from the received signal to continuously adjust the BF algorithm to improve the quality of the signal. This is particularly useful in dynamic environments where the signal sources or environmental conditions may change over time. On the other hand, cont-BF refers to using prior knowledge about the environment to design a BF algorithm that optimizes the signal quality in that specific environment. This prior knowledge can include information about the location and number of signal sources, the electromagnetic or RF properties of the environment, and other factors that can affect the quality of the received signal. Whereas, location-assisted BF primarily utilizes the spatial positions of user devices or antennas to dynamically adjust signal directionality, aiming to optimize signal strength and quality based on geometric relationships. These techniques have their strengths and weaknesses.

1. Adaptive BF

An adaptive beamformer is a tool for performing adaptive spatial signal processing using an array of transmitters or receivers. The resulting electromagnetic waves add up in a way that the signal intensity to and from a specific direction is increased. Signals from and to other directions are combined constructively or destructively, resulting in degradation of the signal from and to the undesired direction. This method is utilized in both RF arrays to achieve directional sensitivity without physically changing the receivers or transmitters.[33–35]

Adaptive BF was first developed in the 1960s for military sonar and radar applications. There are various modern applications for BF, with commercial wireless networks such as long-term evolution (LTE) being one of the most popular. Adaptive BF's first applications in the military were primarily focused on radar and electronic countermeasures to counteract the effects of signal jamming. In phased array radars, BF can be seen. These radar applications use either static or dynamic/scanning BF; however, they are not truly adaptive. Adaptive BF is used in commercial wireless standards such as 3GPP LTE and IEEE 802.16 WiMAX to enable important services within each standard.[36] The concepts of wave transmission and phase relations are used in an adaptive BF system. A greater or lower amplitude wave is formed, for example, by delaying and balancing the received signal, using the concepts of superimposing waves.

The adaptive BF system is adaptive in real time to maximize or minimize desirable parameters, including the SINR. There are numerous approaches to BF design, the first of which was achieved by Applebaum in 1965 by increasing the SNR.[37] This method adjusts the system parameters to maximize the power of the received signal while reducing noise (jamming or interference). Widrow's least mean squares (LMS) error method[38] and Capon's maximum likelihood method (MLM)[39] introduced in 1969 are two further approaches. The Applebaum and Widrow algorithms are quite similar in that they both converge on the best option. However, these strategies have difficulties in terms of implementation. Reed demonstrated a technique called sample matrix inversion (SMI) in 1974.[40] Unlike Applebaum and Widrow's approach, SMI determines the adaptive antenna weights directly.[33–35]

The Wiener solution[41] can be used to create statistically optimal weight vectors for adaptive BF in data-independent BF design methods. On the other hand, the asymptotic second order statistics of SINR were assumed. Statistics fluctuate over time in cellular networks where the target is mobile and interferes with the cell area. An iterative update of weights is required to follow a mobile user in a time-varying signal propagation environment.[42] This enables the spatial filtering beam to adjust to the time-varying direction of arrival (DoA) of the target mobile user and to provide the desired signal to the user. To address the challenge of statistics (which can vary over time), adaptive algorithms that adapt to changing environments are frequently used to determine weight vectors. The functional block diagram of an adaptive array of n elements includes an antenna array of n elements and a digital signal processor with a feedback and/or control loop algorithm. The signal processing unit receives the data stream gathered by an array and computes the weight vector using a specific control method.

On the contrary, the adaptive antenna array is divided into two categories: (a) steady-state and (b) transient state. These two categories are determined according to the array weights of the stationary environment and the time-varying environment. If the reference signal for the adaptive method is known from prior information, the system can update the weights adaptively through feedback.[43] To change the weights of the time-varying environment at every instance, several adaptive algorithms (mentioned in the further section) can be utilized. Figure 2 shows the block diagram for adaptive BF, which consists of a digital signal processor (DSP), RF chain, splitter, and N-phase shifter, followed by antenna assembly along with an adaptive system providing feedback to shifters.

2. Contextual beamforming (cont-BF)

The ability to forecast the next location of the receiver, which is based on tracking previous movements, can be useful for creating intelligent applications like automobiles, robotics, AR/VR,

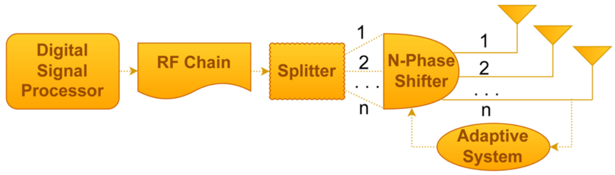

FIG. 2. Basic block diagram of adaptive BF.

etc. The advancement of location prediction apps and services is enabled by the growth of methodologies for predicting and projecting the receiver's position in the future.[44] A wireless system, in general, controls a location-predicting framework by capturing and communicating critical data before application. The sender must be able to determine the receiver's location at any given time to interact effectively with them. ML methods have already been used to predict the receiver's location. Context is created by recording, processing, and transcribing the receiver's status data at a certain time.

The majority of the existing mmWave beam tracking research focuses on communication-only protocols. The usual beam tracking technique requires the transmitter to send information to the receiver, which then determines the angular position and sends it back to the transmitter. It is worth noting that in high-mobility communication circumstances, such as the one depicted in Fig. 3, it is not enough to merely track the beam. To meet the crucial latency requirement, the transmitter should be capable of predicting the beam.[45] An example design with such state prediction and tracking using the classic Kalman filtering process is demonstrated in Fig. 4. The antenna array at the base station is capable of adjusting the direction of the transmitted or received beam. The mobile user is located at a certain range (r), with specific polar (ϕ) and azimuth (θ) angles. These angles are crucial for directing the beam toward the user.

The Kalman filter is a recursive algorithm that estimates the state of a dynamic system based on a series of noisy measurements. In the context of beam tracking, the state we are interested in, includes the range r and angles ϕ (polar angle) and θ (azimuth angle), denoted as x, which we want to estimate over time.

The Kalman filter equations for a simple 2D system (tracking ϕ and θ) can be represented as follows:

1. State Prediction:

$$\hat{x}_{k|k-1} = F \cdot \hat{x}_{k-1},$$

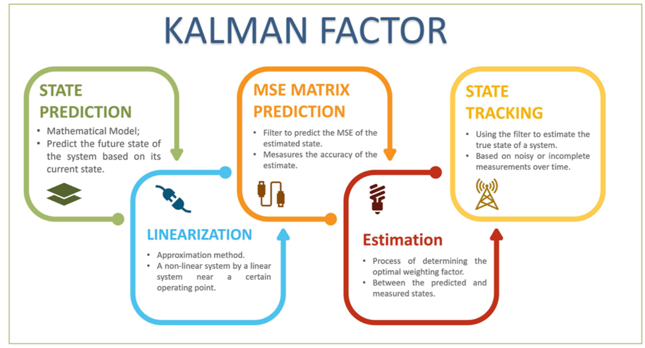

FIG. 4. A standard procedure of user tracking based on the Kalman filter.

2. Error Covariance Prediction:

$$P_{k|k-1} = F \cdot P_{k-1} \cdot F^T + Q,$$

3. Estimation:

$$K_k = P_{k|k-1} \cdot H^T \cdot \left(H \cdot P_{k|k-1} \cdot H^T + R\right)^{-1},$$

4. State Update:

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k \cdot \left(z_k - H \cdot \hat{x}_{k|k-1}\right),$$

5. Error Covariance Update:

$$P_k = (I - K_k \cdot H) \cdot P_{k|k-1}.$$

Here, $\hat{x}_k$ is the state estimate at time k (includes ϕ, θ, and r), F is the state transition matrix, $P_{k|k-1}$ is the predicted state covariance, Q is the process noise covariance, K_k is the Kalman gain, H is the measurement matrix, z_k is the measurement at time k (includes ϕ, θ, and r), and R is the measurement noise covariance.

Some potential applications of cont-BF for 5G technology include the following:

1. **Improved coverage**: cont-BF can help extend the coverage of 5G networks by focusing the transmission beam toward the

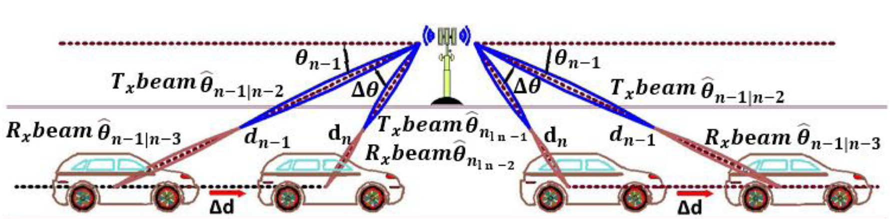

FIG. 3. Base station to vehicle scenario.

receiver. This can help overcome obstacles such as buildings and trees that may obstruct the signal.

