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COGNITIVE RESOURCE MANAGEMENT IN 5G NETWORKS

By Kelvin M. Franco-Argueta*

I. INTRODUCTION

Data consumption has exploded in recent years as smart device utility, video streaming and network-based connectivity have increased. The 4G network is quickly approaching its limitations and is expected to soon be supplanted by the 5G network. The 5G network presents a paradigm shift in the Long-Term-Evolution (LTE) network as it envisages an extended range of radio frequency access to smart devices. Devices are projected to achieve throughput rates which are orders of magnitudes greater than those of the 4G network. Additionally, 5G will develop and enable low latency communication, enhanced mobile broadband and massive machine type communication (*M. Yao, M. Sohul, V. Marojevic, and J. H. Reed*). The versatile applications which these network improvements offer will unify the facets of our lives which were once considered separate from each other. The constituent elements which make the network will enable lightning speed connectivity which has never before been achieved. To meet the heights of these demands, we must turn to a system which can respond equally as fast to this dynamic environment—one that is founded on a feedback structure. Machine learning offers such a solution. Machine learning paves the way for the implementation of AI enabled communication networks that rapidly adapt to fluctuating user activity. In this way, the network becomes

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autonomous and modulated by its users. The structural platform then integrates the hardware components with intelligently enhanced software algorithms. The totality of this network consequently enables the enhanced spectrum utility of smart devices. Collective investigative efforts in the field of Artificial Intelligence (AI) have resulted in the development and application of various neural networks which can interpret and store a large influx of user data and be applied to base stations (BS). These neural networks (NN) are responsible for efficient bandwidth allocation, spectrum usage, and the development of efficient path loss models. The remainder of this article investigates the 5 pieces of technology that make up the 5G network and the challenges these technologies encounter. Solutions are proposed for maximum network efficiency.

II. FIVE DIFFERENT TECHNOLOGIES OF THE 5G NETWORK

As previously mentioned, 5G network is made of 5 key pieces of technology which are millimeter wave, small cell station, massive MIMO, beamforming and full duplex. The following section details the purpose of these 5 key technologies as they relate to the totality of the network. This section is a description of the hardware components and is a precursor to cognitive resource management of the system.

1. Millimeter Wave:

The new network aims to transmit signals in a new band of the radio frequency spectrum. This band includes millimeter waves which range between 30 and 300 GHz and have 1-10 mm wavelengths. A transmission to this domain of the RF spectrum will allow our devices to operate more efficiently and obtain much higher throughput. However, there remains a problem to be solved. Common knowledge of Electromagnetism shows that EM waves with small wavelengths can easily be attenuated and disrupted by physical objects. We must therefore find a way to maintain signal strength and accurate delivery. Small cell stations pose as a viable candidate to solve this problem.

