A Primer on Contextual Beamforming Techniques that Exploit a User's Location Information

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***Abstract*—Wireless telecommunication is the backbone of mainstream technologies such as automation, smart vehicles, virtual reality, and unmanned aerial vehicles. Today, we are witnessing a wide-scale adoption of these technologies in our daily lives. The endless opportunities generated due to rapid deployments of new technologies have also brought about new challenges, chief among them is ensuring reliable system performance of cellular networks in mobility scenarios. Beamforming is an integral part of modern mobile networks that enable spatial selectivity and hence improved network quality. However, most of the beamforming techniques are iterative in nature; therefore, they introduce additional unwanted latency into the system. Lately, we are witnessing an ever-increasing interest in exploiting the location of a mobile user to speed up beamforming. This paper presents a comprehensive discussion of how location-assisted beamforming strategies improve performance, such as latency and signal-to-noise ratio. Furthermore, we also show how artificial intelligence schemes such as machine learning and deep learning are also used to implement contextual beamforming techniques that exploit the user's location information.**

***Index Terms*—Beamforming Classification, Adaptive and Contextual Beamforming, Machine and Deep Learning, Artificial Intelligence.**

I. Introduction

EVERY successive generation of cellular communication has enabled technologies that allow increased data speeds and capabilities by at least a factor of five [1]. The first generation (1G) offered the very first cell phones, second-generation (2G) enabled text message service, third-generation (3G) enabled internet streaming, and chief amongst the highlights of the fourth-generation (4G) was the introduction of broadband internet coverage. However, because of the rapid increase in user demands, 4G networks have hit their capacity limits, just as customers need more data for their cell phones and other smart devices. We are approaching commercial deployments of fifth-generation (5G) cellular technology, which can carry thousands of times more traffic than currently available networks and evolve ten times faster than long-term 4G development (LTE) [2]. We expect that the 5G cellular networks will soon springboard large-scale deployment of technologies such as augmented reality (AR), autonomous vehicles, the internet of things (IoT), and more [3]. There are five new 5G technologies that are at its core; full-duplex, massive multi-input multi-output (MIMO), millimetre waves (mmWaves), smart cell, and beamforming (BF). Smartphones and certain other electronic gadgets employ radio frequency (RF) frequencies that are typically less than 6 GHz [4], [5]. Such frequencies are becoming increasingly congested because different communication technologies and multiple mobile carriers squeeze the frequency from the small spectrum out of the industrial, scientific and medical (ISM) band. Mobile phone carriers can fit only so many bits of data onto the same amount of RF spectrum. Slower services and more lost connections will become more common as more devices come online [6]. The answer is to create a new frequency spectrum. Researchers have investigated GHz ranging from 30 to 300 GHz [6]. Although satellite communication has been taking place in this millimetre wave frequency band for a while, only recently have we started to see mobile communications exploiting the millimetre wave. As a result, more bandwidth has opened up to everyone. However, there is a problem associated with it, the roots of which lie in the underlying physics of the propagation of electromagnetic waves (EM). Despite offering a larger frequency spectrum for communications, the use of millimetre waves comes with a major challenge. mmWaves, unlike lower frequency bands, cannot pass through houses and other obstructions and are lost to the environment [7]. Smart cell networks are required to overcome this problem. Large high-power cell towers can now transmit their information over long distances due to current cellular connections [8], [9]. However, higher-frequency mm waves cannot travel through obstacles, which means if the user is not within line of sight, then the user experiences a significant drop or a complete loss of communication signal. Thousands of small low-power access points (APs) can be used in a smart cell network to solve this problem [10], [11]. These APs will not only be substantially closer but they will also be spatially grouped in a relay to carry signals around obstructions. This method eliminates reliance on LOS and will be particularly effective in urban areas. When the user equipment (UE) travels behind an obstruction, it will immediately switch to a new AP, ensuring that cellular service is uninterrupted. Today modern 4G BSs include twelve ports for antennas that handle all data traffic (a port is a phrase for signal transmission under identical channel circumstances). Massive MIMO can, in spite of its drawbacks, multiply the capacity of a mobile adhoc network by a factor of 22 or more [11], [12]. Massive MIMO, on the other hand, has its drawbacks [13], [14].

To communicate over a time-division multiplexing system, UE must take turns whilst speaking and listening, which not only lengthens the whole communication but makes the entire process inefficient. In today's cellular BSs, an antenna can either broadcast or receive at any fixed instant. Although multiplexing can be used to increase performance, transmit and receive signals are typically propagated at different frequencies. Current cellular antennas send data in all directions at the same time, potentially causing major interference [15]–

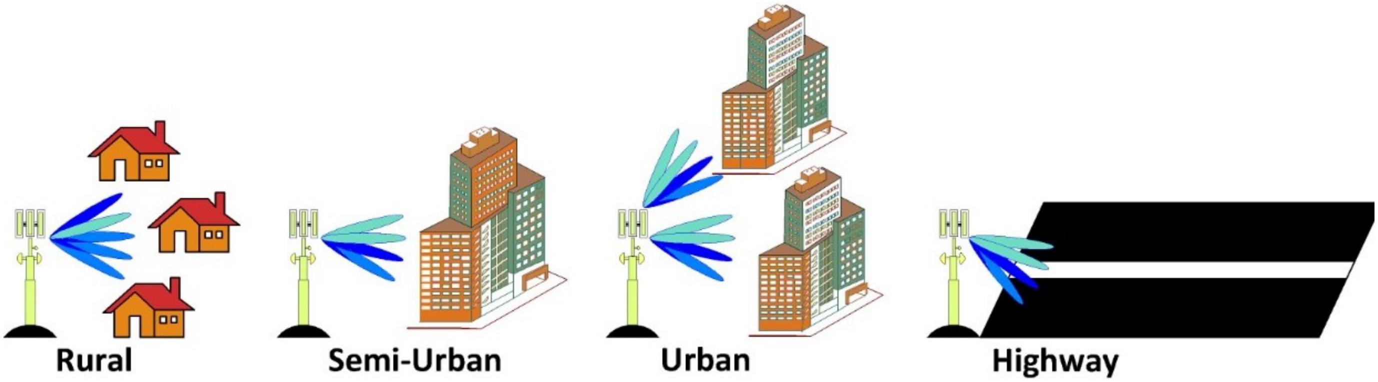

Fig. 1. Illustration of BF according to the scenario (rural, semi-urban, urban, highway).

