Softwarization and Optimization for Sustainable Future Mobile Networks: A Survey

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***Abstract*--Due to the tremendous growth in mobile data traffic, cellular networks are witnessing architectural evolutions. Future cellular networks are expected to be extremely dense and complex systems, supporting a high variety of end-devices (e.g., smartphone, sensors, machines) with very diverse QoS requirements. Such amount of network and end-user devices will consume a high percentage of electricity from the power grid to operate, thus increasing the carbon footprint and the operational expenditures of mobile operators. Therefore, environmental and economical sustainability have been included in the roadmap towards a proper design of the next-generation cellular system. This paper focuses on softwarization paradigm, energy harvesting technologies and optimization tools as enablers of future cellular networks for achieving diverse system requirements, including energy saving. The paper surveys the state-of-the-art literatures embedding softwarization paradigm in densely deployed Radio Access Network (RAN). In addition, the need for energy harvesting technologies in densified RAN is provided with the review of the state-of-the-art proposals on the interaction between softwarization and energy harvesting technology. Moreover, the role of optimization tools, such as machine learning, in future RAN with densification paradigm is stated. We have classified available literature that balances these three pillars namely, softwarization, energy harvesting and optimization with densification, being a common RAN deployment trend. Open issues that require further research efforts are also included.**

Keywords: Softwarization, SDN, NFV, Energy Harvesting, Optimization, Ultra-Dense Networks, Machine Learning, Sustainability.

I. INTRODUCTION

Global mobile data usage is growing exponentially. This trend pushes the current mobile networks to their capacity limits and there is a strong desire for a new cellular network architecture, also known as 5G, that can support the various requirements as well as multiple ranges of connected devices. There is a consciousness among mobile network operators and standards organizations that 5G will be available commercially by 2020 [1]. A closer look at the requirements of 5G reveal that the successful deployment of 5G will require architectural evolution in cellular networks and specifically in the Radio Access Network (RAN) segment. The main 5G requirements, as compared with 4G, are [1][2][3]: (i) supporting 1000x more mobile data volume, (ii) 100x more user data rate, (iii) 1000x more number of connected devices, (iv) 1/10x lower energy consumption, (v) 1/5x lower end to end latency, (vi) 1/5x lower cost of network management, (vii) 10x longer battery life and (viii) 1/1000x lower service deployment times. Hence, satisfying these diverse requirements calls for a paradigm shift in the design of cellular networks, RAN in particular. To this end, cellular networks are embracing new paradigms, technologies and tools. We have identified **softwarization and densification** paradigms, **energy harvesting** technologies and **optimization** tools, as the three key pillars to meet the main 5G goals. Softwarization and densification paradigms are needed to meet the demands of high capacity, cost reduction, improved agility, lower latency, and low service deployment times. Furthermore, Energy Harvesting (EH) technology ensures sustainable and cost effective operation of cellular networks. The specific advantages of softwarization, densification and EH should be combined in timely and optimal way according the system requirements. For this reason, the applications of network optimization tools are crucial for lowering network management costs and to enable network wide intelligence and automation.

This paper surveys various architecture proposals for future RAN based on the paradigms of densification and softwarization. We provide a classification of the different trends in the literature regarding the different 5G RAN architecture evolutions. In addition, the issue of energy saving is explored by elaborating on the application of EH from the viewpoints of the available literature. Moreover, the various Machine Learning (ML) and Dynamic Programming (DP) based optimization proposals for automating and managing the different architectures are provided. The paper presents the state of the art literature that dealt with balancing and harmonizing the three pillars of future RAN, namely softwarization, EH and optimization tools within the densification paradigm. The research gaps and challenges in embedding EH and optimization platforms with softwarization is highlighted. The work can be used as a basis to understand the RAN architectural evolution trends with paradigms of softwarization, densification, EH and optimization.

The rest of the paper is organized as follows. The motivations on the need for softwarization paradigm, EH technologies and optimization tools are briefly provided below in Section II. Various RAN architecture trends based on densification and softwarization are given in section III. Section IV provides an overview of EH in RAN and the implication of EH in the different architecture paradigms. Moreover, in Section V, the application of optimization tools, such as ML and DP, in RAN together with their interaction with EH and the architectures in section III are presented. Open issues that needs further exploration and a roadmap for future research directions are provided in section VI. Section VII, finally, concludes the paper.

II. THE THREE PILLARS

A. *Softwarization in RAN*

Softwarization of cellular networks is mainly facilitated by the adoption of *Cloud Computing*, *Software-defined Networking* (SDN), and *Network Function Virtualization* (NFV) technologies. Cloud computing is a model for delivering computing services on demand basis over the Internet [4], [5]. In cloud computing, resources such as processing, data storage and networking are provided to end-users as general utilities like electricity. SDN, on the other hand, advocates for separation of the control and data planes [6] [7] [8]. Canonically, SDN comprises of a central controller that manages the data plane switching elements to activate the desired switching policies. Therefore, the switching elements apply the rules stated by the centralized controller and the interface between the controller and such forwarding elements can be, for instance, a standardized interface such as Openflow [8]. SDN through separating control and data planes and by adopting centralized control enables many advantages such as programmability, automation, and significant cost reductions due to lower complexity in the switching elements. On the other hand, NFV enables softwarized implementation of network functions on a general purpose hardware [9] [7]. Therefore, NFV decouples the network functions from proprietary hardware-dependent implementations and enables the use of a hardware resource for many network functions. NFV has many advantages ranging from improved scalability and flexibility to significant cost reduction through sharing of a hardware resources for many network functions. It is important to note that SDN and NFV are independent but complementary technologies and the adoption of both in a network architecture will maximize their advantages in terms of improved flexibility, scalability, and cost reduction.

Moreover, cellular networks are increasingly becoming dense due to the deployment of multi-tier base stations in the same coverage area. Densification significantly increases the offered capacity to end-users through frequency reuse. Such multi-tier base stations are already being deployed by 4G Mobile Network Operators (MNOs) to meet the growth in demand and are expected to be deployed in huge numbers in the coming years. Densified RAN deployment results in a large number of resources to be managed. Hence, softwarization is highly required in densified deployments than legacy ones as an enabler for automated network management, flexibility and cost reductions. Therefore, densification coupled with softwarization are paradigms of agile RAN supporting high data rate end-users.

B. *The need for EH in RAN*

While densification is important to meet high capacity demand, it poses challenges in the power consumption of the network. These challenges come from three directions. These are: i) Densification results in high demand of electrical power to ensure uninterrupted operations. Such high demand for energy increases the cost of operation of a network; ii) Dense deployment of base stations also increases CO_2 emission from mobile networks operation. Environmental footprints need to be reduced to limit the impact on climate change. iii) Most of the base stations, mainly the so-called small cells (SCs), are expected to be deployed in hot spots. This makes grid power supply access to these base stations difficult sometimes. These reasons drive an adoption of EH in RAN, which accounts for around 80% of energy demand from cellular networks [10]. EH is a solution to power communication nodes from natural or man-made activities by scavenging energy physically or chemically [11]. The use of *Energy Harvesting Base Stations* (EHBSs) is multi-fold. Its potential advantages are: i) Significant reduction of operational costs, since the only incurred cost is due to energy harvesting hardware and site access. Once installed, the energy obtained is free. ii) It minimizes the carbon footprint from the operation of network infrastructure. This enables MNOs to be aligned with sustainability goals, regulations and directions. iii) EHBSs are independent of grid power access, which can improve MNOs network planning. As a result, MNOs need to consider only network performance related parameters prior to installation. These factors lead to EHBSs deployment and massive usage of them is expected in the future 5G networks. With EH, energy is a dynamic resource and it is interesting to study the interaction and harmonization of EH with other RAN architecture paradigms, namely softwarization and densification.