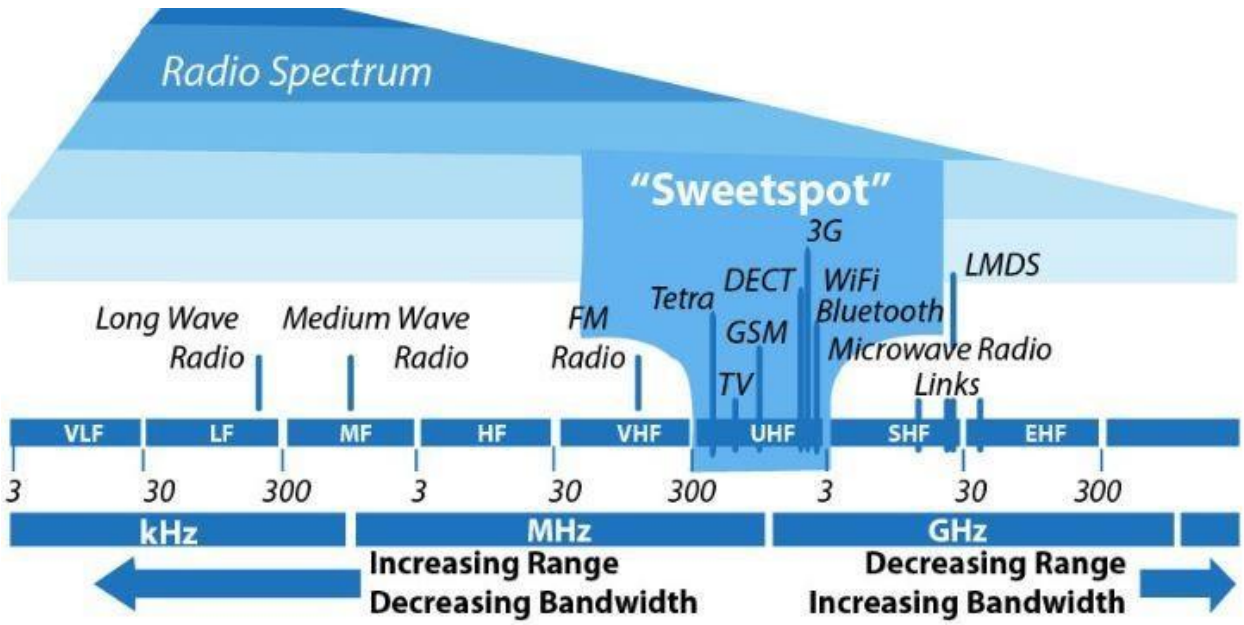

Figure 1. Different parts of the radio frequency (RF) spectrum are demonstrated above for reference purposes.

2. Small Cell Stations:

Small cell stations are small scale base stations which are placed throughout a city. Applying these stations in close proximity to each other throughout a city will allow for more efficient transmission and reception of signals. Each station will be packed with hundreds of small antennas. The ubiquity of these small cell stations will make it possible for frequencies of one station to connect with users of one area and to also be reused by users in another area. This increases efficiency of bandwidth allocation and spectrum access.

3. Massive MIMO:

5G base stations incorporate many more antennas in a single array. This implies that these base stations would be able to receive and transmit many more signals at once, thus increasing the capacity of our network by at least ten fold. A multiple-input-multiple-output interface between devices and stations would also increase the likelihood of signal interference. Beamforming technology helps preserve signal power that is necessary for quality of service end user experience.

4. Beamforming:

Beamforming technology uses signal processing algorithms which help increase transmission of information and simultaneously decrease signal interference throughout an area. User information is broken down to packets of data and is routed through some efficient path to a destination. The data packets are then integrated for reception of some server. The base stations for 5G contain AI-based algorithms which gather network/environment information to create directionally guided transmission of signals. This information allows us to 'learn' to optimize the path taken by signals. It therefore follows that beamforming technology helps maintain signal power. In an attempt to maximize throughput, 5G offers implementation of transceivers which can receive and transmit data at the same time.

5. Full Duplex:

Full Duplex technology enables the simultaneous transmission and reception of data. To implement this communication scheme, engineers must design a circuit that prevents collision between incoming and outgoing signals. Radio waves have a tendency towards reciprocity since antennas work equally as well as transmitters and receivers. This causes patterns that are radiated and received by BS antennas to be identical. The high frequency transmitters required for high throughputs characteristic of the 5G network can't be realized with conventional semiconductor technology. Gallium-Nitride based transistors can operate over 5 times the voltage used by conventional transistors. Operating current can be decreased by 20%. In this way, these circuits can reduce power consumption.