2. **Higher data rates**: By directing the signal toward the receiver, cont-BF can help increase the data rates of 5G networks. This can enable faster downloads and uploads, as well as smoother streaming of high-definition content.
3. **Reduced interference**: cont-BF can help reduce interference from other devices or networks by steering the transmission beam away from sources of interference. This can improve the reliability and quality of 5G connections.
4. **Energy efficiency**: By directing the transmission beam toward the receiver, cont-BF can reduce the amount of energy required to transmit the signal. This can help improve the energy efficiency of 5G networks, which is an important consideration for mobile devices that rely on battery power.

3. Location-assisted BF

A priori information on the location of the user can enable the system to work more efficiently. The sorting of prior information can reduce energy footprints. As an example, the branch predictor[46] in computer architectures can improve the flow in the instruction pipeline to achieve highly effective performance. In the case of location-aided or location-aware BF, a similar concept has been seen. Figure 5 shows the block diagram for predictive or location-assisted BF consisting of a digital signal processor (DSP), RF chain, splitter, and N-phase shifter followed by antenna assembly along with a feedback loop providing current target user location to shifters. Line of sight (LoS) communication in mmWave transmission systems provides multi-gigabit data transmission with BF toward the user direction to mitigate the substantial propagation loss. However, abrupt performance degradation caused by human obstruction remains a major issue; thus, using possible reflected pathways when blocking occurs should be considered.[47]

The usage of location-aware BF and interference mitigation techniques in ultradense 5G networks composed of densely scattered access nodes (ANs) has been investigated in the literature. The development of user environment area networks (UEANs) with short distances in a packed environment results in higher levels of signal interference, but network densification enhances the chance of LoS and, as a result, leads to more accurate UE placement. This enables the use of spatial dimensions by BF and interference reduction. The accuracy of radio network positioning systems currently available is inferior to that of fiber optic communication systems in radar stations and atomic clock-based satellite navigation systems. Future 5G networks are expected to provide positioning accuracy on the order of 1 m. The authors of the work of Sand *et al.*[23] proposed approaches such as weighted centroid geometric (WCG) and

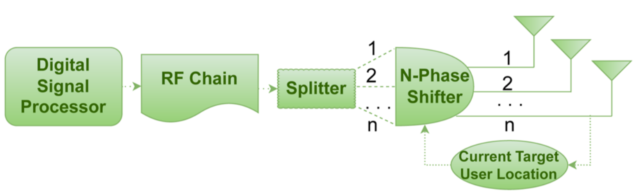

FIG. 5. Basic block diagram of location-assisted BF.

a joint positioning and tracking framework based on the extended Kalman filter (EKF) to achieve accurate and reliable 3D positioning for industrial IoT systems where anchor locations are not precisely known. They also suggested a position-aided BF (PABF) approach that outperforms conventional BF in terms of initial access latency and spectral efficiency, especially for UE moving at a speed greater than 0.6 m/s.

The authors of the work of Sellami *et al.*[48] proposed a neighbor-aided localization algorithm for outdoor UEs operating in challenging channel conditions. The algorithm selects two neighbors based on reference signal power measurement, and the BS performs BF over an angular interval determined by the calculated distance and angle of arrival (AoA) of the first neighbor to discover two candidates for the UE post.[49] The work provided location assistance (LA) direction of departure (DoD)-based BF technique that is appropriate for wireless communication in high-speed rail (HSR). The algorithm's goal is to modify the phase at the transmitter to increase the output SNR at the receiver. The performance of both ideal DOD BF and approximated DOD with location error-related variation is assessed.

The study described in Ref. 50 suggests LAMA (Location Assisted Medium Access), a Medium Access Control (MAC) protocol based on locally shared position data for position awareness beaconing. Their contention-free method manages to effectively minimize interference, especially hidden-terminal type, through coordinated spatial reuse and scales effectively with high neighbor numbers. In Ref. 51, the authors implemented location-aware BF and interference mitigation techniques in 5G ultradense radio networks to improve the use of space. They also estimated the positioning accuracy limitations of the user equipment using the direction of arrival measurement processing in three-dimensional space with metrics of the Cramer–Rao lower bound ellipsoid.

Similarly, Ref. 52 proposed a location-aware BF design for the reconfigurable intelligent surface (RIS)-aided mmWave communication system without the channel estimation process, which took into account the limitations of conventional channel state information (CSI) acquisition techniques for the RIS-aided communication system. They also created a worst-case robust BF optimization problem to counteract the impact of location inaccuracy on the BF design.

The likelihood of positioning-aided BF systems experiencing an outage has been investigated in Ref. 53. The authors took into consideration the positioning error, link distance, and beamwidth to generate closed-form outage probability constraints. They demonstrated that the beamwidth should be maximized with the transmit power and connection distance to reduce the likelihood of an outage. In Ref. 54, a DL-based location-aware predictive BF technique was proposed to follow the beam for unmanned aerial vehicle (UAV) communications in a dynamic environment. They developed a long short-term memory (LSTM)-based recurrent neural network (LRNet) to predict the UAV's expected location, which could be used to calculate a forecast angle between the UAV and the base station for efficient and quick beam alignment.

In a multicell, MIMO communication system aided by optical positioning,[49] a location-based energy-efficient optimization approach for the BF matrix has been proposed. The authors increased the system's achievable ergodic rate by estimating the channel coefficient matrix based on the location data. In Ref. 55, position-aided BF (PABF) architecture was proposed for improved downlink communications in a cloud-oriented mmWave mobile network. The authors demonstrated that the proposed PABF outperformed the traditional codebook-based BF in terms of effective transmit ratio and initial access latency, demonstrating its potential to accommodate high-velocity mobile users.

Finally, Ref. 56 proposed an effective beam alignment solution for mmWave band communications by utilizing the mobile user's location data and potential reflectors. The suggested method enabled the base station and mobile user to jointly search a small number of beams within the error bounds of noisy location information. Additionally, Ref. 57 proposed a method for BF that tracked the spatial correlation of strong pathways that were currently accessible between the transmitter and the receiver. They demonstrated the robustness of their approach to position information uncertainty and how it could reliably maintain a connection with a user who was traveling along a trajectory.

In summary, all the above-mentioned research shows the effectiveness of knowing the user location, either static or on the move, to leverage the existing cellular communications. The location information can assist in predicting the precoding weights accurately and eventually steering the beam in the direction of the user with low latency and high throughput.

B. AI, ML, and DL approaches for cont-BF [RQ:2]

AI is a term that encompasses a vast array of techniques and technologies that grant machines the ability to perform tasks that would usually demand human intelligence, such as learning, problem-solving, and decision-making. Within AI, there are two primary categories: narrow or weak AI and general or strong AI. Narrow or weak AI machines are designed to accomplish specific tasks, while general or strong AI strives to create machines capable of performing any cognitive task a human can do. In contrast, ML is a subfield of AI that specializes in the development of algorithms and statistical models that enable machines to improve their performance on a task over time by learning from data. ML algorithms can be classified into three primary categories: supervised learning, unsupervised learning, and reinforcement learning (RL). In supervised learning, the algorithm is trained on labeled data, where the correct output is already known, to forecast new outputs for unseen data. In unsupervised learning, the algorithm is trained on unlabeled data to identify patterns or structures in the data. In reinforcement learning, the algorithm learns through trial and error, receiving feedback in the form of rewards or penalties based on its actions. AI finds application in various domains, including natural language processing (NLP), image recognition, and robotics.[58]

Regarding BF, AI can refer to any technique that allows machines to enhance the quality or efficiency of BF by learning from data, making predictions or decisions based on that data, and adapting to changing conditions. The amalgamation of BF and AI represents a compelling advancement in signal processing and communication systems. BF, a technique used in radio communications and signal processing, involves the direction of a signal toward a particular location or direction. By integrating signals from multiple antennas, BF amplifies signals in the desired direction while suppressing interference from other directions. On the other hand, AI employs computational algorithms and computer programs that can learn from existing data to make decisions or predictions.