C. *The need for optimization tools*

The vision of future mobile network, sketched in the above, correspond to a highly heterogeneous and complex system, including several types of end-devices with diverse QoS requirements, multiple cell layers working in different radio technologies and spectrum bands, and dynamic reconfiguration and placement of network functions. A general 5G network architecture platform that incorporates multiple technologies including massive MIMO, cognitive radio, device-to-device (D2D) communication, small cell networks, cloud, NFV and SDN is proposed in [12]. The proposed architecture gives insight into the complexity of the 5G. Such a complexity needs an intelligent, timely and automated control to balance many, often conflicting goals, and to ensure efficient deployment and operation of the available spectrum, energy and computational resources. Hence optimization tools such as *Machine Learning* (ML) and *Dynamic Programming* (DP) need to be incorporated in the control functions of the future RANs to analyze the environment and take the appropriate actions. In fact, ML and DP may include an end-to-end knowledge of the system to achieve a *proactive optimization*, able to exploit the huge amount of data available and to even incorporate additional dimensions, such as the characterization of end-user experience and behavior, the energy consumed and harvested.

ML is a technique of detecting patterns in data-sets automatically [13]. ML is applied to those kinds of problems where writing an explicit computer programs are impossible or extremely challenging due to the complexity of patterns that need to be detected. One of such systems with complex datasets are cellular networks. Because of the diverse nature of cellular network systems, which results in diverse set of data, applying analytical modelling and performance prediction is not feasible. Besides, DP (or Reinforcement Learning as its approximation) can help to determine optimal decisions for a given optimization problem [14]. DP algorithms solve complex sequential decision making processes by minimizing a certain cost function. The great benefit of such methods is that optimization takes into account that decisions are not isolated in time: the objective is to balance the desire for low present cost with the undesirability of high future costs.

III. RAN ARCHITECTURES

In this section we first describe the common trend towards densification regarding RAN planning and deployments. Then, we present RAN architecture proposals based on softwarization.

A. Network densification

HetNet is an architecture that supports several base station co-existence in cellular networks each having their own parameters such as transmission power and coverage area [15]. HetNets were primary adopted as a means to enhance the capacity of cellular networks in areas of high traffic loads, such as indoor and areas of coverage holes around cell edges. Multi-tier cellular networks encompassing multiple types of BSs co-exist in the coverage area of a HetNet deployment.

The BSs in a HetNet can be classified as macro BSs and low power base stations (small cells). The low power BSs are usually further classified as pico, femto and relay cells [16], as shown in Figure 1. Pico cells are typically deployed in hotspots to enhance the performance of the network in the selected areas. They are deployed in a planned manner by operators and they are open to all users in their coverage area. Hence, pico cells are similar to regular base stations with the only difference being lower transmission power, and hence, coverage area. On the other hand, femto cells are deployed for indoor environments in unplanned manner (i.e. deployed by customers) [16] [17]. Depending on whether femtocells allow access to all UEs or restrict some UEs from access, they are classified as open or closed respectively. Femto cells can also be configured in a hybrid mode by granting access to some terminals with lower priority. Femto cells typically utilize end-users' backhaul, such as cables or digital subscriber lines (DSL). Relay cells, on the other hand, are used to boost the signal from BS to users in selected locations. Hence, they are deployed mainly for throughput improvement and coverage extension in areas of coverage holes.

HetNets may also include multi Radio Access Technology (RAT) deployments, where other RATs such as Wi-Fi are used for offloading traffic [17]. Inter-tier interference and coverage holes created by closed femto cells are identified, as the main challenges in HetNets [16], [17].

Conventional HetNets are evolving into the notion of *ultra-dense HetNets*. Ultra-densification deployment trend is characterized by having many number of over-lapping base stations. Some authors even claim that in ultra-dense HetNets, the number of cells exceeds the number of active User Equipment (UEs) [18], [19]. In such deployments, due to the high density of small cells (SCs), idle mode of operations, when there are no active users, proper propagation models and mobility management mechanisms are necessary.

In ultra-dense HetNets, SCs can be deployed either in co-channel mode or non-co-channel mode [18]. In co-channel deployment, SCs and macro cells share the same frequency band whereas in non-co-channel deployment, a different frequency band is used for SCs. Moreover, the authors in [18] showed that, typically macro cells use around 1 – 2 GHz licensed spectrum, whereas SCs can use unlicensed 5GHz band. Such deployments help to reduce the interference between macro and SC tiers and improve planning of cellular networks. This is due to very large number of SCs in ultra-dense deployments and co-channel existence with the baseline macro cells will be extremely challenging due to severe interference. The European METIS project identified ultra-dense networks as one of 5G architecture enablers. The project further identified that, utilization of higher frequency spectrum, use of multi-RATs and switch on/off scheduling of SCs are essential techniques in such ultra-dense deployments [3] .

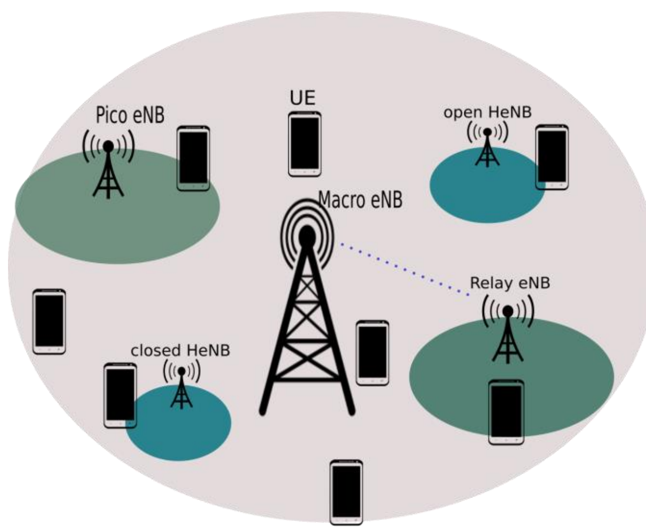

Fig. 1. HetNet architecture [16]

B. Cloud Radio Access Network (CRAN)

CRAN is an architecture that integrates the emerging Information Technology (IT) cloud technology into the RAN of cellular systems. In CRAN, the baseband processing operations are done in a centralized Base Band Unit (BBU) pool or central cloud (see [20][21][22]). Therefore, the base station at the cell sites are reduced to simple Radio Remote Heads (RRHs). The various RRHs and the central cloud are connected via fronthaul links. The connectivity between central cloud and core of the network is provided by transport network. In its original proposal of CRAN, the RRH and central cloud connectivity is defined to be optical fiber fronthaul [20].

CRAN has a lot of advantages ranging from simplified BSs at cell sites to centralized processing at the cloud. Cloud operation leads to a more resource efficient utilization of available resources with the same analogy in today's IT cloud computing. CRAN also enables decoupling of processing and transmission and opens a room to apply data plane cooperation techniques, such as CoMP [23] [20] [24].

Some of the challenges in CRAN arise from the fronthaul connectivity between RRH and central cloud. Optical fiber fronthaul provides the required high capacity and very low latency connectivity between RRH and central cloud. However, using optical fiber fronthaul for every RRH is not scalable and flexible due to high cost and unavailability [6]. Another challenge in CRAN emerge from the concept of cloud in mobile networks. Cloud computing in traditional IT scenario and radio networks are different. Cloud processing in mobile networks requires a very tight synchronization and processing time, as compared to processing in IT data centers. Therefore, the central cloud must be tailored to use appropriate data center designs, according to specific requirements of mobile networks.

Heterogeneous CRAN (HCRANs) are extension of CRAN architectures that include a presence of High-Power Nodes (HPNs) for control plane functions and coverage [25]. Data transmission is handled by RRHs. HCRANs are similar in many aspects to CRAN, but they are slightly different since HPNs are interfaced to the central cloud for mitigation of cross-tier interferences by cooperative techniques at the cloud [25]. HCRANs partially alleviate the fronthaul problem in CRANs by decoupling the control signaling from data. All the control signaling is delivered via HPNs and the fronthaul only carries data. In addition to reduced fronthaul requirements, HCRANs also open a room for multi-tier cooperation advantages [27].