[19]. For example, Fig.1 shows the illustration of BF (signal in all directions at once) in rural, semi-urban, urban and highway areas.

In this paper, we discuss some of the unique features of BF chief amongst them how BF can free up the frequency spectrum through full-duplex communication. In Section I, we present a preliminary discussion of BF, followed by discussions of the types of BF by the antenna and system design in sections II and III respectively. The advanced BF techniques consisting of adaptive BF algorithms, contextual BF and location-assisted BF have been reviewed in Section V. Section VI discusses how artificial intelligence can assist to mitigate the challenges of BF adaptive systems following the conclusion in section VIII.

II. Beamforming

Cellular networks can use BF as a signalling technique. Rather than radiating an omnidirectional beam which is inefficient, BF enables a transmitter to generate a directed signal to a given user [20]. This accuracy eliminates interference and improves communication efficiency, allowing BS to handle more traffic at any given time. For instance, consider a person trying to make a phone call in a group of buildings. The EM waves from the phone antenna reflect or bounce off the buildings nearby, crisscrossing with signals from other nearby users. All of these signals are received by a massive MIMO BS, which keeps track of their arrival time and direction. It then triangulates where each signal is originating from using signal processing methods and maps the optimal transmission back to each phone over the air. To protect the signals from interfering with each other, it will sometimes bounce off individual packets of data in various directions from infrastructures and other objects. The end result is a logical data stream that is sent only to the primary user [11], [21], [22]. This is a multidimensional problem that researchers are actively studying in order to optimise mobile communication. In this paper, we discuss some aspects of BF that can potentially help and reduce conflicts arising due to signal interference as described in [78]. Along with the classification of BF that has been done according to antenna design, system design, and advanced techniques and are shown in Fig.2.

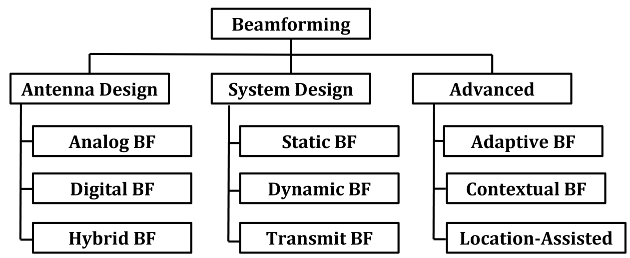

Fig. 2. Classification of BF.

III. Types of BF by System Design

Before discussing types of BF, it is essential to understand how an antenna array plays a crucial role in BF. An antenna array is a group of several antenna elements that help to generate a directed signal [24]–[28]. It is a means of concentrating radio frequency energy in a specific direction or where the client or user is located [29]–[31]. Static BF, dynamic BF, and transmit BF are the three main types of BF.

A. Static Beamforming

BF in the static sense is carried out with the help of multiple directional antennas that are aimed away from the centre to provide fixed radiation patterns [25], [30], [32]. It is usually done with an indoor sectorized array where a sector antenna (a form of directional microwave antenna that radiates in a sector-shaped pattern). A sectorized antenna has very low back lobe levels, hence interference is very low with other channels. For instance, if one sector antenna covers 60 degrees of the area and emits radiation on channel 1 and the other sector antenna covers other 60 degrees of the area and likewise, multiple sector antennas can be used to cover a complete 360 degrees or the whole area over different channels such as 6, 11, and so on. Stacking together multiple antennas covers a wider area known as static BF. By simply working non-overlapping transport channels (medium), the interference is reduced by using sector antennas. This could be considered a major advantage of sector antenna BF.

B. Dynamic Beamforming

There are many similarities between dynamic and static BF, except for the fact that in the former, we can adjust

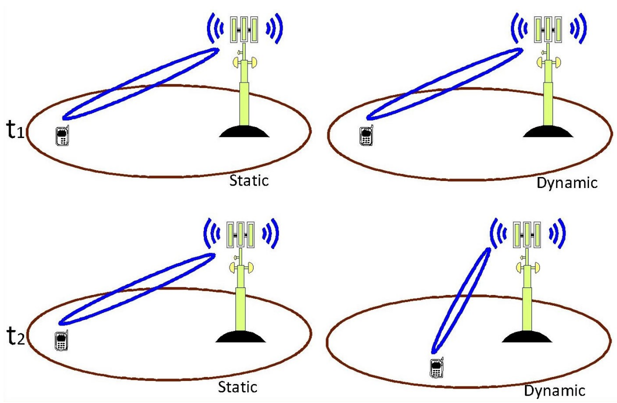

Fig. 3. Illustration of dynamic and static BF at different time instances.

or reconfigure the radiation pattern to cater to the optimum signal/beam for every UE. It employs an adaptive antenna array to steer a beam/signal toward the intended user or receiver. Smart antenna technology or beam steering are a few other terms for this concept because of its properties, that is, the beam is directed at the target client/user.