By combining BF and AI, communication systems can witness remarkable improvements in their performance. AI algorithms can scrutinize signals received by multiple antennas and determine the optimal BF configuration for a given situation. This can result in enhanced signal quality and reduced interference. Additionally, AI can dynamically adjust BF parameters in response to current environmental and signal characteristics using reinforcement learning or other AI techniques, which is particularly useful in complex and dynamic environments where traditional BF techniques may struggle to adapt. AI is also beneficial for optimizing BF algorithms themselves by adjusting the parameters employed to combine signals from different antennas. This can enhance the accuracy and efficiency of the BF process, leading to more reliable communication. Furthermore, BF and AI can significantly improve the performance of communication systems in various applications, from cellular networks to satellite communication systems.

Recent research has delved into AI-assisted cont-BF, which can be optimized using AI algorithms to filter out unwanted noise from the signal or to automatically identify the location of a sound source. This can be accomplished by training models on datasets of sound signals and corresponding locations and using the models to predict the location of new sound sources or to identify and remove noise from new signals. By pointing the microphone array toward the predicted location, sound can be captured more effectively. In multiuser multiple-input-single-output (MISO) systems, BF is a useful way to improve the quality of incoming signals. Traditionally, finding the best BF solution has relied on iterative techniques, which have significant processing delays and are unsuitable for real-time applications.[59] With recent advancements in DL algorithms, identifying the best BF solution in real time while taking into account both performance and computational delay has become possible.[59] This is accomplished by offline training of neural networks before online optimization, allowing the trained neural network to identify the optimal BF solution. This approach reduces computational complexity during online optimization, requiring only simple linear and nonlinear operations.[59]

Figure 6 illustrates the neural network architecture for BF, which comprises input, hidden layers, and output to extract features for further processing. The architecture comprises two primary modules: the Neural Network Module and the BF Recovery Module. The former encompasses layers such as the input layer, convolutional (CL) layers, batch normalization (BN) layers, activation (AC) layers, a flattened layer, a fully connected (FC) layer, and an output layer. The latter, the BF Recovery Module, has the design of its functional layers based on expert knowledge of BF optimization, aiming to map the output key features from the previous module to the BF matrix. Note that such expertise is problem-specific and lacks a standardized form while proven to be highly useful in significantly reducing the number of variables to be predicted. A typical example of this expert knowledge for BF is the uplink–downlink duality.[59]

In complex indoor or outdoor contexts with multiple pathways, propagation loss, noise, and Doppler effects create additional issues. Liu's approach involves employing an ML regression method based on efficient BF transmission patterns to predict the position of users on the move, following the collection of large volumes of

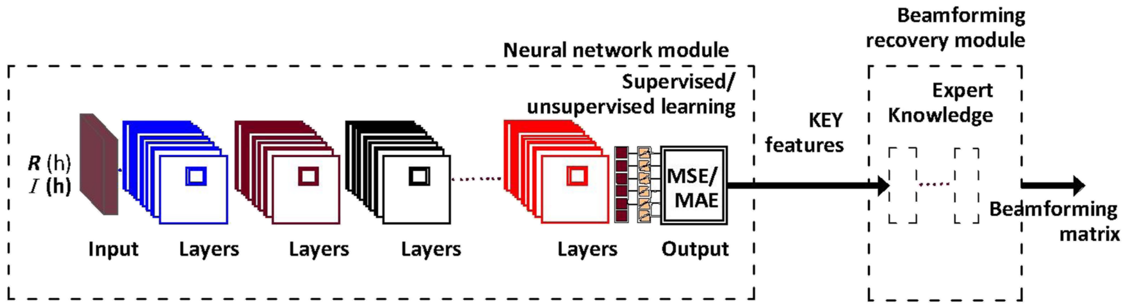

FIG. 6. Basic architecture of a deep neural network that consists of input (extracted features), hidden layers (as per required framework), output (desired results), and a feed for postprocessing.

LoS and non-line-of-sight (NLoS) data.[60] In the domain of location estimation, the authors of the work of Bhattacharjee *et al.* presented two distinct approaches for training neural networks, one using channel parameters as features and the other using a channel response vector, and evaluated the results using preliminary computer simulations.[61,62] The same group also conducted experimental work on the localization of drones and other application areas using different approaches.[63] The authors of the work of Wang *et al.* proposed a weighted loss function to enhance the performance of localization with sparse sensor layouts, achieving an accuracy boost of over 50%.[64] We also presented results for future location estimation of mobile users using a deep neural network in Ref. 65.

As a typical application scenario, 5G vehicular communication has seen cont-BF implementation using various ML and AI techniques. The performance and precision of BF systems, which are essential for efficient communication in moving situations, are to be improved by these techniques. ML has the potential to significantly advance 5G technology, as evidenced by the growing complexity of constructing cellular networks. DL has demonstrated effectiveness in ML tasks like speech recognition and computer vision, with performance growing as more data are accessible. The proliferation of DL applications in wireless communications is constrained by the scarcity of huge datasets. To create channel realizations that accurately depict 5G scenarios with mobile transceivers and objects, this study describes an approach that combines a car traffic simulator with a ray-tracing simulator. Section III B 1 offers a unique dataset along with various ML as well as AI techniques used for examining millimeter wave beam selection methods for car-to-infrastructure communication. The application of datasets produced with the suggested methodology is demonstrated by experiments including DL in classification, regression, and reinforcement learning problems.[66] Moreover, Table I shows the performance of different cont-BF techniques based on results from various studies.

1. Deep learning

The extraction of valuable characteristics from input signals and the provision of more precise predictions have been accomplished using DL techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs).[67]

For instance, the authors of the work of Wang *et al.* used DL to simplify BF weight estimation in 5G systems.[64] They developed a channel model and trained convolutional neural networks on generated data. The networks predicted BF weights based on channel data, reducing complexity. Results show the potential of DL for digital and hybrid BF, and performance comparison with conventional techniques was presented.[68] Moreover, Ref. 69 proposed a method that aims to improve the performance of Random Forest, Multilayer Perceptron, and k-Nearest Neighbors classification models by increasing the amount of data through synthetic data inclusion. Their experimental results showed that the inclusion of synthetic data improved the macro F1 scores of the models. The Random Forest, Multilayer Perceptron, and k-Nearest Neighbors achieved macro F1 scores of 0.9341, 0.9241, and 0.9456, respectively, which are higher than those obtained with the original data only, thus indicating better performances.

Reference 70 proposed a DL-based fast-BF design method for sum rate maximization under a total power constraint. The method was trained offline using a two-step training strategy. Simulation results demonstrated that the proposed method is fast while obtaining comparable performance to the state-of-the-art method. They derived a heuristic solution structure of the downlink BF through the virtual equivalent uplink channel based on the optimum MMSE receiver. BPNet is designed to perform joint optimization of power allocation and virtual uplink BF (VUB) design and is trained offline using a two-step training strategy. A DL-enabled BF neural network (BFNN) is proposed, which can optimize the beamformer to attain better spectral efficiency. Simulation findings reveal that the proposed BFNN achieves significant performance gain and high robustness to imperfect CSI. The proposed BFNN greatly decreases the computational complexity compared to conventional BF algorithms. Spectral efficiency, performance gain, robustness to imperfect CSI, and computational complexity (measured in floating point operations) are the main outcomes of BFNN.[71]

Reference 59 proposed a BF neural network (BNN) for the power minimization problem in multi-antenna communication systems. The BNN was based on convolutional neural networks and the exploitation of expert knowledge. It achieved satisfactory performance with a low computational delay. A deep fully convolutional neural network (CNN) was used for BF, providing considerable

TABLE I. Performance comparison of different cont-BF techniques based on results from various studies.

Technique name	Description	Advantages	Limitations	Type of data required
Geometric-based	Determines the location of the user using the arrival times of signals from multiple antennas	•Low computational cost	•Limited accuracy in indoor environments •Vulnerable to multipath fading	•Antenna array data •User location data
Channel state information (CSI)-based	Uses CSI data from multiple antennas to estimate the user's location	•High accuracy •Robustness to multipath fading	•Requires high-quality CSI data •Complex algorithms	•CSI data from multiple antennas •User location data
Hybrid-based	Combines geometric and CSI-based techniques to improve accuracy and robustness	•High accuracy •Robustness to multipath fading and noise	•Requires complex algorithms •May have high computational cost	•Antenna array data •CSI data from multiple antennas •User location data
ML-based	Uses ML algorithms to learn the relationship between antenna array data and user location	•High accuracy •Can adapt to changing environments	•Requires large amounts of training data •May have high computational cost during training	•Antenna array data •User location data for training
DL-based	Uses DL algorithms to learn the relationship between antenna array data and user location	•High accuracy •Can adapt to changing environments •Can handle large amounts of data	•Requires even larger amounts of training •May have high computational cost during training data than ML-based techniques	•Antenna array data •User location data for training

performance gains. The CNN was trained in a supervised manner, considering both uplink and downlink transmissions, with a loss function based on UE receiver performance. The neural network predicted the channel evolution between uplink and downlink slots and learned to handle inefficiencies and errors in the whole chain, including the actual BF phase.[72] A DL model is employed to learn how to use these signatures for predicting the BF vectors at the base stations.[31] Additionally, Ref. 31 discussed a novel integrated ML and coordinated BF solution to support highly mobile mmWave applications. The solution used a DL model to learn how to use signatures to predict BF vectors at the base stations. This rendered a comprehensive solution that supports highly mobile mmWave applications with reliable coverage, low latency, and negligible training overhead.