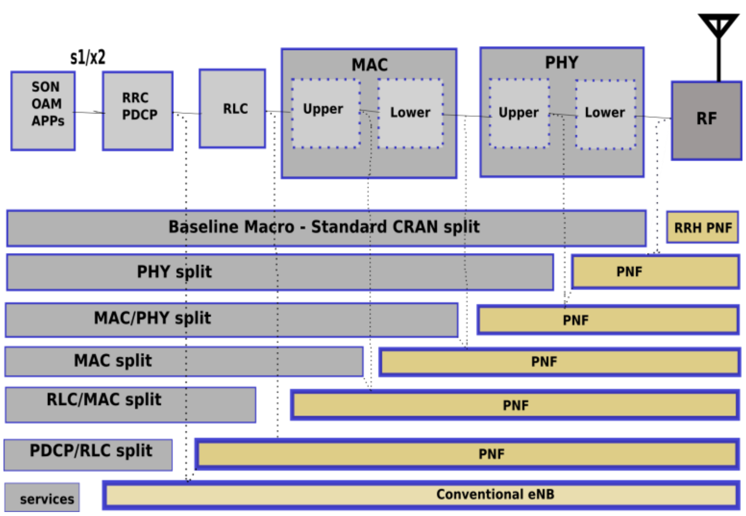

Fig. 2. LTE functional split options in CRAN [26]

Regarding this notion, the authors in [28] showed different CRAN options, ranging from centralized RAN, Layer 2 (L2) locally coordinated architecture and fully integrated at the edge architectures. They showed that each functional split option has its own advantages and limitations, and one may typically fits only certain deployment scenarios. This, in turn, emphasizes the need for re-configurability in the architecture. They also highlight the importance of incorporating NFV into these architectures to ensure the 5G evolution and to guarantee flexibility and cost effectiveness. Based on the ETSI NFV use case for mobile base stations [29], the authors in [26] identified the requirements of fronthaul capacity at various functional split options. In addition, they indicated the various radio functions that can be supported in functional split between RRH and central cloud, at various layers ranging from PHY to PDCP-RLC, as shown in Figure 2.

C. *Fog Radio Access Networks (FRANs)*

FRAN is proposed to embed the advantages of fog computing to alleviate the aforementioned limitations of CRAN, such as capacity constrained fronthaul, latency and heavy burden at central cloud [30]. In FRAN, shown in Figure 3, in addition to the central cloud of CRAN, edge devices such as RRHs and UEs can be used for local signal processing, cooperative radio resource management and content storage [23] [30]. Such paradigm of using edge devices for computing and storage is called fog computing [31][32] [33] [34] and it helps to partly address the fronthaul and central cloud heavy burdens in CRAN. Fog computing is gaining increasing interest recently as a complementary technology to alleviate cloud computing drawbacks. This is evidenced by initiatives such as OpenFog [35] and ETSI-MEC [36] to define an architecture of fog/mobile edge computing as a complement to cloud computing technology. The authors in [21] suggest a harmonization mechanism for co-existence of both CRAN and fog-nodes in the same environment with the objectives of maximizing benefits in terms of resource optimization.

One major functionality in FRANs is Edge caching. Edge devices, such as RRHs and UEs, can be used as local storages of certain contents to reduce latency as compared to accessing the content from far servers. Various edge caching strategies in FRANs are presented in [30]. The authors in [37] compared pure CRAN with FRAN and propose that for the edge and CRAN

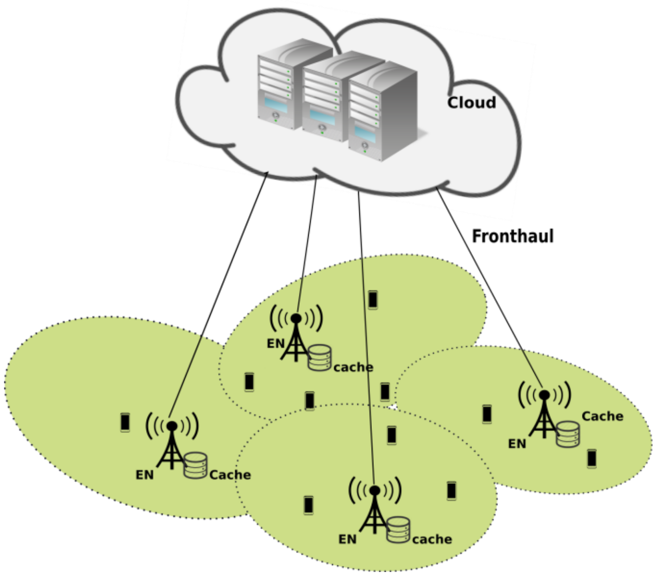

Fig. 3. FRAN architecture [37]

architectures can be combined by edge cache functionality to minimize latency. Their work proposes an information theory based metric called Normalized Delivery Time (NDT) which tries to find optimal policy to balance performance (latency) and resources (cache storage and fronthaul capacity).

D. Generic SDN/NFV/Slicing based RAN architectrues

Here, we have classified RAN proposals in three categories. The first category deals with proposals that apply SDN to RAN. These works mainly focus on decoupling the RAN control from the RAN data plane with the aim of centralizing the RAN control plane functions. In the second category, namely NFV applied to RAN, we included novel proposals that primarily focus on virtualizing RAN control and data plane functions and increasing the flexibility in allocating RAN network functions among the different mobile network segments. Finally, the third category summarizes the work conducted on end-to-end slicing, that is, the allocation of logical networks including network and IT resources. It is important to note that the three categories can potentially include both SDN and NFV technologies, but they are categorized under SDN or NFV or slicing based on their main proposed novelties.

1) SDN applied to RAN

One of the pioneers in this category is SoftRAN [38], shown in Figure 4. SoftRAN proposes a centralized Radio Resource Management (RRM) control plane function of many BSs by abstracting them as virtual big BS in a central SDN controller. In SoftRAN, all the radio resources belonging to a region are abstracted in a 3D resource grid with time-frequency-location indices. SoftRAN also proposes to distribute part of RRM control functions that can be efficiently implemented locally by individual BSs. Another similar proposal of SDN empowered RAN is software defined RAN (SDRAN) proposed in [39]. SDRAN, proposes to separate the RAN control functions from the data plane. To realize this, three controller deployment models are proposed. These are: (i) fully centralized controller where a single controller is responsible for the control plane functions of the entire RAN; (ii) distributed controller where a single controller is only responsible for a subset of base stations and (iii) hybrid controller where the central global controller and local regional controllers are involved in the control plane functions of the RAN. The way to engage legacy network elements is also highlighted, such as loosely and tightly coupled evolution of legacy elements and a clean slate model. SoftMobile, in [40], identifies the need for principle based evolution of the control plane in heterogeneous wireless networks and the need for abstraction in the control plane to achieve optimal performance.

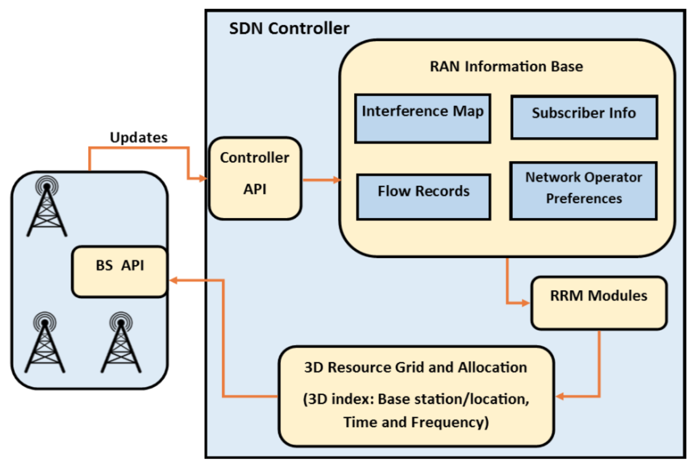

Fig. 4. SoftRAN architecture [38]

While the works [37–39] are mainly principle based, without details of implementation platform, the authors in [41] propose a software defined RAN platform called FlexRAN. In FlexRAN, south and northbound Application Programming Interfaces (APIs) with master-agent controller architecture are proposed. Moreover, FlexRAN is designed to be used as an implementation platform to evaluate SDN applications in RAN. Various use cases and practical evaluations show the feasibility of the platform for RAN.