To understand this, let's consider three scenarios. The first scenario assumes an ideal case in which no BF is associated. An omnidirectional antenna access point serving 3 clients is placed by emitting radiation at a particular frequency. Clients are receiving and able to transmit signals to and from the access point. Sometimes, there is another transmitter in the vicinity of this scenario that transmits at the same frequency, causing interference in the signal and resulting in data loss. To overcome this interference problem, dynamic BF comes into play as has been incorporated into the IEEE 802.11n standard. The second scenario assumes how dynamic BF helps to overcome the problem that occurred in the first scenario. The access point is enabled to perform dynamic BF, so it can form narrow beams instead of covering a wider area or broader beam by sensing the links to serve the clients in the vicinity. This way, it would not affect the signal as there is no data loss due to the absence of interference of signals from the transmitter. Due to the shorter beam width of these narrow beams, the concentration is higher. As a result, the power consumption is also lower and supports a high data rate. However, this is not always the case, sometimes during transmission, the interference persists (because of the change of direction of radiation from transmitters). So, here is the third scenario that assumes the practicality or dynamicity of dynamic BF. The signal emitted from an access point can change its beam path in such a way that the client is served without interference caused by the transmitters. Regardless of such advantageous techniques, there are only a few vendors that support this BF [32]. The figure 3shows that, in discrete instances, a beam projected toward a designated receiver using an adaptive array could be easily handled using dynamic BF instead of static BF. The user at time t_1 gets the signal from the base station in static and dynamic BF. However, at time t_2, only in dynamic BF, does the user get the signal. Beam steering or smart antenna technology are other names for this technology. Only the transmission station has access to this

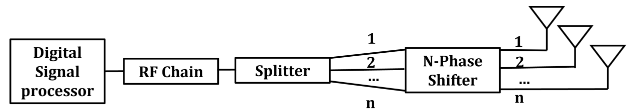

Fig. 4. Basic block diagram of analog BF.

capability.

C. Transmit Beamforming

In transmit BF, a series of out-of-phase beams/signals with the aim of in-phase signals arriving at the receiver side [33]–[35] are generated. For example, if a signal is transmitted through multiple antennas, multiple paths may be required to reach the receiver in phase. Due to the phase matching, we observe an increase in the overall gain and, therefore, the received signal amplitude is increased as well. However, if the signal reaches the receiver end out of phase, then the signal faces amplitude cancellation as well as gain reduction. Transmit BF is a process in which the access point transmits the signal with phase shift so that it can reach the receiver in phase. These phase-shifted signals will add up and result in high amplitude and gain. Transmit BF, unlike dynamic BF, neither alter an antenna's radiation pattern nor produce a directional beam. Therefore, the former is a digital signal processing technique, not an antenna technology. It replicates the sent signal on several antennas to provide a combined signal that is optimised for the user. In short, transmit BF is about adjusting the phase transmission, and can be done explicitly or implicitly [36].

IV. BF Based on Antenna Design

The above-mentioned types can be considered while on the antenna front end. However, in the era of massive MIMO, BF is its subset. BF in massive MIMO is classified as analogue, digital, and hybrid BF. The distinction between them is explained in detail as follows:

A. Analog Beamforming

Analog BF is the simplest type of BF with less complex and low power consumption electronics back end. Fig.4 shows the block diagram for analog BF, which consist of a Digital signal processor (DSP), RF chain, splitter, and N-phase shifter.

The beam is regulated by analog phase shifters and a shared RF source is shared between many antenna elements [37]. After the digital to analog converter (DAC) at the transmitter side, the amplitude/phase modulation is introduced on the analog input, and the signal received from separate antennas is merged before applying to the analog to digital converter (ADC) at the receiver end [38]. In analog BF, a single RF chain is used with a power combiner (receiver side), power divider (transmitter side), and a series of phase shifters, one with each antenna port. However, only a single beam of the signal can be produced with this approach and this ability to transmit in direction of of the user at a given time hinders the BF use. In other words, a single beam is created with a phase

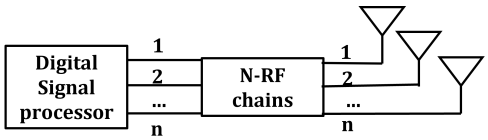

Fig. 5. Basic block diagram of Digital BF

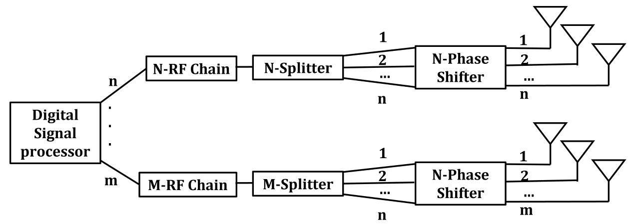

Fig. 6. Basic block diagram of Hybrid BF

delay, or time delay applied to each antenna element. By using phase shifters and/or variable gain amplifiers (VGAs), complex coefficients or weights are used to modify RF signals. On the transmitter side, DAC converts the coded baseband in-phase and digital bit streams to continuous-time analog signals.

The analog signal is passed by a low pass filter to suppress out-of-band spectral contents. This filtered signal is then modulated with a high-frequency carrier signal or local oscillator (LO) signal using a mixer. A mixer is a nonlinear component and produces harmonics at a higher frequency which reduces signal power as well as might interfere with other communication links. However, an appropriate bandpass filter helps to mitigate this effect. At last, the signal is amplified using a power amplifier to enhance the signal power to the desired level and then transmitted through the antenna. analog BF is further classified into analog RF BF, analog LO BF, and analog baseband BF depending on the position of the phase shifter. These topologies have their benefits and drawbacks dependent on the performance characteristics of the phase shifters and their frequency-dependent characteristics. analog BF is a simple and effective way to generate high BF gains from a large number of antenna elements in an array. However, it has fewer beams and less multiplexing to gain flexibility. Time-domain BF is mainly implemented using analog BF techniques. Analog BF technique can be achieved by tunable phase shifters, switchable lens antenna, or using different circuit-switched techniques [39].