Reference 73 proposed a DL-based energy BF scheme for a multi-antenna wireless powered communication network (WPCN). We used offline training for the deep neural network (DNN) to provide a faster solution to the real-time resource allocation optimization problem. Simulation results showed that the proposed DNN scheme provided a fair approximation of the traditional sequential parametric convex approximation (SPCA) method with low computational and time complexity.

2. Supervised learning

Different kinds of RF environments have been classified and predicted using supervised learning methods like the support vector machine (SVM) and decision trees. A modified SVM technique is proposed for 3D MIMO BF in 5G networks. The Advanced Encryption Standard algorithm is employed for more security, and interference is reduced in two stages. The suggested ML-3DIM method outperforms existing methods in terms of throughput, SINR, and SNR by up to 20%, 30%, and 35%, respectively, according to simulation results.[74] Reference 75 investigated the ML-based BF design in two-user MISO interference channels. It proposed an ML structure that takes transmit power and channel vectors as input and then recommends two users' choices between maximum ratio transmission (MRT) and zero-forcing (ZF) as output. The numerical results showed that our proposed ML-based BF design found the best BF combination and achieved a sum rate of more than 99.9% of the best BF combination.

Reference 76 introduced an SVM-based approach for linear array processing and BF. It showed how the new minimization approach can be applied to the problem of linear BF with BER performances of the adopted LS and SVM for various noise levels ranging from 0 to 15 dB.

ML BF approach based on the k-nearest neighbors (k-NN) approximation has been considered, which was trained to generate the appropriate BF configurations according to the spatial distribution of throughput demand. Performance was evaluated statistically via a system-level simulator that executes Monte Carlo simulations in parallel. The ML-assisted BF framework achieved up to 5 Mbits/J and 36 bps/Hz in terms of energy efficiency (EE) and spectral efficiency (SE), respectively, with reduced hardware and algorithmic complexity.[77] BeamMaP was a BF-based ML model for positioning in massive MIMO systems.[78] Simulation results showed that

BeamMaP achieved Reduced Root-Mean-Squared Estimation Error (RMSE) performance with an increasing volume of training data. BeamMaP was more efficient and steady in the positioning system compared with k-NN and SVM.[78]

Reference 79 discussed an ML method for BF at the receiver side antennas for deploying LoS communication in satellite communication (Satcom). It described how the antenna array weights are pre-calculated for a number of beam directions and kept as a database. The signal weights that were calculated for each array element by using their progressive measured phase difference were due to the arriving signal, which was given as input to a linear regression ML model, and the DoA of the signal is predicted. A method for determining an appropriate precoder based on knowledge of the user's location was proposed. The proposed method involved a neural network with a specific structure based on random Fourier features, allowing us to learn functions containing high spatial frequencies. The proposed method was able to handle both LoS and NLoS channels.[80]

3. Unsupervised learning

Unsupervised learning methods like clustering and principal component analysis (PCA) have been used to spot trends and put related data points in one category. For instance, Ref. 81 proposes a BF algorithm for fifth-generation and later communication systems. The approach combines the benefits of conventional optimization-based BF techniques with DL-based techniques. To create the initial BF, a novel architecture is proposed, and performance is increased by building a deep unfolding module. The entire algorithm is unsupervised and trained, and simulation results demonstrate enhanced performance and reduced computing complexity when compared to current approaches.

Reference 82 proposed a novel unsupervised learning approach to design the hybrid BF for any subarray structure while supporting quantized phase shifters and noisy CSI. No-BF codebook was required, and the neural network was trained to take into account the phase-shifter quantization. Simulation results showed that the proposed DL solutions can achieve higher sum rates than existing methods.

4. Reinforcement learning (RL)

The performance of cont-BF systems has been enhanced using reinforcement learning techniques like Q-learning and policy gradient methods.[83] For instance, to make network design and maintenance more straightforward, a brand new intelligent algorithm for massive MIMO BF performance optimization is proposed in this research. To produce accurate user mobility patterns, pertinent antenna designs, and an estimate of the effectiveness of the generated antenna diagrams, the system uses three neural networks that apply a deep adversarial reinforcement learning workflow. This method has the advantage of learning independently and without requiring big training datasets.[84]

The authors of the work of Sun *et al.* investigated the use of deep reinforcement learning to predict coordinated BF strategy in an ultradense network and found that the optimal solution is a balanced combination of selfish and altruistic BF.[85] The BF vectors were obtained efficiently through the learned balancing coefficients. RL-based algorithm for cognitive BF was proposed for multi-target detection in massive MIMO (MMIMO) cognitive radars (MMIMO CRs). The proposed RL-based algorithm outperformed the conventional omnidirectional approach with equal power allocation in terms of target detection performance. The performance improvement was even more remarkable under environmentally harsh conditions such as low SNR, heavy-tailed disturbance and rapidly changing scenarios.[86]

Reference 87 proposed a blind beam alignment method based on RF fingerprints of user equipment obtained from base stations. They used deep reinforcement learning on a multiple-base station cellular environment with multiple mobile users and achieved a data rate of up to four times the data rate of the traditional method without any overheads. Reference 88 proposed a novel multiagent reinforcement learning (MARL) formulation for codebook-based BF control. It took advantage of the inherently distributed structure in a wirelessly powered network and laid the groundwork for fully locally computed beam control algorithms. A cognitive BF algorithm based on the RL framework is proposed for colocated MIMO radars. The proposed RL-based BF algorithm is able to iteratively sense the unknown environment and synthesize a set of transmitted waveforms tailored to the acquired knowledge. The performance of the proposed RL-based BF algorithm is assessed in terms of probability of detection (P_D).[89]

Reference 90 proposed an RL approach called the combinatorial multi-armed bandit (CMAB) framework to maximize the overall network throughput for multi-vehicular communications. They proposed an adaptive combinatorial Thompson sampling algorithm, namely adaptive CTS, and a sequential Thompson sampling (TS) algorithm for the appropriate selection of simultaneous beams in a high-mobility vehicular environment. Simulation results showed that both of their proposed strategies approach the optimal achievable rate achieved by the genie-aided solution.

5. Hybrid learning

The performance of cont-BF systems has also been improved using hybrid methods that incorporate several ML and AI techniques, such as deep reinforcement learning. To address the hybrid BF issue in huge MIMO systems, deep reinforcement learning is suggested. The suggested techniques reduce computing complexity while achieving spectral efficiency performance that is close to ideal.[91] Hybrid BF, combining digital baseband precoders and analog RF phase shifters, is an effective technique for mmWave communications and massive multi-input multi-output (MIMO) systems. ML techniques can be used to improve the achievable spectral efficiency of hybrid BF systems. The proposed two-step algorithm can attain almost the same efficiency as that achieved by fully digital architectures.[92]

Reference 93 described the design of ML-based hybrid BF for multiple users in systems that use mmWaves and massive MIMO architectures. The simulation results showed that the ML-based hybrid BF architecture can achieve the same spectral efficiency (bits/sec/Hz) as the fully digital BF designs with negligible error for both single-user and multiuser massive MIMO scenarios. Reference 94 proposed a novel received signal strength indicator (RSSI)-based unsupervised DL method to design the hybrid BF in massive MIMO systems. They proposed a method to design the synchronization signal (SS) in initial access (IA) and a method to design the codebook for the analog precoder. They showed that the proposed method not only greatly increases the spectral efficiency, especially in frequency-division duplex (FDD) communication, by using partial CSI feedback, but also has a near-optimal sum rate and outperforms other state-of-the-art full-CSI solutions.

Deep neural networks (DNNs) can be used to approximate the singular value decomposition (SVD) and design hybrid beamformers. DNN-based hybrid BF improved rates by up to 50%–70% compared to conventional hybrid BF algorithms and achieved a 10%–30% gain in rates compared with the state-of-the-art ML-aided hybrid BF algorithms. The proposed approach had low time complexity and memory requirements.[95]

Table II summarizes the advantages and disadvantages of different types of ML and AI techniques used in cont-BF.