Improvement of CRAN by applying SDN is proposed in [42], which identified the limitation in CRAN due to its one-to-one mapping of RRH and BBU in central cloud. They introduce SDN based flexible mapping architecture, which is called Software Defined Fronthaul (SDF). SDF improves flexibility and also guarantees seamless mobility and improved resource utilization. The CONCERT architecture in [43] defines a converged edge infrastructure for future cellular networks. In CONCERT, SDN is applied to improve the CRAN architecture by ensuring flexibility and dynamic reconfiguration of radio resources to meet the traffic requirements. This architecture consists of a data plane of all physical resources that are interconnected via software defined switches and a control plane that is implemented by a conductor that orchestrates and virtualizes the resources in the data plane. The proposal enables a convergence of both cloud computing and mobile communications through software defined abstraction and management of the RAN resources.

2) NFV applied to RAN

On the other hand, some of the existing works on 5G RAN architecture focus mainly on the application of NFV principles. The ETSI NFV use case for virtualization of mobile base station [29] is one example. They have proposed RAN virtualization use case in a C-RAN architecture, where the BBU functions can be executed in a Network Function Virtualization Infrastructure (NFVI) environment such as a data center. Based on this ETSI use case, the authors in [44] propose an architecture for LTE RAN virtualization. In this proposal, virtual radio processing units are responsible for executing LTE data plane stacks and a controller for interfacing virtual RAN to the core network and other RANs is devised.

Similarly, the authors in [45] devise a NFV architecture for HCRAN that encompasses virtualization of radio and computing resources of both intra and inter RAN technologies. They emphasize on the need for transparency among virtual BSs of the same physical infrastructure. An architecture for virtualizing both RAN and core network functions with NFV is proposed in [46]. Here RRHs are directly connected to the core of the network and all BBU and core network functions are executed on Virtual Machines (VMs) on demand basis. On the other hand, the authors in [47] identified the key issues of NFV in the context of 5G and they have proposed a network overlay concept of decoupling physical address from virtual addresses as well as isolation of traffic in virtual networks. With SDN and network overlay as enabling technologies for NFV implementation in 5G, the authors in [47] identified candidate network functions that can be executed as virtual network functions (VNFs).

In [48], a two layer architecture of radio and network cloud that also integrates dense small cell deployments with NFV is proposed. In this architecture, the edge infrastructure is designed to perform RAN lower layer (i.e. PHY&MAC) functions and other higher level functions are defined in the cloud infrastructure. Cloud scalability is achieved by NFV and the notion of separation of coverage and capacity is emphasized in the proposal. A similar proposal called RAN as a Service or RANaaS [6] is proposed to ensure flexible functional split between central cloud, as in CRAN, and distributed operation, as in conventional mobile networks. The proposal aims to take advantage of flexible implementation of virtualizing RAN functions, where some functionalities remain to be executed at the BSs whereas, less delay stringent functions are centrally located.

3) Network slicing proposals

With the advent of vertical industries (i.e., eHealth, automotive, robotics), the deployment of multiple end-to-end logical networks with different requirements on top of the mobile physical infrastructure, including the RAN segment, becomes a necessity. The management and orchestration of these virtualized (logical) networks encompassing network and IT resources is also referred to as *network slicing*. Network slices are E2E logical networks running on top of a physical (or even virtual) infrastructure [49]. The internals of each network slice are managed and orchestrated in an independent way by each individual vertical sector, hence being flexible enough to accommodate the different technical and business demands [50]. An important property to satisfy amongst network slices running in parallel is that of isolation. Strong isolation is required i) to meet the particular per-slice KPIs, ii) to attain per-slice security in the sense that attacks in one slice should not affect other slices, and iii) to enable each vertical to manage each network slice in a self-contained manner.

SDN/NFV are enabling technologies for network slicing. The authors in [50] propose network slicing as a service model for mapping various requirements to service models of operators, with the ultimate goal of enabling provision of customized end-to-end networks as a service. For the case of Mobile Virtual Network Operators (MVNOs), authors in [51] devised a broker architecture for enabling infrastructure providers to dynamically allocate portion of their offered capacity to tenants such as mobile virtual network operators. The proposed broker architecture aims to allocate resources from infrastructure providers to enable demand driven allocation of their offered capacity. Thus, it supports multi-tenancy on the same physical infrastructure. The authors in [52] took a further step in slicing by proposing a network store for providing end users with a slice, according to demands, via programs that allocate and deploy necessary software and network elements. The network store architecture is shown in Figure 5. It works in the same analogy of Apple´s App Store and Google´s Play Store, to motivate third parties to deploy network applications. In addition to the network store, they also provide 5G slicing architecture, based on NFV and SDN paradigms, with a network store for creation of network slices.

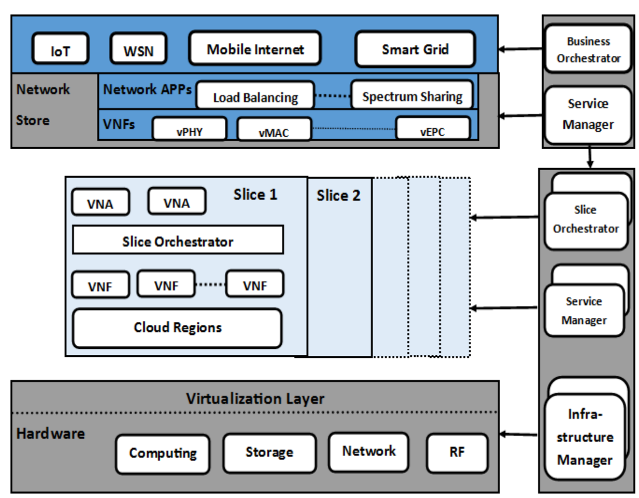

Fig. 5. Creation of slices with network store [52]

Two key challenges to enable physical infrastructures and radio resources to be shared among different parties are resource allocation and isolation among multiple slices [53] [54]. Resource allocation mechanisms decide on how to embed a virtual wireless network onto the physical infrastructure i.e. deciding on which resources, nodes and links to be picked and optimized based on requirement constraints from service providers [53]. Unlike wired networks, resource allocation mechanism in virtualized wireless environment is challenging due to the inherent nature of wireless communication such as interference, mobility, radio channel variability and roaming. In addition, the authors in [53] show that due to the variability in the number of end users and aggregate mobile traffic in a certain area, resource allocation mechanisms should be dynamic to avoid over and under provisioning and in some cases to ensure that the allocated virtual resources do not exceed the underlying physical substrate capacity. Once proper resource allocation is made, ensuring isolation among slices is necessary. Isolation is preventing degradation in the performance of a slice due to changes in another slice, addition of a new slice or removal of a slice [54]. Isolation in the context of wireless networks is complex due to a shared and broadcast nature of wireless medium and associated factors such as mobility, variation in RATs and interference. Both challenges, i.e. resource allocation and isolation are coupled and in some cases isolation can be translated as maintenance of the allocated resources. If, for example, the allocation mechanism ensures that there is no resource overlapping, then isolation among slices is implied. Softwarization technologies namely SDN and NFV, in addition to being enablers for slicing, they can also be applicable to alleviate the aforementioned challenges of slicing. These ideas are highlighted in [54] where the potential of SDN through decoupling of hardware and control logic can be exploited to enable per slice control plane and centralized management. In addition, NFV enables location independent implementation of network functions according to specific scenarios. Hence, NFV helps to ease allocation and isolation issues [54].