B. Digital Beamforming

The RF signals are processed using a digital signal processing system in digital BF, which allows more flexibility and degrees of freedom to construct efficient BF algorithms. Digital BF is accomplished by multiplying a certain coefficient by the modulated baseband signal per RF link using digital precoding. The digital BF transceiver may direct beams in a theoretically limitless number of directions at the same time because of precoding in the digital domain [79]; however, these are not identical. Precoding pertains to the software implementation of the communication concept. It entails individual management of the amplitudes and phases of the signals sent from the multiple transmit antennas, as well as the optimisation of the information stream to leverage broadcast diversity. On the other hand, the term BF is more related to hardware implementation and antennas and can be applied to both the transmitter and receiver sides [34].

In digital BF, precoding and BF are implemented together to efficiently focus the energy on the desired receiver. At the transmitter, precoding associates channel state information (CSI), which involves delivering a coded message to the receiver. In turn, every user sends their individual CSIs back to the transmitter. The feedback signal is then utilized to create a precoding matrix for the data transfer that follows [40]. The N-RF chains in digital BF are equivalent to the number of antennas involved, thus it provides high flexibility and BF gain in rich multi-path environments. Fig.5 shows the block diagram for Digital BF which consists of a Digital signal processor (DSP), N-RF chains followed by antenna assembly. Nevertheless, digital beamformers are complex, expensive, and power-hungry. This is due to the fact that ADC consumes an equal amount of power/energy like a thousand logic circuits. Moreover, in the implementation of digital baseband algorithms as a result of Moore's law (claiming that the transistors on an integrated circuit are doubled every two years), the power consumption in ADC is still about three times higher than that of the other electronic circuitry. However, there are certain advantages of digital BF over analog BF such as high resolution, low side lobes, greater flexibility in power and time management, spectral efficiency, and high system [41].

Digital BF is implemented primarily for frequency domain BF. Digital BF has proven helpful in various applications such as speech, sonar, wireless communication, radio astronomy, radar, acoustics, biomedicine, seismology, as well as beyond 5G communication [41]–[43]. Table Iillustrates the key distinctions between analog and digital BF.

C. Hybrid Beamforming

To intelligently construct beam patterns over a wide antenna array, hybrid BF combines analog BF with digital precoding. A network of analog components like switches and/or phase shifters integrate a limited set of RF chains to a multi-antennas in hybrid BF. Fig. 6 shows the block diagram for Hybrid BF which consists of a Digital signal processor (DSP), n X m RF chain, n X m splitter, n X m phase shifter followed by antenna assembly. The main goal of hybrid BF is to increase the multi-user total rate while maintaining hardware prices, complexity, and power consumption within acceptable limits. The N-RF chains are more than one but mainly less than the multi-antennas. It provides sharp beams with phase shifters and switches in the analog waveform and flexibility in the digital domain. Thus, a combination of the low hardware cost and low complexity of analog BF, along with the high resolution, gain, and flexibility of digital BF makes hybrid BF an efficient choice for a cost- and energy-efficient system. A comparison between hybrid and digital BF in terms of power and hardware cost is reported [34], [36].

Hybrid BF is further categorised into sub-connected and totally

TABLE I
COMPARISON BETWEEN ANALOG AND DIGITAL BF.

Analog BF	Digital BF
Adaptive transmit/receive weights at RF to form beam	Adaptive transmit/receive weights at baseband
One transceiver unit and one RF beam with high antenna gain	Each antenna element or antenna port has a transceiver unit, high number (>8) of transceiver units.
”Frequency flat” beam forming	”Frequency selective” beam forming
Best for coverage (due to low power consumption & cost characteristics)	Best for capacity and flexibility (subject to high power consumption & cost characteristics when bandwidth increases)

connected architectures. Every RF chain is only linked to a subset of the existing antennas in the sub-connected configuration. Every UE's data from multi-beams is digitised/precoded before being delivered to the analogue BF through an RF chain. After then, the signal is transmitted with a sub-array of antenna elements. The sub-connected architecture is simpler and more power-efficient than a fully connected one, but it is less spectral efficient [44]. Each RF chain in a fully integrated design is linked to all antennas [38]. The signal is precoded and processed by each RF chain before being sent through a common analogue BF unit to each antenna element in the array. This approach results in high performance but creates high complexity and high energy consumption [44]. Both architectures have trade-offs in terms of complexity and gain. The number of signal processing paths in fully connected architecture is proportional to the square of the N-RF chains involved with greater spectral efficiency but high complexity, whereas for sub-connected arrays the gain is reduced by a factor of the inverse of the number of RF chains.

V. ADVANCED BEAMFORMING TECHNIQUES

An adaptive beamformer is a tool for performing adaptive spatial signal processing using an array of transmitters or receivers. The signals are integrated in such 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 utilised in both RF and acoustic arrays to achieve directional sensitivity without physically changing the receivers or transmitters [45]–[47]. 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 noticeable. 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 IEEE802.16 WiMAX to enable important services within each standard [48]. 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 signal-to-interference ratio and noise ratio (SINR). There are numerous approaches to BF design, the first of which was achieved by Applebaum in 1965 by increasing the signal-to-noise ratio (SNR) [49]. 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 and Capon's maximum likelihood method (MLM) 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 [50]. Unlike Applebaum and Widrow's approach, SMI determines the adaptive antenna weights directly [45]–[47].

A. *Adaptive Beamforming*

The Weiner solution can be used to create statistically optimal weight vectors for adaptive BF in data-independent BF design methods. On the other hand, the asymptotic 2^{nd} 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 [20]. This enables the spatial filtering beam to adjust to the time-varying 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. 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 stationary environment and 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 [37]. To change the weights of the time-varying environment at every instance, several adaptive algorithms (mentioned in the further section) can be utilized. Fig.7 shows the block diagram for adaptive BF which consist of a digital signal processor (DSP),

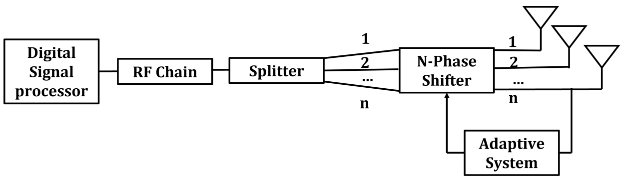

Fig. 7. Basic block diagram of Adaptive BF

RF chain, splitter, and N-phase shifter followed by antenna assembly along with an adaptive system providing feedback to shifters.