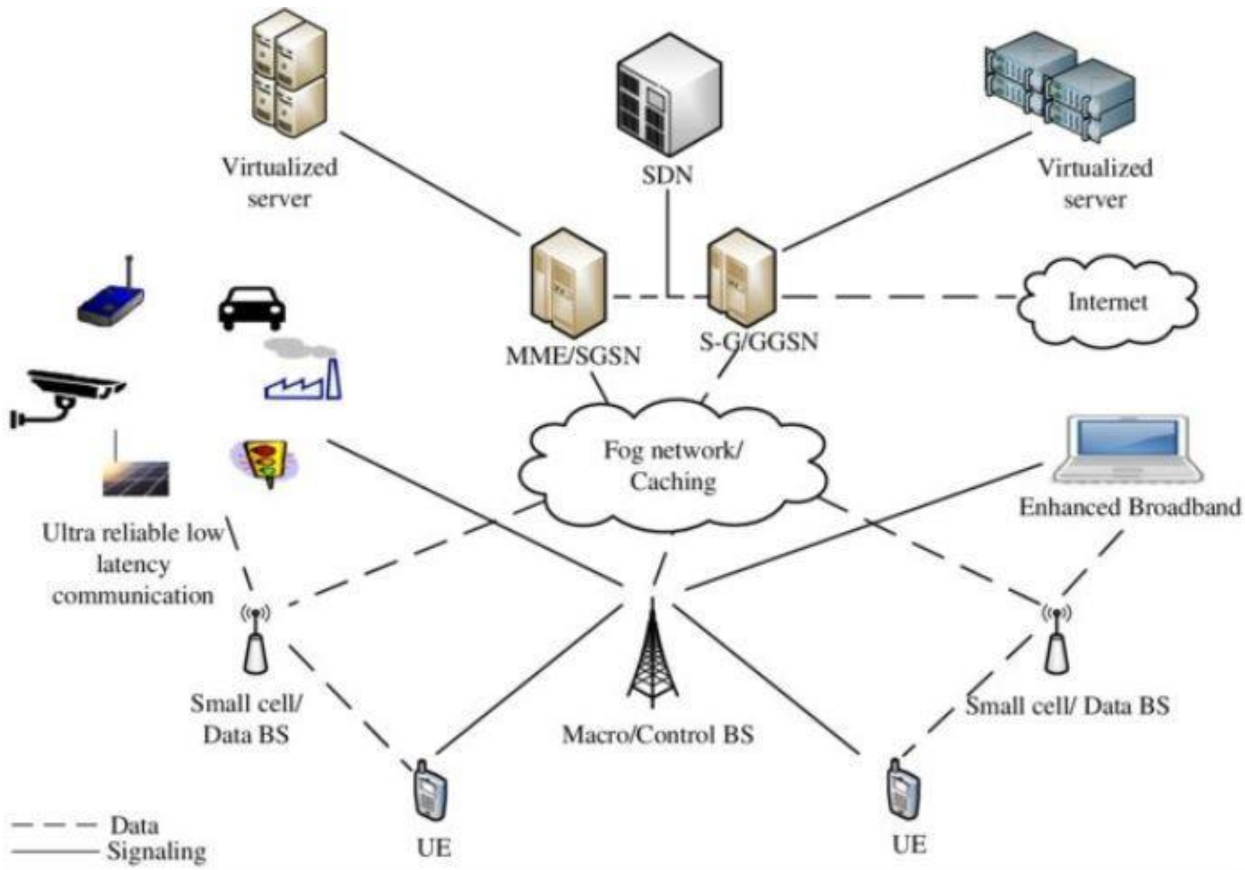

Figure 2. The illustration above shows the architecture of 5G technology.

III. UNITY OF 5G AND AI

Up to this point, sufficient attention has been placed on the hardware components of the 5G network architecture. The following section outlines the problems encountered by the previously mentioned 5G technologies and solutions which surmount these problems as they relate to machine learning implementation.

A. Pathloss:

5G millimeter waves are vulnerable to propagation issues. Electrical size of antennas is determined by wavelength and frequency of carrier signal and can be expressed as $\lambda * f_c = c$. It can be observed that as frequency increases the antenna size shrinks. Free space path loss between a transmitter and receiver antennas increases by f_c^2 when frequency increases. If transmitter and receiver antennas aperture are held constant then free space path loss decreases by a factor of f_c^2 (*R. D. Taranto, S. Muppirisetty, R. Raulefs, D. Slock, T. Svensson, and H. Wymeersch*). This observation will help counteract the noise interference encountered by millimeter waves. Massive MIMO technology aims to include an array of many antennas which have been decreased in size to suit the increase of frequency. It becomes challenging to productively make use of energy without interference. It’s therefore imperative that pathloss models be implemented to maximize path efficiency of signal transmission. Pathloss models fall under two categories: random and deterministic. Prediction of pathloss can be modeled by using Artificial Neural Network architectures.