C. Datasets for cont-BF classification [RQ:3]

Researchers often need datasets that contain location data, RF signals, and other pertinent elements to identify cont-BF approaches. The following are a few examples of datasets that have been applied in earlier research.

1. Vehicular networks dataset (VeND)

The University of California, Los Angeles (UCLA), created this dataset,[96] which includes observations from a vehicular network testbed. The dataset contains data about the cars and their movements in addition to details about the wireless channel, such as the signal-to-noise ratio (SNR) and the channel impulse response (CIR).[97]

Reference 98 presented a realistic synthetic dataset, covering 24 h of car traffic in a 400 km^2 region around the city of Koln, in Germany. The dataset captures both the macroscopic and microscopic dynamics of road traffic over a large urban region. Incomplete representations of vehicular mobility may result in over-optimistic network connectivity and protocol performance.

2. 5G-VICTORI

This is a project financed by the European Union that aims to create 5G technologies for a range of applications, including vehicular communication. With regard to vehicular communication, the project has created a number of datasets, including assessments of the RF channel and network performance in practical settings.[99]

Reference 100 discusses how the new 5G network technology would impact the digitalization of various industries, including modern railway transportation. The Future Railway Mobile Communication System (FRMCS) service requirements and system principles were well-mapped to 5G concepts, but deployment paradigms needed to be established to prove their effectiveness. The 5G-VICTORI project aimed to deliver a complete 5G solution for railway environments and FRMCS services, and this paper discusses the key performance indicators and technical requirements for an experimental deployment in an operational railway environment in Greece.

3. 5G-EmPOWER

This EU project aims to develop 5G technology for a range of applications, including vehicular communication. With regard to vehicular communication, the project has created a number of datasets, including assessments of the RF channel and network performance in practical settings.[101]

TABLE II. Table summarizing the different types of ML and AI techniques used in cont-BF.

Technique name	Description	Advantages	Limitations
Support vector machines (SVM)	Supervised learning algorithm that learns a decision boundary between classes	•Can handle high-dimensional data •Effective in binary classification tasks	•May overfit with noisy or imbalanced data
Random forest	Ensemble learning method that combines multiple decision trees to improve performance	•Can handle high-dimensional data •Can handle missing or noisy data •Can provide feature importance measures	•May overfit with noisy or imbalanced data
Convolutional neural networks (CNN)	Neural network architecture that uses convolutional layers to extract features from input data	•Highly effective for image and signal processing tasks •Can learn complex spatial patterns	•May require large amounts of training data •Maybe computationally expensive
Recurrent neural networks (RNNs)	Neural network architecture that can process sequential data by maintaining a memory of past input	•Effective for time-series data and natural language processing tasks •Can handle variable-length inputs	•May be prone to vanishing or exploding gradients •May require large amounts of training data
Reinforcement learning (RL)	Learning paradigm in which an agent learns to make decisions through trial and error in an environment	•Can adapt to changing environments •Can handle complex decision-making tasks	•May require significant computational resources •May require careful tuning of hyperparameters

3GPP is embracing the concept of Control-User Plane Separation, a cornerstone concept in software-defined network (SDN) in the 5G core and the Radio Access Network (RAN). An open-source SDN platform for heterogeneous 5G RANs has been introduced, which builds on an open protocol that abstracts the technology-dependent aspects of the radio access elements. The effectiveness of the platform has been assessed through three reference use cases: active network slicing, mobility management, and load-balancing.[101]

4. Network simulator 3 (ns-3)

Network Simulator 3 (ns-3) is an open-source network simulator that is useful for simulating and modeling vehicular communication in 5G networks. In addition to mobility models for simulating the movement of vehicles, ns-3 has various built-in modules for modeling the wireless channel.[102]

Reference 103 presents a framework for the ns-3 network simulator for capturing data from inside an experiment, subjecting it to mathematical transformations and ultimately marshalling it into various output formats. The application of this functionality is illustrated and analyzed via a study of common use cases. The design presented provides lessons transferrable to other platforms.

5. Connected automobiles and cities

The National Renewable Energy Laboratory (NREL) created this dataset, which contains information from a field investigation of connected automobiles in a smart city setting. The dataset contains details about, among other things, network performance, traffic flow, and vehicle trajectories.[104]

In Ref. 105, big data from the cellular network of the Vodafone Italy Telco operator can be used to compute mobility patterns for smart cities. Five innovative mobility patterns have been experimentally validated in a real industrial setting and for the Milan metropolitan city. These mobility patterns can be used by policy-makers to improve mobility in a city, or by Navigation Systems and Journey Planners to provide final users with accurate travel plans.

6. DeepSense6G

DeepSense 6G is a collection of data that includes different types of sensing and communication information, such as wireless communication, GPS, images, LiDAR, and radar. These data were gathered in real-life wireless environments and represent the world's first large-scale dataset of this kind. The dataset contains over one million samples of this multimodal sensing-communication data and was collected in over 30 different scenarios to target various applications. The collection of data was done at several indoor and outdoor locations with high diversity and during different times of the day and weather conditions. Additionally, there are tens of thousands of data samples that have been labeled both manually and automatically.

The authors of Ref. 106, present the DeepSense 6G dataset, which is a large-scale dataset based on real-world measurements of co-existing multimodal sensing and communication data. The DeepSense dataset structure, adopted testbeds, data collection and processing methodology, deployment scenarios, and example applications are detailed in the paper. The paper aims to facilitate the adoption and reproducibility of multimodal sensing and communication datasets. The researchers[107] had a 400 GB dataset containing hundreds of thousands of WiFi transmissions collected "in the wild" with different signal-to-noise ratio (SNR) conditions and over different days. They also had a dataset of transmissions collected using their software-defined radio testbed, and a synthetic dataset of LTE transmissions under controlled SNR conditions.

7. SUMO

The Simulation of Urban MObility (SUMO) is an open-source traffic simulation software that allows modeling and simulating traffic flow in urban areas. It can simulate individual vehicles, pedestrians, public transportation, and various road networks. SUMO has a variety of applications, including traffic planning, intelligent transportation systems, and autonomous driving. A synthetic dataset generator was developed to support research activities in mobile wireless networks. The generator uses traces from the SUMO simulator and matches them with empirical radio signal quality and diverse traffic models. A dataset was created in an urban scenario in the city of Berlin with more than 6 h of duration, containing more than 40 000 UEs served by 21 cells.[108]

D. Miscellaneous datasets

1. 5G3E dataset

Reference 109 introduced the 5G3E dataset, designed to contain thousands of time series related to the observation of multiple resources involved in 5G network operation. This dataset was specifically created to support 5G network automation, encompassing a variety of collected features ranging from radio front-end metrics to physical server operating system and network function metrics. The testbed associated with the dataset was deployed to facilitate the generation of traffic, starting from real traffic traces of a commercial network operator.

2. 5G trace dataset

Another dataset is the 5G trace dataset from a significant Irish mobile operator introduced by Ref. 110. This paper presents a 5G trace dataset collected from a major Irish mobile operator. The dataset was generated from two mobility patterns (static and car) and across two application patterns (video streaming and file download). The dataset was composed of client-side cellular key performance indicators (KPIs) comprised of channel-related metrics, context-related metrics, cell-related metrics, and throughput information. Additionally, the authors provided a 5G large-scale multicell ns-3 simulation framework to supplement our real-time 5G production network dataset. This framework allowed other researchers to investigate the interaction between users connected to the same cell through the generation of their synthetic datasets.

3. SPEC5G dataset

Reference 111 curated SPEC5G, the first publicly accessible 5G dataset for natural language processing (NLP) research. The dataset contains 134×10^6 words in 3 547 587 phrases taken from 13 online websites and 13 094 cellular network specs. The authors utilized this dataset for security-related text categorization and summarization by utilizing large-scale pre-trained language models. For protocol testing, pertinent security-related attributes were also extracted using text classification techniques. Additionally, Ref. 112 presented a novel mobility dataset generation method for 5G networks based on users' GPS trajectory data. It aggregated the user's

GPS trajectories and modeled his location history by a mobility graph representing the cell base stations he passed through. The generated dataset contained the mobility graph records of 128 users. The user mobility dataset for 5G networks based on GPS geolocation is valuable for predicting user mobility patterns.