1) The Least Mean Square Algorithm: The least mean-square (LMS) algorithm is a popular adaptive filtering method that is utilised in a variety of communication systems [49], [51]–[53]. It has low computing complexity and has been demonstrated to be reliable because of its widespread use. It iteratively minimises the mean-square error by incorporating fresh observations. The LMS algorithm updates the weight (w) with the expected gradient direction using the negative steepest descent strategy [54]. The operation of the LMS algorithm is depicted in the block diagram in Fig.8.

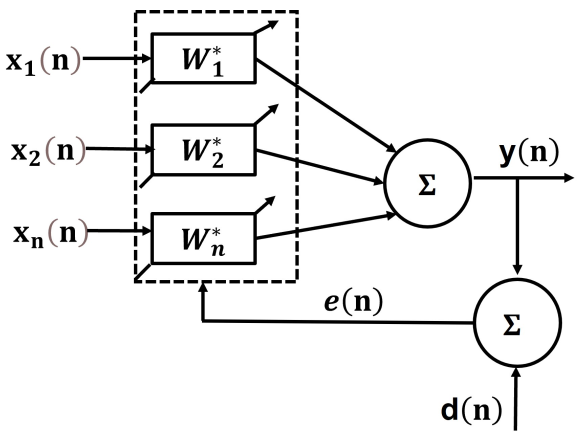

Fig. 8. Schematic of minimum mean squares error system

The approximation of the gradient vector is based on the input vector $x(k)$. For each k in :

$$\begin{aligned} e(k) = d(k) - wH(k)x(k) \\ w(k+1) = w(k) + \mu e^*(k)x(k) \end{aligned} \tag{1}$$

where K is the adaptation index, $d(k)$ is the reference signal, $e(k)$ is the error between $d(k)$ and the output of the weighted matrix, and μ is a scalar constant that regulates the convergence rate and the stability of the algorithm. To provide stability in the mean squared sense, the step size μ in the interval should be in the range $0 \leq \mu \leq \frac{2}{\lambda_{\text{max}}}$ for $\lambda_{\text{max}} \leq$ trace R_{xx}

where δmax is the maximum eigenvalue of R_{xx} and R_{xx} is the total input power. It takes around 2N complex multiplications/iteration. where N is antenna elements in an array. If the eigenvalue spreads (which happens when convergence is slow), the LMS algorithm may not converge to the optimal solution due to a lack of enough iterative weights, but real-time adaptation to a time-varying environment is impossible. It is necessary to have a sufficient understanding of the desired signal. This approach is inapplicable, particularly for fast-fading conditions.

2) The Recursive Least Squares Algorithm: The weight vector $w(k)$ is chosen in the least-squares technique to minimise a cost function comprised of the sum of squares of the error with respect to time, i.e., the least square (LS) solution is minimised recursively [20], [37].

Algorithm 1 The recursive least square algorithm [62]

For each k
{
$K(k) = R - 1(k-1)x(k)$
$K(k) = k(k)/\ \delta\ +xH(k)K(k)$
$R - 1(k)$ = 1/δ $[R - 1(k-1) - K(k)H(k)$/(δ
+ $xH(k)K(k))]$
$e(k) = d(k) - wH(k)x(k)$
$w(k+1) = w(k)$ + μ $e^*(k)x(k)$
}

where $R - 1(0) = \delta - 1$ I, δ is a positive constant and I is the identity matrix N $\times$.

As a result, the convergence rate is generally faster than that of the basic LMS method. Each iteration of the algorithm 1 necessitates $4N2 + 4N + 2$ complex multiplications. where N is antenna elements in an array. In a finite-precision environment, this algorithm faces significant divergence behaviour, a stability challenge, high cost, and complexity [52], [56]–[59].

3) The Constant Modulus Algorithm [62]: The complex envelope of various phase-modulated/frequency communication signals, such as frequency modulation and continuous phase frequency shift key modulation, is constant. Signals can use prior knowledge of this characteristic to design an adaptation approach for obtaining a desired static response from the array for a variety of communication applications. It is appropriate for transmitting a baseband signal over a wireless medium since noise and interference degrade the desired constant modulus (CM) characteristic of the signal. The CM property of a signal travelling through a frequency selective channel is almost always lost. Modifies the weight vector of the adaptive array to reduce the variance of the intended signal in the array. Once the convergence of the algorithm is over, a signal is pointed in the desired direction, and the null signals are inserted in the interfering sites [51], [52]. The convergence of the algorithm is determined by the coefficients p and q. The CM algorithm search for a weight vector that reduces the cost function of the form:

$$J_{p,q} = \epsilon\{||y(k)|p - 1|q\} \tag{2}$$

where p and q produces a special cost function called the (p, q) CM cost function. The algorithm 2 is a pseudocode for the CM $(p = 1, q = 2)$ algorithm. The goal of CM BF is to convert the array output $y(k)$ to a constant envelope signal.

TABLE II
COMPARISON OF THE LMS AND CM ALGORITHM.

LMS Algorithm	CM Algorithm
d(k) is important	y(k)/|y(k)| is important
The reference signal d(k) must be sent from the transmitter to the receiver and must be known for both the transmitter and receiver.	The reference signal is not required to generate the error signal at the receiver.