Conclusions:

The various architecture options for 5G RAN indicate the trend in ultra-dense and cloud enabled RANs. The notion of ultra-dense shows high BS density and cloud enables centralized processing for BBU functions. The HetNet and CRAN options are unified in HCRAN architecture. HCRAN is shown to be an architecture of future cellular radio access networks but challenges, mainly due to capacity constrained fronthaul and severe interference, need to be addressed. For this reason, incorporating flexible functional split adapted to the fronthaul capacity and enabling edge infrastructures with processing capacity, as in FRAN, are essential to address some of these issues. In addition, SDN and NFV are technologies needed for managing the complexity in fronthaul mapping and control in HCRANs with dense deployment. Hence, an architecture for using fog and cloud premises optimally with layered control plane separation by SDN is required to achieve 5G requirements. In addition, future networks will be based on slicing paradigm, where different service providers sharing the same infrastructure and ensuring proper resource allocation mechanisms and end-to-end performance isolation among slices are major challenges. In a nutshell, the issues (i) the notion of flexible functional split based on fronthaul, fog and central cloud capacity and QoS demands; (ii) integration with legacy networks and (iii) control plane evolution and separation via SDN/NFV together with tenant isolation in network slicing paradigm, need further study. Table I summarizes the softwarization and densification elements and trends in RAN.

TABLE I. DENSIFICATION AND SOFTWARIZATION IN RAN

Architecture		Elements and Evolution
Densification		➢ HetNets with Multi-tier, co-existing cells [15][16][17] ➢ Multi-RAT, multi-tier [17] ➢ Evolved to Ultra-dense HetNets [18] [19]
Softwarization	***CRAN***	➢ BBU operation in central cloud [20] [21] [22] ➢ Extended to HCRAN [25] ➢ Evolved to the notion of flexible functional split [28] [26] [6]
	FRAN	➢ Central BBU cloud with edge devices capable of processing [23] [30] ➢ Co-existence with CRAN [21] ➢ Edge-caching in FRAN [30] [37]
	Generic SDN/NFV based RAN Proposals	➢ SDN principle applied to RAN [38][39][40][41] ➢ SDN applied to improve CRAN [42] [43] ➢ NFV principle applied to RAN [29][44][45][46][47] ➢ NFV based CRAN modification [6] [47] ➢ Network slicing architectures [49] [50] [51] [52] ➢ Challenges in network slicing and state-of-the-art proposals [53] [54]

IV. ENERGY HARVESTING IN RAN

The common natural phenomena for scavenging energy from are sunlight and wind, but other sources such as motion, vibration and electromagnetic radiation can also be used as sources of energy to decrease the dependency of the network from the power grid. Earlier works such as [55], of adopting renewable energies for cellular networks aim at regions where power supply from the conventional grids are difficult and unreliable, such as in rural areas. But recently EH is also studied to be feasible for urban scenarios. This is mainly due to the trend of densification in RAN leading to many base stations with low transmission power requirements. This, in turn, results in lower initial investment for initial site access and harvesting hardware, that lead to low OPEx in the long term [15]. This trend is valid regardless of the different architectures, such as ultra-dense HetNets having standalone low power pico/femto cells, CRAN with RRHs for a very small area coverage or FRAN, which combines RRHs and standalone low power BSs or edge devices. Therefore, the interest to partially or completely power BSs with energy harvesters is increasing [15]. The benefits of powering BSs with energy harvesters is not only lower OPEx, but also reduction of CO_2 emissions [15].

A system model for an EH cellular networks with local BS on/off strategy is analyzed in [56]. In this model, each BS decides when to switch on/off regardless of the state of other BSs. This model characterizes self-powered BSs by their availability metrics and optimal region identification of where BSs exhibit similar performance, as those with reliable energy sources. In addition to self-powering of BSs, hybrid powered BS deployments are also viable options. Hybrid powered BSs are characterized by both grid and renewable energy supplies and the goal of system wide design is to maximize the utilization of harvested energy, when they are available in order to decrease the total grid energy consumption [57].

The advancement of renewable energy technologies such as solar panels and wind turbines, also paves the way for the increasing interest in terms of EHBSs. Renewable energy technologies, particularly solar panels and wind turbines are expected to enhance in efficiency and their costs will continue to decline [58]. This trend is favorable for mobile network operators to use EH and achieve both sustainable and cost efficient goals. Solar panels and wind turbines are the two promising energy harvesting technologies due to sufficient energy harvesting rates, longer life times with very low maintenance costs and mature industry eco-systems producing them [59]. Moreover, solar and wind turbines are complementary energy sources and hybrid powering BSs with solar panels and wind turbines is an interesting solution to balance the challenge due to energy arrival dynamics. For instance, solar energy output is high in summer seasons, while, in many areas, wind turbine power output peaks during winter months [59]. Due to these reasons, BSs that are completely powered by renewables may combine hybrid sources of wind and solar panels.

In order to deploy EHBSs, finding optimal trade-off among network performance, density of BSs and grid power consumption is a challenge that requires careful investigation [59]. Hence, network deployment guidelines are needed to balance such trade-offs. For instance, [59] stated that it is effective to use more number of EHBSs than using BSs with high energy harvesting capacity namely large size of solar panel and/or large diameter of wind turbine. Moreover, they also pointed out that, when the density of EHBS is too large or too small, the battery capacity has little impact on network performance and grid consumption reduction. The authors in [60] proposed FreeNet, a joint spectrum and energy harvesting network architecture. FreeNet is promised to be useful for scenarios, such as emergency communications and rural broadband provisions, but due to dynamic nature of both spectrum and energy resources, their joint design is challenging.

Some literatures also noted that energy harvesting base stations can also be part of smart grid architecture as both consumers and producers of energy ([61], [62]). These ideas will open a new paradigm of integrating cellular and smart grid systems with dynamic and price aware strategies. The joint integration provides additional revenues for mobile network operators and performance gains for smart grid operators. The energy management concept in traditional cellular networks, where its main goal was only the reduction of power consumption, is evolved with EH to include not only energy efficiency goals but also sustainability and smart grid awareness objectives [62].

While many existing literatures studied the issues of EH in wireless networks, including the challenge of having intelligent energy management by applying methods of machine learning and optimization (the reader can refer to section V), most of the works are based on the HetNet architectures. Studies of EH applied to other architectures such as CRAN and FRAN are not widely available. EH with CRAN is studied in [63]. Here, the authors propose a green CRAN architecture where the RRHs of CRAN are powered by renewable energies and algorithms for sustainable resource management to ensure QoS and sustained operation of RRHs are proposed. One notable work to adapt EH with software defined RAN is [64]. In this work, a virtual distributed load balancing scheme that balances the trade-off between QoS and green energy availability is studied. The algorithm is designed to be applied on the central controller of the SDN based RAN architecture and is shown to sacrifice little QoS, such as increase in latency, for a higher proportion of energy benefit. In addition, the energy fluctuation due to EH and the mechanism of energy cooperation among RRHs in HCRAN is highlighted in [45]. However, it is a more generic inclusion of EH in HCRAN without specific EH related details. On the other hand, the authors in [65] defined an architecture for EH with FRANs. They identify two critical policies, which require careful design in EH mobile edge computing systems: (i) offloading policy to determine how much work is offloaded to a central cloud and (ii) an auto-scaling policy to determine how much server capacity is provisioned.

An inherent nature of EH communication is the intermittent and unreliable nature of the energy sources. In order to cope with these challenges, EH communication systems require new protocols, planning, cooperation schemes and possibly techniques of using hybrid sources of energy and real-time interaction with smart grid.