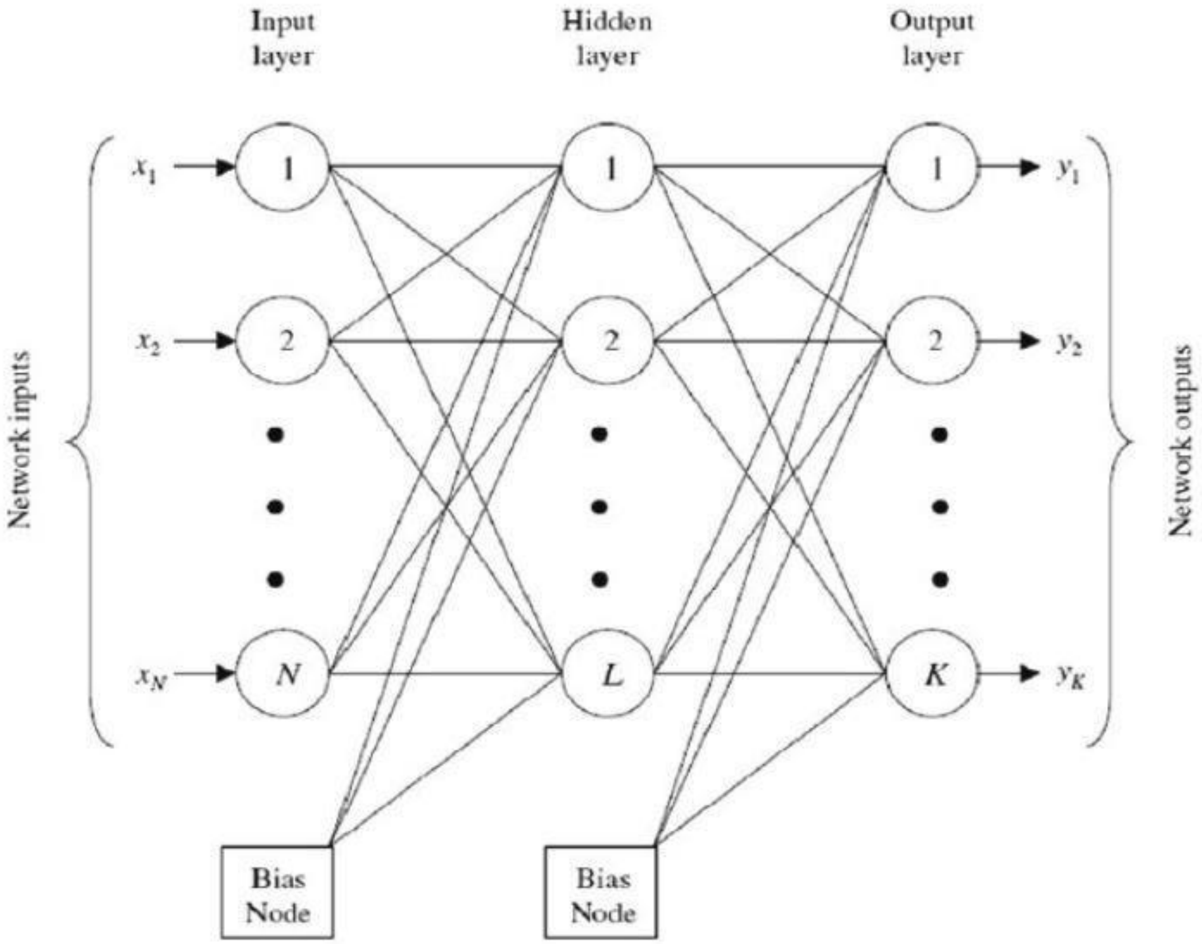

*Figure 3***.** *A feed forward Artificial Neural Network architecture is shown*.

The size of the Artificial Neural Network must be determined before any data is fed into it for training purposes. To predict an optimal path for signal transmission, it is important to find the optimum type of artificial neural network to create the path loss model (*S. P. Sotiroudis, S. K. Goudos, K. A. Gotsis, K. Siakavara, and J. N. Sahalos*). In this case it becomes more practical to use a differential evolutionary (DE) algorithm to find the optimum design of the Artificial Neural Network. DE optimizes a problem by iteratively trying to improve a solution given a certain measure. DE does not require optimization problems to be differentiable. This makes DE useful in the domain of discrete problems (*S. P. Sotiroudis, S. K. Goudos, K. A. Gotsis, K. Siakavara, and J. N. Sahalos*). Instead, agents are used as potential solutions and are tested at separate points in a space that corresponds to the optimization output. Points in space that produce optimum outputs are kept and are otherwise discarded.

B. Signal Linearity:

Massive MIMO requires an array of small-scale antennas. The number of antennas is greatly increased. Each small cell station therefore needs one Power Amplifier per antenna. The problem encountered by this design is a tradeoff between amplifier efficiency and linearity (*J. Liu, R. Deng, S. Zhou, and Z. Niu*). If linearity of signal at receiver end improves, then efficiency must commensurately decrease. To increase network capacity and improve throughput, 5G technology will need to be self-configurable and adaptable to change. This requirement suggests that frequencies assignment will be a lot more dynamic than they currently are. At present, power amplifiers will need to account for network susceptibility to nonlinear distortion (*M. Yao, M. Sohul, V. Marojevic, and J. H. Reed*). PAs must therefore improve linearity at the expense of efficiency. In this case it becomes important to decide the quality of linearity that will bring us the maximum profit to decrease capital and operational expenditures. Artificial Neural Networks offer a great cost-performance tradeoff analysis by taking massive amounts of network data and detecting time variant relationships between inputs and outputs.