For each k
{
e(k) = d(k) - w^H(k)x(k)
w(k+1) = w(k) + μ e*(k)x(k)
}
	For each k
	{
	y(k) = wH(k)x(k)
	e(k) = y(k)/|y(k)| - y(k)
	w(k+1) = w(k) + μe*(k)x(k)
	}

Algorithm 2 CM Algorithm [62]

For each k
{
$y(k) = wH(k)x(k)$
$e(k) = y(k)/jy(k)j - y(k)$
$w(k+1) = w(k) + \mu\ e^*(k)x(k)$
}

where k is the adaptation index, $x(k)$ is the input data vector, $e(k)$ is the error between $y(k)/|y(k)|$ and weighted array output $y(k)$, μ is the step size and $e^*(k)$ is the conjugate of $e(k)$. Table IIrepresents the differences between the LMS and CM 2 algorithms.

4) The Affine Projection Algorithm: The affine projection (AP) method can be thought of as a generalised data reuse algorithm that can reuse any number of data pairs [60]. Adjusts its coefficients vector so that the new solution is located at the intersection of the P hyperplanes defined by the current and $P-1$ prior data pair $x(i), d(i)$, $k_i = k - P + 1$.The AP algorithm was developed using the following optimisation criterion:

$$\begin{aligned} w(k+1) &= \text{arg min}||w - w(k)||^2 \\ &\text{subject to } d(k) = XT(k)w^* \end{aligned} \tag{3}$$

where $d(k) = [d(k), d(k-1), ..., d(k-P+1)]H$ and $X(k) = [x(k), x(k-1), ..., x(k-P+1)]$

Algorithm 3 The AP Algorithm [62]

For each k
{
$e(k) = d(k) - XT(k)w*(k)$
$t(k) = [XH(k)X(k) + \delta\ I] - 1e^*(k)$
$w(k+1) = w(k) + \mu\ X(k)t(K)$
}

where k is the adaptation index, $x(k)$ is the input data vector, $d(k)$ is the reference signal, δ is the small positive constant, $I = NxN$, $e^*(k)$ is the conjugate of $e(k)$. A step size mu is introduced to manage the stability, convergence, and final error, where $0 < \mu < 2$. A diagonal matrix $delta$ I is used to regularising the inverse matrix in the procedure to improve robustness [58], [61].

5) The Quasi-Newton Algorithm: The recursive least square (RLS) algorithm's rapid convergence is calculated on the basis of the inverse of the correlation coefficients R-1(k), which must be symmetric and positive for the process to stay stable. On the other hand, the introduction of infinite precision may cause R-text1(k) to become indefinite. The quasi Newton (QN) algorithm is one algorithm that has a convergence speed equivalent to the RLS algorithm but is guaranteed to be stable even under high input signal correlation and fixed-point short word length arithmetic. The weight vector is updated in the QN algorithm as follows:

$$w(k+1) = w(k) + \mu(k)h(k) \tag{4}$$

where $mu(k)$ is the step size determined by an accurate line search and $h(k)$ is the update direction determined by,

$$h(k) = -R - 1(k-1)\frac{\partial J_{w,w*}}{\partial w*} \tag{5}$$

where the cost function, $J_{w,w*} = |e(k)|^2$ is an precise line search that gives a step size $\mu\ (k) = \frac{1}{2}x\ HR - 1(k-1)x(k)$ as a rough estimate of R-1(k-1). This makes it robust, as it maintains positive definiteness even when input signals are strongly linked and word-length arithmetic is small.

Algorithm 4 QN Algorithm [62]

For each k
{
$e(k) = d(k) - wH(k)x(k)$
$t(k) = R - 1(k-1)x(k)$
$\tau\ (k) = xH(k)t(k)$
$\mu(k) = \frac{1}{2}\tau(k)$
$R - 1(k) = R - 1(k-1)$ + [μ (k) - 1]$t(k)tH(k)/\tau$ (k)
$W(k+1) = w(k)$ + α (e*(k)/τ (k)) $t(k)$
}

In the algorithm4, α is the positive constant and It's used to manage convergence speed and misadjustment. For $0 < \alpha < 2$, convergence in the mean and mean squared sense of the weight matrix is assured if $R - 1(k-1)$ is positive constant [60].

Optimal BF strikes a balance between giving maximum power to a single user while decreasing or eliminating signal interference at other users. When the maximum ratio transmission (MRT) BF technique is used in an MU-MIMO system, the transmitter transmits a beam to every user according to its weight vector. The resultant power received by each user for the signal intended for that user is calculated as the product of the channel gain and weight vector. Because the MIMO system transmits to multiple users at the same frequency, a critical performance metric for the system is the signal-to-interference-plus-noise ratio (SINR) for each user. This concept has been proved in [78] that shows how SINR can be significantly improved by 28.83 dBm and/ or 53% (Fig. 9) by using MRT in comparison with no BF.

Fig. 9. SINR comparison of MRT with No-beamforming in University campus scenario

B. Contextual Beamforming

The capacity to forecast the receiver's next location based on previous movements is useful for creating intelligent applications like automobiles, robotics, augmented/virtual reality 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 [62]. A wireless system, in general, controls a location-predicting framework by capturing and communicating critical data prior to application. The sender must be able to determine the receiver's location at any given time to interact effectively with them. Machine learning (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. Several machine learning algorithms, such as DNN, CNN, GAN, and others, have been recognised as aiding in the technological advancement of location forecasting. Furthermore, depending on the application, machine learning algorithms can be modified and customised to match their objectives [80]. The majority of existing mmWave beam tracking research is focused on communication-only protocols. The unusual beam tracking technique necessitates the transmitter to send information to the receiver, which then determines the angular position and delivers it to the transmitter again. It is worth noting that in high-mobility communication circumstances like the one depicted in Fig.10, it is insufficient to just follow the beam. To achieve the crucial latency requirement, the transmitter should be able to predict the beam [63]. The state prediction and tracking designs in Fig.11 are based on the classic Kalman filtering process.