To summarize the trends of EH in RAN, hybrid and self-powered BSs with the aim of grid-consumption reduction in HetNets are studied in [15] [56] [57]. Moreover, [61] [62] study the potential of EHBSs as players in smart grid architectures opening a new frontier of revenues for mobile network operators. In addition there are some works that attempt to study the possible interaction with EH and softwarization technologies including the study of EH with SDN [64], EH with CRAN [63], and EH with FRAN [65]. The challenges arising from the unreliable nature of energy arrival in EH communication are attempted to be tackled by optimization tools including machine learning and dynamic programming. For detailed description of these proposals, the readers can refer to section V.

Conclusions:

EH in RAN is a promising direction to ensure sustainable mobile networks business in both economic and environmental terms. However, EH also brings its own challenges in RAN design. These include uncertainty in energy arrival rate, provisioning of energy storage devices, energy management to decide when to use the harvested energy and traffic handling mechanisms when energy arrival is not sufficient to operate a particular BS. In addition, there are gaps in the current literatures in integrating EH with new cellular network architectures namely, CRAN, FRAN or SDN and NFV based RANs. The case of EH with softwarized architectures need further investigation and EH should be treated as one element of the architecture due to the increasing adoption and interest of EH for both rural and urban scenarios.

V. Role of Optimization Tools

Future RANs will have to handle diverse QoS and QoE requirements of thousands of heterogeneous devices, multiple slices (also known as tenants) on the same infrastructure, multiple radio access technologies (multi-RAT), dynamic energy availability, possible interaction with the smart grid as well as dynamic reconfiguration decisions where to perform certain network functions. Handling these decisions optimally and automatically requires a control platform with tools such as ML and DP. In this section, we focus on three application areas, namely, optimization with EHBSs, optimization with CRAN and general learning frameworks.

A. Optimization with EHBSs

Optimization tools have been used to solve several issues in HetNets and many proposals can be found in the literature. A typical study case is the interference coordination between macro cells and randomly deployed closed femto cells. In [66], for example, the authors model interference coordination problem as a non-cooperative game. Heterogeneous reinforcement learning is applied for each femto cell to learn its own interference avoidance strategy. However, dynamic energy arrivals in EHBS include new variables in the optimization problem, which seem still uncovered. In contrast to conventional grid powered RANs, in EHBSs, energy is a dynamic resource that depends on time (seasons), location and to the possibility of storage. For this reason, optimization tools are required to achieve intelligent energy management in the RAN and literatures are available in this domain. Among these, the problem of minimizing the grid power consumption of BSs that are powered by both grid and EH is studied in [67]. They consider BSs without energy storage and the problem of minimizing grid consumption is formulated as a problem of Mixed Integer Non-Linear Programming (MINLP), shown to be NP-hard and non-convex. Both centralized algorithm, based on univariate search technique and distributed algorithm are proposed. A similar problem of hybrid powered BSs is formulated as a weighted combination of minimizing grid consumption and QoS parameter (blocking probability) in [68]. A two stage Dynamic Programming (DP) algorithm is designed, having lower computational complexity, as compared to applying DP directly. The case when BSs are completely powered by EH with finite storage is studied in [69]. Here the authors formulate the problem of optimal on/off scheduling while ensuring QoS (delay minimization) with EH uncertainty. A randomized online algorithm based on ski-rental framework is shown to find optimal on/off scheduling, of each BSs without prior knowledge of energy arrivals. A system with combination of BSs powered by grid and EH is considered in [70]. In such systems, sleep mode coordination among the two types of BSs to minimize grid consumption and avoid energy outages is shown to be formulated and solved by both DP algorithm, which entails high complexity and heuristic algorithm with lower computational complexity.

While the works [67]–[70] use particular optimization techniques mainly MINLP and DP, the authors in [71] applied reinforcement learning to find an optimal energy management strategy for BS powered by EH. A distributed Q-learning algorithm is used in such a way that each BS will learn their optimal energy management policy. Energy saving optimization for HetNets with macro, pico and femto tiers is studied in [72]. In this work, they have used a distributed learning approach based on Multi-Armed Bandit, where each type of cell learns a proper cell expansion bias to maximize its own energy efficiency, without incurring message exchanges among cells. On the other hand, the authors in [73] studied multi-cell cooperation techniques in HetNets powered by hybrid energy supplies. The problem of multi-cell cooperation in HetNets with EH is formulated as an optimization problem with further decomposition into cooperation and green energy planning sub problems. The former is approached by employing local search heuristic algorithms while the latter is solved by allocating the green energy in a greedy manner for each active transmission slots. In [74], energy cooperation among EH nodes, where transmitters decide the amount of harvested energy to send to other nodes is formulated in a Markov Decision Process (MDP). Reinforcement learning is applied for each node to learn its own energy cooperation policy. The authors in [75] considered EH with MIMO links with the aim of throughput maximization and total grid power consumption minimization. For the offline solution, they showed that both throughput maximization and grid consumption minimization problems can be solved by convex optimization and, in particular, a two stage spatio-temporal water filling solution is proposed. For the online algorithm, they employ MDP to find the optimal solution. However, due to its computational complexity, near-optimal solutions are also provided.

Even though many literatures exist for attaining intelligent energy management algorithm in RANs with EH, they considered mainly a HetNet architecture with multi-tier and overlapping standalone BSs with renewable or hybrid energy supplies. The application of ML with EH in other types of architectures, such as CRAN or FRAN is less explored. One notable work in this regard is [65], which considered the renewable energy allocation in fog computing based RANs. Reinforcement learning based online algorithm that solves the problem of offloading and auto scaling in EH edge devices is proposed. Particularly a post decision based reinforcement learning solution, which incorporates partial prior knowledge for learning, is applied and is shown to have better runtime performance than conventional methods, such as Q-learning.

It is important to note that the application of optimization tools in EHBSs is highly dependent on the underlying mobile traffic load and energy arrival models. Both mobile traffic and energy arrival models are inputs to the optimization algorithm. However, accurate representation of traffic load and energy arrival information is not straightforward, since both entail spatial and temporal variations. Hence, spatio-temporal analysis of both mobile traffic and energy arrival data are necessary. To this end, the authors in [76] analyze aggregate mobile traffic data of a number of operator owned base stations in an urban scenario to visualize and represent the temporal variation of the mobile traffic load in specific geographical positions. They have developed a model that combines both time and location information for analyzing large scale cellular network data. They provide a spatial distribution of cellular traffic in terms of geographical traffic density. The spatial distribution shows the traffic generation at different times of the day in a certain geographical area. The result reveals strong correlation between temporal and spatial characteristics. Moreover, the temporal distribution analysis provides the traffic pattern in different time scales such as hourly, daily and weekly basis. In addition, their results show that such an urban coverage area exhibits five mobile traffic patterns, namely residential, office, entertainment, transport and comprehensive, with a model that also captures the daily mobile traffic variation in different hours both in week days and weekends. However, cellular network data is of a large volume with variety of information, which makes it big data. Nonetheless, an extensive big-data analysis of cellular network data including their spatio-temporal distribution is missing in the literature. One of the challenges for a lack of large-scale mobile traffic data analysis is lack of large-scale data that captures a realistic trace of cellular network activities. Most of the data are operator owned with limited availability for research.