4. Labeled dataset for 5G network

In another study, Ref. 113 discussed a methodology for collecting a labeled dataset for a 5G network. It described how to build a 5G testbed and use it to collect data. This dataset can then be used to construct a 5G-based labeled dataset. A 5G testbed was built to observe 5G network features by replaying the collected data. A specialized network collector system was implemented to collect 5G edge network traffic data. A re-collecting methodology using the proposed 5G testbed and network collector can be used to construct a 5G-based labeled dataset for supervised learning methods.

5. 5G users measurement campaign

Moreover, Ref. 114 utilized the results from a publicly available measurement campaign of 5G users and analyzed various figures of merit. The findings indicated that the downlink and uplink rates for static and mobile users can be represented by either a lognormal or a generalized Pareto distribution. Moreover, the time spent in the same cell by a mobile (driving) user was observed to be best captured by a generalized Pareto distribution. Additionally, the prediction of the number of active users in the cell was found to be feasible.

6. 5G tracker

Furthermore, Ref. 115 discusses a crowdsourced platform called 5G Tracker that includes an Android app to record passive and active measurements tailored to 5G networks and research. It has been used for over 8 months and has collected over 4×10^6 data points. The platform is useful for building the first-of-a-kind, interactive 5G coverage mapping application. 5G Tracker is a crowdsourced platform to enable research using commercial 5G services. 5G performance is affected by several user-side contextual factors, such as user mobility level, orientation, weather, location dynamics, and environmental features. 5G Tracker has been used to collect over 4×10^6 data points, consuming over 50 TB of cellular data across multiple 5G carriers in the United States.

7. Mobile edge computing in 5G

Moreover, bringing computational and storage technologies closer to end users with strategically deployed and opportunistic processing and storage resources, mobile edge computing in the 5G network was developed by Ref. 116 as a very attractive computation architecture. This paper used data mining and statistical methods to analyze Baidu website data. The analysis results gave suggestions to improve the design and development of 5G services. Data mining and statistical analysis of Baidu cloud services in the 5G network revealed that clustering, outlier detection, prediction, and statistical methods can be used to evaluate smart city services. The analysis results provided insights into the design and development of 5G services (API website). The findings suggested that mobile edge computing in 5G networks can be used to improve the performance of smart city services.

8. 5G+ industrial Internet

Finally, Ref. 117 discusses a project to collect "three-level" edge layer data from equipment manufacturers, equipment users, and spare parts manufacturers. The goal was to establish a unified data standard and help companies build general services around equipment data. 5G+ Industrial Internet is used to collect data from three levels of edge layers: spare parts manufacturers, equipment manufacturers, and equipment users. Data are assimilated and unified into a single standard. A large-scale and shallow informatization project of incremental equipment is implemented in the Yangtze River Delta in a short period of time.

Moreover, Table III lists a few 5G datasets consisting of channel state information (CSI), phase, received power, etc., that can be used for user localization.

E. Optimization techniques for cont-BF [RQ:4]

While using AI-based techniques, system optimization is a crucial step. AI-based cont-BF models can be optimized using various strategies to ensure real-time processing. One method to accelerate computations is through hardware acceleration techniques like GPU processing. Additionally, by using pre-trained models or reducing the number of parameters in the model design, the model can be

TABLE III. Table listing datasets related to user location.

Dataset name	Source	Characteristics
IEEE 802.11n channel measurement	IEEE 802.11n working group	Channel state information (CSI) from multiple antennas
KTH localization dataset	KTH Royal Institute of Technology	Received signal strength (RSS) and angle of arrival (AoA) from multiple antennas ground truth location data
CSI-hotel dataset	University of California, Santa Barbara	CSI data from multiple antennas in an indoor environment
DeepMIMO dataset	New York University	Synthetic data generated by a ray-tracing tool for a variety of scenarios, including urban and indoor environments
iNEMO dataset	STMicroelectronics	Acceleration, magnetic field, and angular velocity data, along with ground truth location data

optimized. To decrease the model size and boost computational effectiveness, techniques like pruning, quantization, and knowledge distillation can be applied. Improving the feature extraction and input data preprocessing phases can also help with real-time processing. Creating specialized algorithms and optimization strategies adapted for certain hardware and deployment conditions can also enhance the performance of cont-BF models.

Figure 7 shows some of the possible ways to optimize cont-BF models for real-time processing, which are explained in detail below.

1. Model simplification

Simplifying the model architecture, such as reducing the number of layers or the number of neurons in each layer, can improve computational efficiency and reduce processing time. For instance, research suggests a strategy that uses ML and hardware performance counter data to optimize power and performance for GPU-based systems. The model can accurately detect power-performance bottlenecks and provide optimization techniques for a variety of sophisticated compute and memory access patterns. The model, which has been validated on NVIDIA Fermi C2075 and M2090 GPUs as well as the Keeneland supercomputer at Georgia Tech, is more reliable and accurate than existing GPU power models.[118]

2. Hardware acceleration

Dedicated hardware, such as graphics processing units (GPUs), field-programmable gate arrays, or application-specific integrated circuits, can speed up the processing of cont-BF models by performing parallel computations. To determine the direction of incoming signals, BF is a signal processing technique that combines signals from a number of receivers. Although it overcomes noise interference, adaptive BF (ABF) is computationally expensive. In current GPUs, ABF can be implemented in parallel. ABF can be parallelized on an NVIDIA GPU using the author's method, which has a lower throughput than serial implementation but can still be improved.[119]

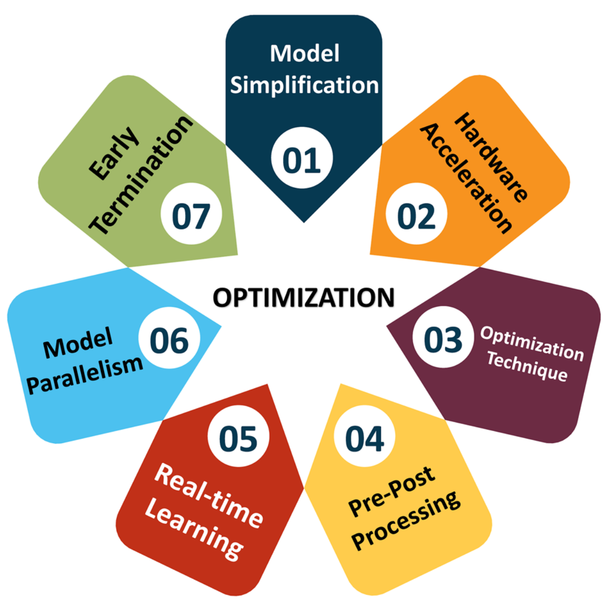

FIG. 7. Optimization techniques for cont-BF.

3. Optimization techniques

Various optimization techniques, such as weight pruning, quantization, and knowledge distillation, can be applied to cont-BF models to reduce their computational complexity and memory footprint without significant loss in accuracy. This research[120] explores the use of the deep neural network (DNN) model as the teacher to train recurrent neural networks (RNNs), specifically long short-term memory (LSTM), for automated voice recognition (ASR). The method successfully trains RNNs without the use of additional learning methods, even with a small amount of training data.

4. Preprocessing and postprocessing

Preprocessing the input data to reduce its dimensionality or complexity, and postprocessing the output data to refine the results or reduce noise can help improve the performance and efficiency of cont-BF models. With the use of DL, a low-complexity precoding design approach for multiuser MIMO systems is suggested in Ref. 121. The suggested method uses methods such as input dimensionality reduction, network pruning, and recovery module compression to produce a performance that is comparable to the conventional WMMSE algorithm with relatively little computational cost.

5. Real-time learning

Using online or incremental learning algorithms instead of offline or batch learning can enable cont-BF models to adapt to changing conditions in real time and reduce the need for frequent retraining. In Ref. 122, two adaptive learning approaches such as ADAM and RAL are proposed for the real-time detection of network assaults in Internet network traffic. These methods achieve excellent detection accuracy even in the presence of idea drifts by dynamically learning from and adapting to nonstationary data streams while lowering the demand for labeled data.

6. Model parallelism

Breaking the model into smaller sub-models and processing them in parallel can improve the overall processing speed of cont-BF models. This can be done using techniques such as data parallelism or model parallelism. This approach focuses on model and data parallelization, which addresses distributed ML architecture and topology, analyses ML algorithms, and provides suggestions for parallelization.[123] The specific needs and demands of communications networks, such as resource allocation and trade-offs between privacy and security, are not addressed.