C. Location-assisted predictive Beamforming

The prior information on the location of the user can enable the system to work more efficiently. The sorting of the prior information can reduce energy footprints. As an example, the branch predictor [64], [65] in computer architectures can improve the flow in the instruction pipeline to achieve high effective performance. In the case of location aided or location-aware BF, a similar concept has been seen. Fig.12 shows the block diagram for predictive or location-assisted BF which consist 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 [66]. With the development of ultra dense wireless communication in 5G compared to earlier mobile generations, 5G has significantly higher requirements. 5G is expected to have a capacity of up to 7.5 Tbps/km^2, a data rate of up to 1 Gbps in downlink (DL) and 500 Mbps in uplink (UL), and significantly higher demands for angular resolution in DL, according to technical standards. Moving user equipment (UE) with speeds up to 0.5 m/s must have an angular resolution of less than 5°, moving UE with speeds up to 10 km/h must have an angular resolution of less than 10°, and static UE must have an angular resolution of less than 30 °, according to 3GPP. Massive MIMO, Direction of Arrival (DoA) estimates, and BF are expected to meet these requirements. The use of DOA and BF together allows for reliable and spectrally effective communication to the required location. DOA is a digital signal processing that calculates the direction of a corresponding incoming signal's originating location. BF is a strategy for directing a maximum antenna radiation pattern (ARP) into the desired bearing direction, while ARP nulls are aimed at interfering sources. The fundamental task of a 5G application is to direct the main lobe of an antenna positioned on an access node (AN) towards the UE. Ultra-dense 5G networks are expected to be made up of densely scattered AN, allowing the widespread use of location-aware BF and interference mitigation techniques to take advantage of the spatial dimension. Short user environment area network (UEAN) distances in a packed environment resulted in higher levels of interference, while network densification enhances

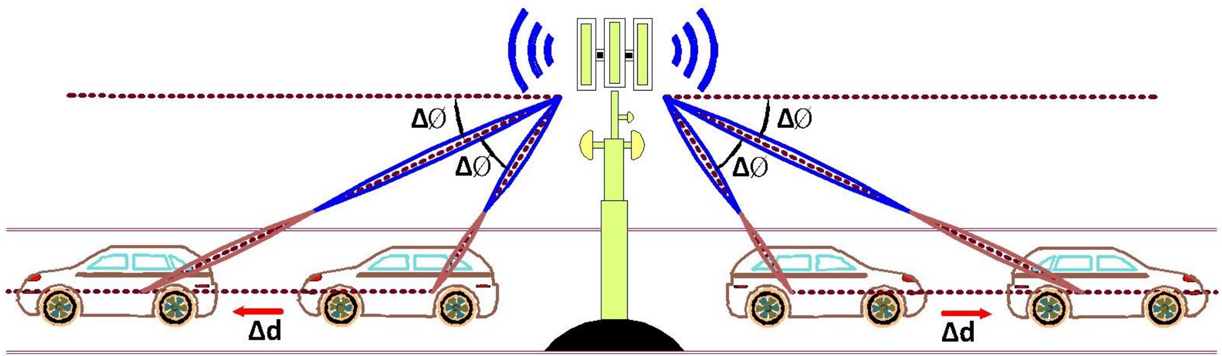

Fig. 10. Base station to vehicle scenario

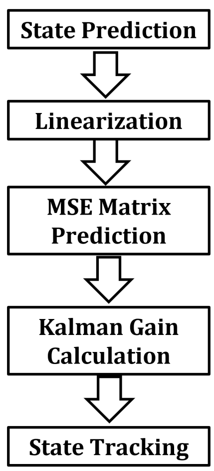

Fig. 11. A standard procedure based on the Kalman filter.

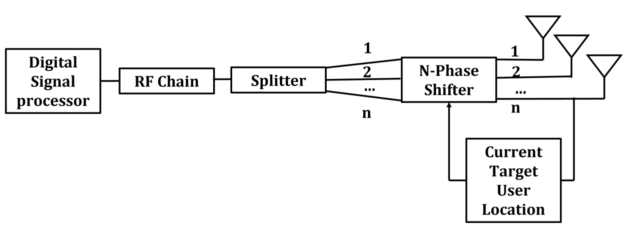

Fig. 12. Basic block diagram of Location-Assisted BF

the chance of LoS and, as a result, leads to more accurate UE placement. The possibilities for acquiring and utilizing UE location data enable the use of spatial dimension by BF and interference reduction. The accuracy of the radio network positioning systems currently available is substantially inferior to that of fibre optic communication systems in radar stations and atomic clock-based satellite navigation systems. Future 5G networks, on the other hand, are expected to provide positioning accuracy on the order of one meter. The goal of this study is to calculate positioning accuracy in 3D using DoA measurement processing and then implement it in real-world location-aware BF environments [67]. Table III shows recent literature on location-aided BF. The location-aware system has been developed by considering the location unaware systems with benchmarking techniques by [68]. Also, conventional beamforming algorithms had been improved by opportunistic BF with channel delay information as feedback to smart antennas [69]. The authors of [70] review a low-complexity shrinkage-based mismatch estimation batch algorithm to estimate the desired signal steering vector mismatch, in which the interference-plus-noise covariance matrix is also estimated by a recursive matrix shrinkage method. whereas, [71] employs a two-stage design approach; the first stage considers the beamforming design, and the second stage considers adaptive power allocation, and modulation designs for fixed beamforming. They [71] propose a novel and general approach to derive the statistical distribution of signal to noise ratio (SNR) by exploiting the structure of the array, the BF type and slow fading channel coefficients, and utilize the derived SNR distribution to design the power and modulation adaptation strategies. The scheme in [72] allows the UE and the base station to perform a coordinated beam search from a small set of beams within the error boundary of the location information, the selected beams are then used to guide the search of future beams. [73] propose an end-to-end deep learning technique to design a structured CS matrix that is well suited to the underlying channel distribution, leveraging both sparsity and the particular spatial structure that appears in vehicular channels. [74] describes that current mmWave beam training and channel estimation techniques do not normally make use of the prior beam training or channel estimation observations. Further, [75] identifying the optimal BF vectors in large antenna array mmWave systems requires considerable training overhead, which significantly affects the efficiency of these mobile systems.