Moreover, energy arrival also exhibits spatio-temporal variation. Hence, accurate models for representing harvested energy with a reasonable time granularity are required for successful application of optimization tools. For this reason, the authors in [77] developed a model that can be used as a tool to determine the amount of harvested solar power for small form-factor devices, including small base stations. The model is based on extensive database of solar irradiation for many years and it gives a reasonable estimate of expected energy arrival considering time of the day, month and status of the day. In addition, the authors in [78] also propose a solar irradiance model that can capture the small time-scale (in order of minutes) fluctuations. However, both papers exploit only the temporal variation of solar energy arrival. On the other hand, the authors in [79] develop a solar irradiance model considering the spatio-temporal variation of solar energy arrival. The model, by exploiting the spatio-temporal correlation, is proved to be of high accuracy. However, it is developed for large-scale power utility applications. In addition to solar, other ambient energy sources, such as wind, also exhibit spatio-temporal variation. For instance, the authors in [80] propose a model of wind energy forecasting by exploiting the spatio-temporal correlation of large dataset of wind speed and direction. However, most of the literature focus on large-scale power system applications. Models of energy harvesting sources that focus on energy harvesting communication devices such as small cells need further study. A key input for developing such models is data. As a result, the National Renewable Energy Laboratory (NREL) maintains national solar radiation database [81] that provides solar radiation data of US territories for 30 or more years. Such open database encourages further investigation in the field of energy source modeling and forecasting and need to be adopted by other regions as well as for other energy sources.

B. *Optimization with CRAN*

Optimization tools are necessary for cloud RAN planning and virtual network function (VNF) placement. The authors in [82] investigated the baseband unit (BBU) pool placement problem in CRAN with the goal of minimizing deployment costs with constraints of processing capacity, synchronization (latencies) and traffic demands. The studied cellular network is served by certain number of BBU pools and Remote Radio Heads (RRHs). The investigation leads to NP-hard integer programming problem and an algorithm base on local search is proposed. A similar approach is also taken in [83], where virtual network function placement and assignment problems are investigated. The placement problem deals with which of the available network nodes can be used as BBU servers, whereas, the assignment problem deals with which subset of RRHs are assigned to a specific BBU server. These problems are formally formulated as binary integer linear programming problem. The ultimate goal here is minimizing server cost, fronthaul costs and latency. In addition, an approximate and faster algorithm is proposed in cases when the size of the network is large and many instances of RRH and BBU servers are possible. The authors in [84] take on a different approach to tackle the problem of splitting baseband function between distributed units and central units. A graph based model of baseband transceiver structure is proposed by assigning weights corresponding to computational and front-hauling costs. An optimal splitting problem is then converted to graph clustering problem and the work uses genetic algorithm to solve the problem imposing a path delay constraint. Genetic algorithms are also applied for dynamic RRH to BBU mapping challenge in CRAN [85]. The proposal aims to achieve dynamic BBU–RRH reconfiguration according to traffic conditions. It is shown that such dynamic mapping between RRHs and BBUs results in enhanced QoS.

Most of the literature focus on enabling dynamic RRH-BBU mapping in CRAN. However, the application of optimization tools in CRAN is far beyond. With the notion of flexible functional split and fog/edge nodes, not only the dynamic mapping between RRH-BBU is necessary, but also where to place certain network functions optimally, considering QoS demands and available resources including energy. This involves network wide data collection, processing the collected data and applying optimization tools to decide on, where and when to deploy certain network functions as well as maintenance of their life cycles.

C. General learning frameworks

Some proposals emphasize the importance of a general purpose learning framework for multi-purpose optimization goals. Such platforms can be used to generate single purpose radio resource management policies by learning on the collected network wide data. Such learning platforms should account for noisy nature of data collection and ensure prediction of what measurements are to be expected. Such network wide ML based cognition platform is proposed in [86]. The authors identified how generative deep neural networks (GDNN) are suited for network wide cognition and full self-organization capability. They also pointed out that the application of un-supervised learning, using GDNN from input network wide measurements, can result in high level abstraction representation of the input measurement data. As a result, supervised and reinforcement learning applications for specific tasks can be developed using such high level abstractions. The proposed framework is called COgnition BAsed NETworkS (COBANETS) which involves cognitive network nodes with an infrastructure for learning, modelling and optimization. The framework is an example of the need for combination of machine learning and softwarization, in particular SDN, as a reconfiguration tool. COBANETS motivates its design based on three recent trends; (i) recent machine learning advances, particularly in the unsupervised deep learning field, which is suitable for unlabeled data as the cellular network data is massive and usually unlabeled, (ii) recent research advances in reconfiguration tools namely SDN and NFV and (iii) the advancement in the computational power in today's state-of-the-art processors. The authors in [87] also emphasize the need for a shift from single purpose RRM algorithms to general purpose learning RRM framework that is capable of generating control policies automatically. In particular, they propose a general reinforcement learning RRM framework, that can be applied to generate and update control policies for various purposes, based on experience, namely data gathered by nodes in the network. Similarly a network wide intelligent architecture, which combines the benefits of SDN and ML for self-automation is described in [88]. Their design is based on the novel knowledge-plane idea proposed by [89] and applied to SDN-enabled networks. Their proposal transforms the network wide collected data into knowledge by leveraging ML, hence resulting a knowledge-defined networking paradigm. However, these general learning frameworks are faced with many obstacles that hinders their practical application. These challenges range from data collection, appropriate format of data representation, identifying domain specific structures including spatio-temporal correlations which can result in better performance of learning by reducing convergence time and lack of real-time test-beds for experimental evaluation.

Conclusions:

Many of the challenges in RAN arising from timely management, configuration, optimization and healing are suited to formulation and solving via ML and DP optimization techniques. These include intelligent energy management with EH, BBU planning and VNF placement in CRAN and interference management in multi-tier HetNets. While many research attempts are made to tackle single challenges, by designing single purpose ML based algorithms, the trend is towards defining a general learning framework, which can generate multiple single purpose algorithms for self-optimization from network wide data. Hence issues of defining such generic learning framework, as part of the RAN architecture and techniques on how to derive optimal algorithms for a single purpose, such as energy management from the generic learning platform, need particular attention. Table II summarizes the interaction among the paradigms of softwarization and densification with EH technology and optimization tools. The table has four main columns. The architecture column shows the architecture considered in the literature namely HetNet, CRAN, FRAN and SDN/NFV based RAN. The EH column describes papers that embed EH element in the different architectures, whereas the optimization column describes literature on the application of ML and DP tools to solve challenges in different architectures. The column named EH+Optimization shows literatures that apply ML and DP tools with EH technology for solving challenges such as minimization of grid power consumption. The different rows in table II correspond to different architectures of RAN.

TABLE II. INTERPLAY AMONG SOFTWARIZATION, DENSIFICATION, EH AND OPTIMIZATION TOOLS

Architecture	EH			Optimization			EH + Optimization		
	Ref.	Purpose/Problem	Methodology	Ref.	Purpose/problem	Methodology	Ref.	Purpose/Problem	Methodology
Densification (Multi-tier standalone base stations) **[HetNets]**	[15]	cost benefit analysis of HetNets powered by hybrid sources	Simulation based on power modelling of hybrid powered HetNets to estimate cost and co2 emission benefits	[66]	interference avoidance in HetNet with macro cell and overlapping closed femto-cell deployments	Simulation based on heterogeneous reinforcement learning	[67] [68] [70]	minimization of grid power consumption for hybrid power supply RAN	Simulations of optimization by dynamic programming and heuristic algorithms
							[69]	optimal switch on/off of BSs completely powered by EH	Simulation based on ski-rental online learning framework
	[90]	dimensioning of renewable energy harvesters and storages for macro cell LTE network	Simulator based renewable energy data for specific locations				[71]	learning optimal energy management policy for EHBS	Simulation based on reinforcement learning particularly Q-learning
							[73] [74]	multi-cell cooperation policy in EH HetNets	Simulation based on local search heuristics and reinforcement learning
	[61]	how to enable energy trading capabilities for HetNets powered by E	Analysis using realistic traces for cooperation with a grid, CAPEx and return on investment from EH				[72]	learning a proper cell expansion bias for user association	Simulation based on multi-armed bandit learning
	[62]	an architecture for integrating EH HetNets with smart grid	Mainly architectural work				[75]	grid power minimization for EH with MIMO links	Simulation based on Markov Decision Processes
Softwarization **CRAN**	[45]	the cloud element in HCRAN can be used for EH cooperation	Mainly architectural inclusion of EH in HCRAN	[82]	BBU pool placement optimization	Simulation using integer linear programming with local search			
				[83]	BBU pool placement and assignment	Simulation based on binary integer linear programming			
				[84]	splitting BBU functions	Simulation based on graph based model and genetic algorithm			
				[85]	dynamic RRH to BBU mapping	Simulation based on genetic algorithms			
FRAN	[65]	an architecture of EH with mobile edge computing systems	System model of EH based edge computing and analysis based on simulation	[84]	splitting BBU functions between central and distributed clouds	Simulation based on graph based model and genetic algorithm	[65]	offloading and auto-scaling policy optimization for mobile edge computing systems with EH	reinforcement learning application and performance analysis based on simulation
SDN/NFV based RAN (architectures embracing the principles of SDN/NFV)	[64]	virtual load balancer that can be implemented on SDN controller for RAN with EH	Mathematical formulation of load balancing algorithm and its performance assessment by simulation	[88]	SDN empowered network automation via ML and network analytics; knowledge defined network architecture	An architectural framework			
				[86] [87]	general learning frameworks that can be applied to various architecture deployment options	General learning architectures for network wide automation, [86] includes practical implementation scenario			