C. AI defined Spectrum management:

Millimeter wave communication is facilitated by focused beams which are directionally guided signals to intended receivers. Although attenuation can be mitigated in this way, the millimeter wave spectrum is still not reliable due to channel variations *(B. Bojović, E. Meshkova, N. Baldo, J. Riihijärvi, and M. Petrova*). To maintain power efficiency, seamless network connection, and traffic under control, a combination of low and high frequencies needs to be maintained. AI facilitates the cooperation of different parts of the spectrum as it stores and interprets user behavior and network conditions (*M. E. M. Cayamcela and W. Lim*). Neural network processing units (NPU) are placed at Base stations to provide spectrum management (*P. Sarigiannidis, A. Sarigiannidis, I. Moscholios, and P. Zwierzykowsk*). Sensing nodes in millimeter wave bands will be distributed to monitor channel state information and communicate massive data sets to AI-based spectrum management systems. These nodes with additional signaling information will help the spectrum management system learn how to aptly allocate the spectrum (*M. Yao, M. Sohul, V. Marojevic, and J. H. Reed*).

D. Efficient beamforming:

Recurrent Neural Networks (RNNs) are well suited to detect nonlinearity in power amplifiers as they can store historical information. As such they pose as one of the best, if not the best, physical layer (PHY) signal processing algorithms. Massive MIMO systems which have more antennas than users create excess degrees of freedom (*M. Yao, M. Sohul, R. Nealy, V. Marojevic, and J. Reed)*. Degrees of freedom in this case is equal to the number of antennas at the base station. Efficient beamforming is obtained by finding a beamforming matrix that results in minimum non-linearities at power amplifiers. This enables the use of low-cost PAs and their operation at higher power levels with increased energy efficiency (*M. Yao, M. Sohul, V. Marojevic, and J. H. Reed*). RNNs work with sequential information to learn from massive data sets. Unlike other neural networks, outputs are dependent on previous computations. An RNN is governed by the following three parameters: input at time step x_t, hidden step at s_t, and output at o_t. The hidden layer s_t captures information from all previous steps. As such, it can be thought of as the memory of the network. Output o_t is calculated based only on what happens at time t.

Recurrent neural networks also perform the same tasks at different steps, so it's unnecessary to have many parameters. Training a recurrent neural network is based on the training conducted on regular neural networks *(Nielsen, 2014)*. During back propagation, the gradient at the output is based on previous time steps of the parameters.

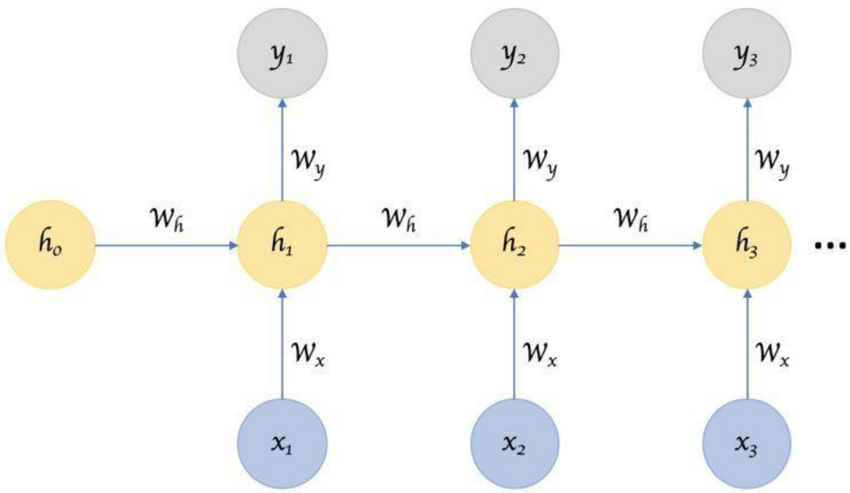

Figure 4. Recurrent Neural Network architecture illustrates network parameters.

The RNNs used in the case of beamforming optimization are based on beamforming nonlinear activation functions that closely model the neuron-activation function. The beamforming nonlinear activation function in the RNN learns nonlinearities of power amplifiers recursively and finds neuron weights which result in minimum multiple user interference non-linear distortion. The RNN models nonlinearity power amplifier arrays and optimizes for minimum transmitted power. Relationships between the antenna set up and energy efficiency can be derived from this model. Previous experiments have shown that energy efficiency of base stations can be drastically improved with this machine learning scheme.

IV. Conclusion

In this article, I briefly introduced the shortcomings of our current communication system network and brought great attention to the multifaceted 5G network. Attention was directed to the 5 key technologies which make up the 5G network and explanation was provided with regards to how they are all interdependent on each other for the conception of 5G technology. Various schemes were presented which detailed how the network can become self-configurable. A presentation of these various schemes makes it clear that without the implementation of machine learning, it becomes near impossible to realize the vision of 5G technology.

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