7. Early termination

Stopping the model's processing early when a certain threshold is reached can reduce unnecessary computation, especially in cases where the output has already converged. Reference 124 promotes early pausing before convergence to prevent overfitting and suggests the use of cross-validation to detect overfitting during neural network training. The study uses multilayer perceptrons with resilient backpropagation (RPROP) training to assess the effectiveness and efficiency of 14 distinct automatic stopping criteria from three classes for a variety of activities. The findings indicate that slower stopping criteria slightly improve generalization, although the training time often increases by a factor of four.

The choice of optimization techniques will depend on the specific requirements of the application and the constraints of the hardware platform. A combination of these techniques can be used to achieve the best balance between performance and efficiency for the real-time processing of cont-BF models.

IV. CHALLENGES ASSOCIATED WITH USING AI, ML AND DL TECHNIQUES FOR CONT-BF

Cont-BF is a technique used in signal processing and communication systems to improve the quality of sound or data transmission by focusing the transmitted or received signals in a specific direction or area of interest. ML techniques have been increasingly used to optimize the performance of cont-BF systems. However, there are several challenges associated with using ML techniques for cont-BF:

1. **Lack of training data**: ML techniques require a large amount of data to be trained effectively. However, in cont-BF, it may be difficult to collect enough data that accurately represent the various environments and scenarios in which the system will be used. This can result in underfitting or overfitting of the model, leading to poor performance.
2. **Complexity of the models**: ML models used for cont-BF can be quite complex, with many parameters that need to be tuned. This can make the training process difficult and time-consuming and can also increase the risk of overfitting.
3. **Robustness to environmental changes**: Cont-BF systems need to be robust to changes in the environment, such as changes in noise levels or the location of sound sources. ML models may not be able to adapt to these changes quickly enough, resulting in reduced performance.
4. **Limited interpretability**: ML models can be difficult to interpret, which can make it hard to understand why the system is behaving in a certain way or to diagnose problems when they occur.
5. **Limited generalizability**: ML models trained on one set of data may not generalize well to other datasets or environments. This can limit the applicability of the system in real-world scenarios.

Table IV compares the computational complexity and processing time of different cont-BF models. To address these challenges, researchers are exploring new techniques such as transfer learning, which involves pretraining models on large datasets and then fine-tuning them on smaller, task-specific datasets. They are also working on developing more interpretable ML models and incorporating robustness and adaptability into the models.

These challenges have been discussed in several research papers, including the following:

Reference 125 proposes a novel approach to enhance the feature engineering and selection (eFES) optimization process in ML. eFES was built using a unique scheme to regulate error bounds and parallelize the addition and removal of a feature during training. Results showed the promising state of eFES as compared to the traditional feature selection process. A weak convolutional network can be used to provide rough label maps over the neighborhood of a pixel. Incorporating this weak learner in a bigger network can improve the accuracy of state-of-the-art architectures. The approach in Ref. 126 is generic and can be applied to similar networks where contextual cues are available at training time.

A multicriteria technique has been developed that allows for the control of feature effects on the model's output. Knowledge functions have been integrated to accommodate for more complex effects and local lack of information. A DL training process that was both interpretable and compliant with modern legislation has

TABLE IV. Table comparing the computational complexity and processing time of different cont-BF models.

Model	Computational complexity	Processing time	Advantages	Limitations
Linear BF	Low	Fast	•Simple to implement •Low computational complexity	Cannot perform well in non-line-of-sight environments
Maximum ratio transmission (MRT)	Low	Fast	•Simple to implement •Low computational complexity	Cannot perform well in interference-limited environments
Minimum variance distor tionless response (MVDR)	High	Slow	•Provide better performance in non-line-of-sight environments	Computationally intensive
Neural network-based BF	High	Slow	•Learn complex nonlinear relationships between inputs and outputs	Require significant computational resources for training
Reinforcement learning-based BF	High	Slow	•Adapt to changing environments and optimize performance through trial and error	Require significant computational resources and careful tuning of hyperparameters

been developed by Ref. 127. Reference 128 proposed a technique to improve the interpretability in transfer learning tasks by defining interpretable features. They examined the interpretability of transfer learning by applying a pre-trained model with defined features to Korean character classification. Feature Network (FN) consists of a Feature Extraction Layer and a single mapping layer that connects the features extracted from the source domain to the target domain.

Reference 129 proposed an actor-critic model that allowed better generalization across goals and scenes. AI2-THOR framework enabled agents to take actions and interact with objects, allowing for efficient collection of training samples. The model converged faster than state-of-the-art deep reinforcement learning methods, generalized to real robot scenarios with minimal fine-tuning, and is end-to-end trainable.

As we forge ahead, it is paramount to establish a symbiotic relationship between AI, ML, and DL and the practical requirements of cont-BF systems. This involves a nuanced understanding of the limitations and capabilities of these techniques, innovative research to mitigate challenges, and a continuous quest for adaptable, interpretable, and robust solutions. Ultimately, the journey toward seamless integration of AI-driven cont-BF stands as an exciting endeavor, marked by ongoing research and the promise of transformational impact across diverse domains.

V. OUR CONTRIBUTIONS TO LOCALIZATION AND BF

In the pursuit of optimizing wireless communication performance, our research emphasizes the significance of optimal BF. This section showcases the high-level contexts of our research and we invite interested readers to refer to our original publications for detailed further reading.

The primary objective of BF is to strike a balance, maximizing the transmit power for individual users while minimizing interference for others. We specifically explore the effectiveness of the maximum ratio transmission (MRT) BF technique within a multiuser multiple-input multi-output (MU-MIMO) system. Our findings, detailed in Ref. 130, showcase a remarkable enhancement in signal-to-interference-plus-noise ratio (SINR), reaching up to 28.83 dBm or 53% (shown in Fig. 8), compared to scenarios without BF. This section aims to underscore the effectiveness of BF techniques, particularly MRT, in elevating wireless communication performance.

We have also published some of the work in context to localization in Refs. 65 and 130–132. These works show how location datasets can be extracted through ray-tracing tools and how data can be utilized for location prediction using deep neural networks (refer to Fig. 9).

Anticipating the growing demand for wireless communication in the era of 5G, our research delves into the BF performance for mobile users in large cells with effective channel throughput. Utilizing the Glasgow University campus model, we estimate channel properties under various BF techniques, including maximum ratio transmission (MRT) for the transmitter and Equal Gain Combining (EGC), Selection Combining (SC), and Max Ratio Combining (MRC) for the receiver in 3GPP long-term evolution (LTE). The implementation of these BF techniques yields an average throughput improvement from 9 Mbps to 14 Mbps. Notably, MRT-MRC demonstrates the best throughput/SINR in comparison to scenarios without BF.[130]

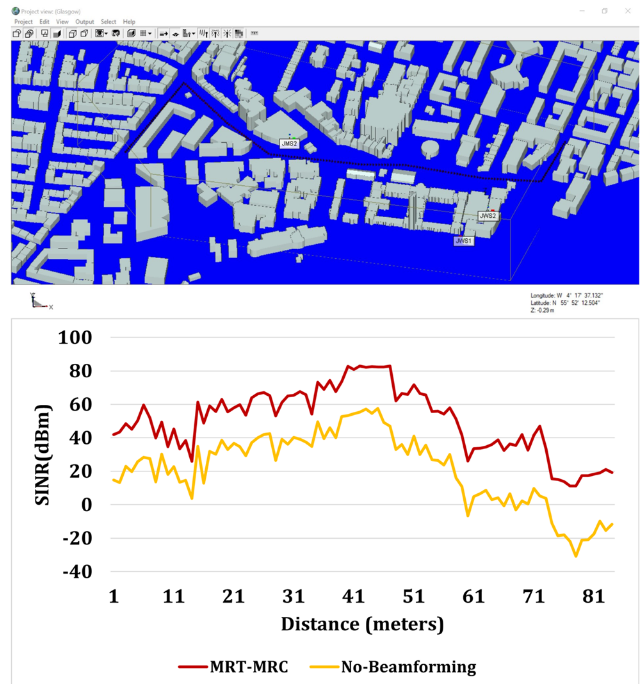

FIG. 8. SINR comparison of MRT with No-BF in university campus scenario.