VI. Open issues

In this section, some of the identified research gaps identified in Table II and challenges towards 5G RANs are mentioned briefly.

Following the many advantages brought by **softwarization** to the wired network domain, there are a number of literatures on embedding softwarization paradigm technologies namely SDN, NFV and Cloud computing to the cellular network domain to benefit from the same advantages. In addition, **network slicing** paradigm pushes the wireless network domain to be more flexible through sharing the infrastructure and resources to various service providers. While considerable attention is given recently on the application of SDN/NFV to the cellular network in both RAN and Core Network (CN) segment, literature on the application of SDN/NFV in the more general virtualized network environment consisting of many slices are limited. The potential of SDN/NFV in solving the challenges of network slicing, particularly towards ensuring proper resource allocation and isolation, requires an extensive investigation.

One of the challenges in the adoption of **SDN/NFV and cloud computing in RAN** is to quantify their potential benefits in improving the utilization of resources such as bandwidth, power and computation. Even though most of literatures claim that these paradigms result in energy and other resource savings, their claim is mainly theoretical, based on the corresponding advantages obtained from wired networks. The cellular network has its own specifics compared to wired networks and the level of benefits obtained in wired networks cannot serve as a guideline for applying SDN/NFV and cloud computing to RAN. A practical analysis for understanding energy and other resources saving advantages of RAN with many fog and cloud resource pools and dense RRHs is missing in the literature. In addition, resource saving potentials of using general purpose hardware, as compared to using specialized hardware, including performance limitations, should be investigated. Such practical analysis will serve as a proof of the claimed benefits of these paradigms in RAN and eventually encourage business players to increasingly adopt them.

Another challenge arises from the notion of **flexible functional split** in cloud and fog RANs that integrate local, fog and cloud level processing. Such traffic aware flexible functional split implementation on dynamic basis require fine-grained network state information collection on available radio and computing resources, the traffic demand in latency and throughput as well as consideration of the available fronthaul resource. While literatures on fronthaul capacity requirements for flexible function split and corresponding architectures are available, they are mainly high level initial attempts, which are far from practical implementation and evaluation. The realization of flexible functional split among local, fog and cloud layers considering traffic, energy and fronthaul capacity, as well as the tight latency and synchronization requirements need further research effort. Cognitive networking via network wide learning platforms can be a step forward to realize this. This calls for ML platforms that learn when and where to execute a certain network function efficiently on the basis of network state including QoS and energy related information. The general learning frameworks that are stated in section V are a step forward to enable such network wide intelligence but a full realization of intelligent network is still far from reality.

Integrating EH with new paradigms of softwarization in RAN is also an open issue that need further investigation. Many of existing literatures focus on solving the issue of EH with multi-tier HetNets that are based on standalone BSs with no function virtualized to the cloud or fog layer. With the notion of Cloud and Fog RANs, the energy requirement and associated EH design issues, such as provision of storage, is different in RRHs serving as RF-ends or Fog Access Points (FAPs) serving as edge devices, supporting some part of BBU processing. In addition, with flexible functional placement, not only energy arrival in EHBSs is dynamic, but also energy demand for operation. Therefore, an intelligent energy scheduling scheme is essential for efficient operations of EHBSs. However, the time scale of the energy arrival rate is slower than the wireless environment variation. The very fast changes in the wireless environment means that the network will experience a significant fluctuation during a time scale of energy scheduling decision. This problem is aggravated in future mobile networks due to dense deployment and shared infrastructures with multiple types of end-devices. Hence, this calls for further investigation to harmonize the very fast changing wireless conditions with the much slower energy harvesting rate.

Network deployment with EH is also a challenge that require further research efforts. EH brings network deployment issues, such as the required density of EHBSs, EH hardware dimensioning, energy storage size, possible module for integrating self-sustaining EHBSs with smart grid and interference coordination with EHBSs are areas of focus for optimal deployment of RAN with EH.

General learning platforms for cellular networks, which can be used to generate purpose-specific optimization algorithms are necessary for network wide optimization objectives. For instance, combining general frameworks, such as generative deep neural networks with reinforcement learning can be one possible direction to realize a platform for multi-purpose optimization objectives. However, to realize a multi-objective optimization platform, there are challenges ranging from data collection methods, appropriate data representation to lack of trial test-beds to evaluate the performance of algorithms. Moreover, telecommunication domain specific studies based on the cellular data to discover patterns, such as spatio-temporal correlations, are required to improve learning platforms performance as applied to telecommunication domain.

Lack of **cellular data sets** for ML training, which represents various realistic network conditions is another issue. In this regard, **open data** can enhance successful deployment of ML ideas for various optimization goals.

However, researchers are facing with obstacles to study big cellular datasets, since most of the realistic large scale datasets are owned by operators. Operators find it difficult to share the datasets to the public, due to business and privacy concerns. For this reason, open data initiatives can be one possible direction to gradually resolve this issue. The initiatives may involve public and private research institutes, including universities, telecommunication operators and governance bodies.

With the increasing interest in making the network an intelligent entity, optimization tools such as ML should be considered as essential **skills of telecommunication** professionals and incorporating them in the existing **curricula** is essential. Most of the present day telecommunication engineering curricula lacks such skills in the training and it is utmost importance to incorporate ML and related skills in the study programs.

Lack of **practical test-beds** for deploying and evaluating new features is also a challenge that limits most of the literatures at theory and simulation levels. Most of SDN/NFV, fog and ML platform literatures for RAN are limited at conceptual level and implementation platforms for feasibility analysis of different paradigms are not widely available. Not only softwarization suffers from lack of test-beds, but also optimization platforms. Most of the recent literatures on general cognitive optimization platforms are limited to architectural level or small scale performance evaluation, due to lack of powerful test-beds for implementation and large scale evaluation.

VII. CONCLUSIONS

In this article, softwarization paradigm, EH technologies and optimization tools have been identified as essential pillars to achieve the goals of 5G and beyond. The paper have provided the motivations behind the need for these paradigms and technologies under a cellular network deployment context of densification. Further, the state-of-art RAN architectures that embed one or more of the softwarization technologies, namely cloud computing, fog-computing, SDN and NFV have been classified and explained with the corresponding challenges. Moreover, EH technology as an enabler for sustainable cellular networks has also been explored through the identification of the recent trends. The research gaps of including EH as an element in softwarized RAN architectures have been highlighted. In addition, the importance of optimization tools for balancing the challenges and benefits of the various embedded RAN technologies namely softwarization and EH is stated with the classification of the recent trends based on the available literatures. The state-of-the-art interaction among the three pillars, explicitly softwarization, EH and optimization tools have been provided with the corresponding open issues and future research directions.

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