VI. Beamforming and Artificial Intelligence

In multi-user multiple-input-single-output (MISO) systems, BF is a useful way to increase the quality of incoming signals. Finding the best BF solution has traditionally relied on iterative techniques, which have a significant processing delay and are hence unsuitable for real-time application [77]. With recent improvements in deep learning (DL) algorithms, it is now possible to identify the best BF in real-time while accounting for both performance and computational delay. This is due to the fact that the DL approach trains neural networks offline before deploying them for online optimization. When the trained neural network is used to identify the

TABLE III
RESEARCH ON LOCATION AIDED BF.

Journal	Year	Method/Approach
[68]	2009	Bench-mark position unaware systems with respect to position aware systems.
[69]	2012	The conventional OBF can be improved by contextual information of location and speed and can obtain high gain.
[70]	2016	LOCSME robust adaptive BF method has been improved to a low-complexity adaptive robust adaptive BF algorithm i. e. LOCSME-CG.
[71]	2020	For the 5G V2I network, adaptive BF, power allocation, and modulation architecture has been suggested.
[72]	2019	A coordinated beam alignment algorithm that takes advantage of the UE's noisy position data and possible reflection points and the algorithm will dramatically increase the beam alignment speed.
[73]	2019	Deep learning can be used to optimize the base matrix in 2D-CCS as a guide.
[74]	2018	The covariance matrices as images in our machine learning model has treated and used the conditional generative adversarial networks to learn the significant characteristics of these images.
[75]	2018	A deep learning model that learns the mapping from omni-received uplink pilots and the beam training result.

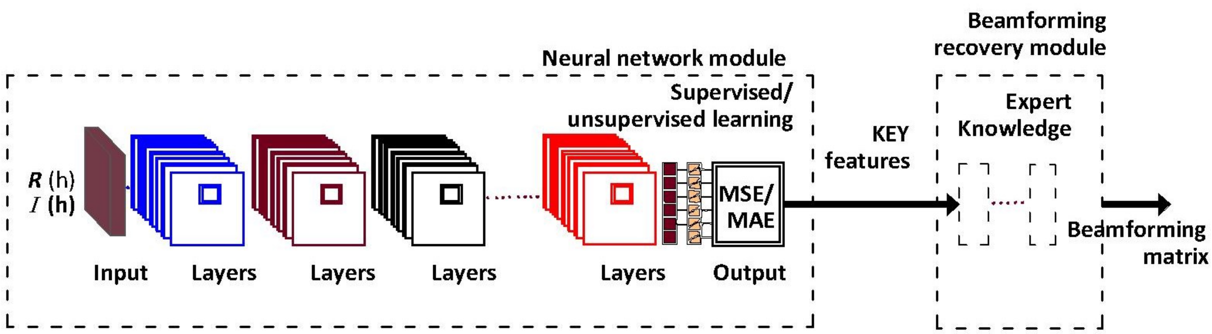

Fig. 13. A Basic Architecture of a deep neural network that consists of input (extracted features), neural layers(as per required framework), output (desired results) and a feed for post-processing.

optimal BF solution, the computational complexity is moved from online optimization to offline training, and only simply linear and nonlinear operations are required, minimizing the computational complexity and time [77]. The deep learning-based neural network architecture for BF is shown in Fig.13 consisting of input, neural layers, and output to extract the features for further processing.

Multiple pathways in complicated indoor or outdoor contexts create additional issues due to propagation loss, noise, and Doppler effects. After collecting large volumes of LoS and NLoS data, Chong Liu's method is to deploy a machine learning regression method that is based on efficient BF transmission patterns to predict the position of users on the move [76].

VII. CONCLUSION

In this study, we first discussed the evolution of telecommunication services from the first to the fifth generation, with a focus on beamforming (BF). Through which many users can be served simultaneously in a desired direction. We provided an overview of advanced adaptive BF in which artificial intelligence techniques such as deep learning (DL) can be used. More importantly, we have shown that with access to contextual information such as prior user location, a wireless network's performance can be improved by through deep learning techniques. With the development of exciting new technologies such as edge computing and federated learning, we believe that the next generation mobile networks will unlock new opportunities. The communication systems will continue to evolve as closed loop systems where data extracted by observing a mobile user will be exploited to improve connectivity and network performance such as the signal to noise ratio (SNR). We have touched upon some of the studies already under way that can harness a user's location, and develop a DL-enabled contextual beamforming strategy that can improve the SNR by 53% on average.

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VIII. Biography Section

Jaspreet Kaur received a first-class bachelor's degree in electronic and communication engineering from the Punjab Technical University, Punjab, India, and a distinction during her MSc in electrical and electronics engineering from Ankara Yildirim Beyazit University, Ankara, Turkey. She was awarded full funds during her MSc under Tubitak and Turkiye Burslari programs. She is pursuing her PhD (funded by EIT Digital) in electronics and electrical engineering from the University of Glasgow, Glasgow, United Kingdom. Her area of interest in microwaves, electronics, and communication encouraged her work on exploiting the location information for Adaptive BF in Transport systems. She is also a graduate teaching assistant at the University of Glasgow, and a student member of IEEE.

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Hasan T Abbas (SMIEEE) received a PhD degree in Electrical Engineering from Texas A & M University USA in 2017. He was the recipient of the prestigious Fulbright Scholarship. He then worked as a postdoctoral research associate at the Department of Electrical and Computer Engineering, Texas A & M University at Qatar. Since June 2019, he is working as a Lecturer at the James Watt School of Engineering, University of Glasgow, the UK where he is part of the Communications, Sensing and Imaging research group. His research interests from electromagnetic scattering and localisation, terahertz plasmonics and the development of numerical electromagnetic methods.