Addressing the need for precise user localization in the context of accelerated data transmission, our study introduces an accurate

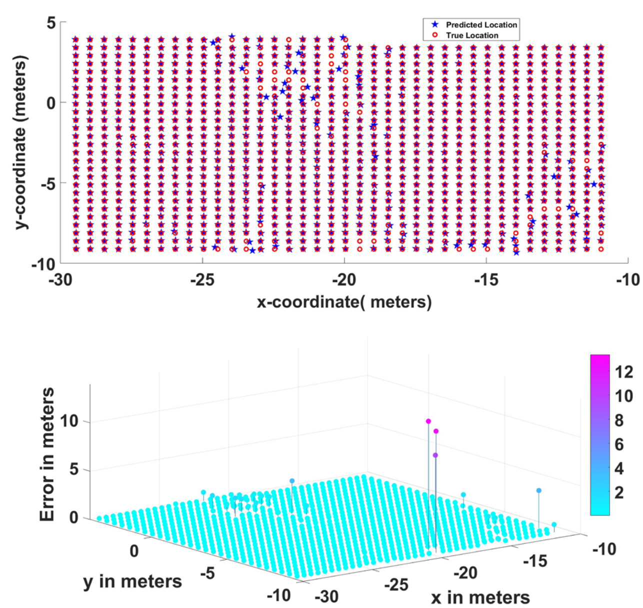

FIG. 9. Location estimation and error between the true location and estimated location.

localization algorithm for mobile users. Leveraging deep neural networks with Bayesian optimization and a communication channel operating at a frequency of 3.75 GHz, our model accelerates the localization process. In computer simulations, our method achieves localization accuracy of less than 1-m error for LoS users, with potential further improvement through higher-rate datasets.[65] This paper introduces a methodology for implementing deep neural networks (DNNs) in localization. The precise estimation of the position of a user's equipment (UE) is achieved through the utilization of channel information and 25 multipath components (MPCs). In this investigation, the DNN is trained using supervised learning approaches, facilitated by synthetic data. The study focuses on a static case, and future research endeavors will delve into more dynamic scenarios, encompassing elements such as foliage and water bodies, for a more comprehensive and realistic environmental analysis.

Furthermore, in the evolving landscape of next-generation wireless networks, we explore the potential use of unmanned aerial vehicles (UAVs) as aerial base stations. Our objective is to assess the feasibility of UAVs as flying base stations, particularly in scenarios with fixed base stations at the University of Glasgow, UK. Ray-tracing simulations indicate the potential benefits of UAV-aided base stations (UAV-BSs) for 5G network communication, including capacity expansion in metropolitan regions, improved coverage in rural areas, and network densification.[132] In this research, we employed ray-tracing simulations to assess the performance of UAV-aided wireless communications. Our study showcased the advantages of utilizing UAV-assisted networks for enhanced coverage compared to fixed base stations (BSs). Additionally, we simulated a more densely populated scenario and presented the effectiveness of our proposed framework. The evaluation incorporates performance parameters, specifically received power, to gauge the utility of UAVs in wireless communication. Similarly, our findings reveal a substantial 70% overall increase in throughput when employing BF techniques compared to scenarios without BF.

A distinctive aspect of our research involves the integration of programming protocol-independent packet processors (P4) for in-network computing, coupled with programmable data planes. P4 is a domain-specific programming language designed to specify the behavior of packet processing devices, enabling the creation of programmable and flexible network devices. This emerging network paradigm presents significant opportunities to reduce both complexity and latency in network operations.

In our paper, recognizing the crucial role of BF in modern wireless communication systems, we propose a novel user-assisted in-network method to optimally approximate the angle of arrival. This approach is implemented in P4 and runs on a Tofino ASIC, taking advantage of programmable data planes and their match-action table (MAT) logic.

Our method operates by expecting periodic location messages reported by the user equipment, processing them within the network, and dynamically reconfiguring base station antennas accordingly. This introduces a user-assisted in-network beam control mechanism, optimizing the angle of arrival approximation. We have conducted extensive evaluations to establish a theoretical bound on the absolute error of the proposed MAT-based angle approximation, aligning well with empirical error distributions.

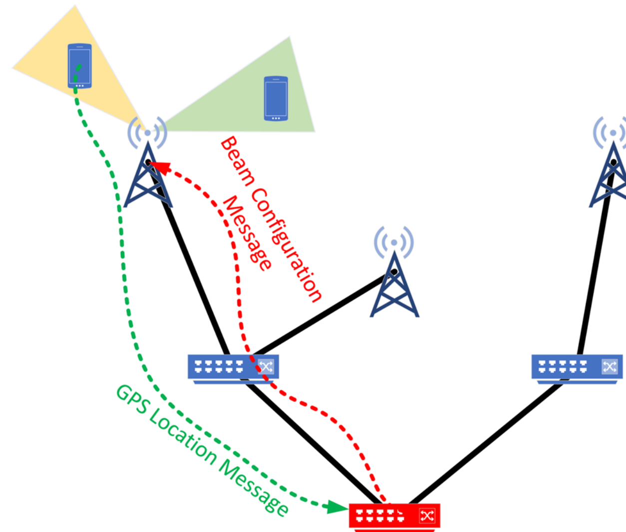

FIG. 10. System architecture of location-assisted BF.[133]

Importantly, our proposed method demonstrates minimal impact on errors attributed to control cycle times and user movement speeds. This ensures effective resource usage without imposing significant per-stage resource overhead on the data plane pipeline. The detailed findings and methodology are discussed in our paper, and more in-depth information can be found in the work of Mallouhi *et al.*[133]

Figure 10 illustrates the segmented network scenario under consideration in this study. Mobile users are connected to the 5G network and indirectly linked to switches within the access aggregation network through core network protocols. Certain switches within this network are assumed to be P4-programmable. In this setup, the mobile user periodically transmits its GPS location to a P4 switch. Subsequently, the P4-switch calculates the angle of the user equipment (UE) concerning the corresponding base station and dispatches a configuration message to the base station, instructing it to adjust the beam toward the UE. We believe that this user-assisted in-network method has the potential to diminish control latency and enhance beam steering more seamlessly and rapidly compared to conventional approaches.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

In this study, we have provided an overview of advanced adaptive BF, incorporating AI techniques such as DL. Importantly, we have demonstrated that with access to contextual information, such as prior user location, DL techniques can enhance a wireless network's performance. As exciting new technologies continue to develop, we anticipate that the next generation of mobile networks will unlock new opportunities. Communication systems are poised to evolve into closed-loop systems, where data extracted from observing a mobile user will be exploited to improve connectivity and network performance. We have touched upon ongoing studies that aim to harness a user's location and develop a DL-enabled cont-BF strategy, projecting future improvement.

Our work not only contributes to the field of adaptive BF and AI applications but also has implications for the broader research community. Integration of DL techniques into communication systems opens avenues for interdisciplinary collaboration between researchers in telecommunications and artificial intelligence. This cross-disciplinary approach is essential for addressing the complex challenges posed by evolving mobile networks.

B. Limitations and future work

While the research surveyed here and the demonstration of our study presented promising results, it is essential to acknowledge potential limitations. The effectiveness of DL-enabled cont-BF strategies may be influenced by factors such as network heterogeneity, varying user mobility patterns, and dynamic environmental conditions. Addressing these challenges will be crucial for the successful implementation of such strategies in real-world scenarios. Consequently, our work sets the stage for future research, with a focus on the following aspects combining the analysis provided in previous sections.

1. DL-enabled cont-BF development: We propose further research to develop DL-enabled cont-BF strategies, with a future aim to improve SINR beyond the scope presented in this paper.
2. Real-world validation: Future studies should explore real-world deployments and extensive field trials to validate the effectiveness of DL-based approaches in dynamic and diverse operational environments.
3. Adaptation to emerging technologies: As technologies continue to evolve, future work should address the integration of DL approaches with emerging technologies, ensuring adaptability and enhanced performance.
4. Privacy-preserving techniques: Recognizing the importance of user privacy, future research should delve into the development of robust privacy-preserving techniques within DL-enabled cont-BF.

By pursuing these future research directions, we invite the research community to aim to contribute to the ongoing evolution of mobile networks, fostering innovation and advancements in the realm of adaptive BF and AI applications.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

Jaspreet Kaur: Conceptualization (lead); Methodology (lead); Visualization (lead); Writing – original draft (lead). **Satyam Bhatti**: Validation (supporting); Visualization (equal); Writing – review & editing (supporting). **Kang Tan**: Supervision (equal); Writing – review & editing (supporting). **Olaoluwa R. Popoola**: Investigation (supporting); Supervision (supporting); Writing – review & editing (supporting). **Muhammad Ali Imran**: Supervision (supporting). **Rami Ghannam**: Supervision (supporting); Validation (supporting). **Qammer H. Abbasi**: Supervision (supporting). **Hasan T. Abbas**: Funding acquisition (lead); Investigation (lead); Supervision (lead); Writing – review & editing (supporting).

DATA AVAILABILITY

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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