Using Reconfigurable Devices to Maximize Spectral Efficiency in Future Heterogeneous Wireless Systems

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Abstract— As broadband data further blends with cellular voice, mobile devices will become the dominant portals to the connected world. However current design practices still involve building independent networks that each make their own resource decisions. In spite of the tremendous amount of related research in this area, there are still several elemental questions that must be addressed. First, is it better to treat wireless systems as independent access networks requiring the user to handle aspects of roaming between disparate wireless networks or is an internet model better where independent autonomous wireless systems (AWS) cooperate to form a single, unified cloud to users, with network level resource allocation? Second, is it better to have dedicated, low power circuitry that supports a limited set of independent wireless Radio Access technologies (RATs) or is it better to build agile handsets that adapt (reconfigure) in real-time to operate over a large range of RAT technologies and operating modes? The results in this paper shed light on these questions. We present preliminary results from a MATLAB-based simulation study that highlights the increase in spectral efficiency as the modality of devices increase. Our analysis takes into account the cost of radio reconfiguration in terms of the temporary communications downtime and the surge of power that occurs with each reconfiguration operation. Our main result suggests that nomadic users benefit the most primarily due to their ability to route traffic over 'hotspot' type of RATs that tend to have high data rates at reduced coverage, and that this in turn helps increase the 3G or 4G bandwidth available to mobile users. All nodes in the system experienced an increase in spectral efficiency ranging from 14% to 75% when compared to a similar scenario that assumes no network cooperation and static radios.

Keywords-heterogeneous wireless networks; reconfigurable radios; 4G wireless systems; cyberinfrastructure;

I. INTRODUCTION

While advances at both the network layer and the physical layer are prompting unprecedented mobile broadband growth, the means by which mobile terminals are offered services have created inefficiencies in both spectrum usage as well as mobile physical resources. The premise behind this issue is that while emerging devices support a multitude of wireless access methods, the current access methods *require the user to select the active access network* either by purchasing an appropriate handset (and service) or, in the case of multimodal smartphones, by manually selecting the access network. While this approach has worked fairly well for current 2G cellular networks, upcoming 3G and 4G systems will face significant challenges as wireless operators are held accountable for poor performance or inadequate coverage. It is well understood that individual systems that manage blocks of spectrum independently are inevitably operating at suboptimal performance.

Until recently, technology was the primary impediment to achieving universal, broadband wireless services that involve multiple radio access technologies. Today, the most significant impediments are the after-effects of antiquated government spectrum allocation policies and the resulting economic forces that drive the wireless industry. The effect is that in many geographic areas licensed spectrum is likely to be underutilized [1]. Current physical MAC layers (i.e., the radio) of a wireless node attempts to achieve the best performance within its own network, generally ignoring impacts of co-located wireless networks. This 'selfish' behavior will usually not lead to optimal resource usage. Techniques or paradigms such as cooperative communications, symbiotic networking, cognitive networking, and dynamic spectrum access attempt to improve spectral efficiency through cooperation at the radio level [2]-[22]. At the network level, architectures and frameworks to support hybrid or heterogeneous networks have been suggested [24-30]. Recent proposals have been based on the IEEE 802.21 standard which provides a framework to support vertical handoffs transferring a mobile user between two networks that are based on different radio access technologies [23].

Although emerging 4G networks embody many of these recent advances, current design practices still involve building independent networks. The economic forces that are driving the cellular industry are reducing the number of cellular providers but causing their wireless networks to become large, heterogeneous systems based on numerous cellular data technologies at various lifecycle stages. At the same time, users are requiring more bandwidth intensive services that might not exist in all coverage areas. On the other hand, 802.11 networks have proliferated to the point that they are now considered to be a part of the computing (cyber) infrastructure. To augment wireless connectivity, some organizations or agencies have deployed site-wide, campus-wide, or city-wide broadband wireless coverage. These trends and the subsequent impacts on end users are becoming commonplace. Using Clemson University as an example, depending on the specific location on campus, one can find multiple 802.11 networks (some operated by the University, some operated by local public safety, others operated by the adjoining city of Clemson or nearby businesses whose coverage spills out over areas of the campus), coverage from an experimental campus WiMAX network, and multiple 2G/3G networks from cellular providers including AT&T, Sprint, T-Mobile, and Verizon. Over the next year, the spectrum on campus will become further cluttered as cellular providers deploy 4G networks. *While wireless technology is advancing rapidly, research that facilitates cooperation across independent networks is still immature.*

In this paper we present an architecture for a wireless system that allows for a 'clean-slate' approach to the problem by making the following assumptions:

1. Incentives are in place motivating independent, autonomous wireless systems (AWSs) to cooperate with each other to provide users a unified network with enhanced coverage and performance than could be achieved by any single AWS.

2. In any given geographic area, a handset might have access to a large number of AWSs. The use of multiple, concurrent radio links will become standard practice at least for a certain class of future smart phones.

3. Due to cost, size, and battery constraints, mobile nodes will be limited to a small number of adaptive radios that must be capable of operating in a relatively large number of supported communication modes and over a range of spectrum.

We envision two economic models that could support these assumptions: a carrier-centric model and an Internet model. In the carrier-centric model, a service provider offers services for specific markets (e.g., commercial wireless access, solutions for public safety). The carrier might own and operate portions of the physical network and possibly broker 'peering' arrangements with other wireless providers. Customers subscribe to a single carrier and gain access to resources or services the subscriber has purchased. For example, one carrier might allow users from another carrier to access its radio and spectrum resources as long as its current users are not adversely affected. Or perhaps cooperation is used for specific services. For example, one can imagine certain emergency situations where it would be advantageous for all available wireless networks to cooperate to provide a robust data service for public safety. An alternative economic model follows the current Internet model: organizations own and operate autonomous networks. Unification occurs through an overlay network that can be achieved through a combination of standard protocols, standard services, and incentive/reward mechanisms that promote peering and collaboration.

We consider a carrier-centric model where a service provider offers services for specific markets (e.g., commercial wireless access, solutions for public safety etc.). The carrier might own and operate portions of the physical network and possibly broker 'peering' arrangements with other wireless providers. The optimal selection of the current active mode (or modes) is performed at a co-operative network level. A centralized scheduler manages bandwidth and user resources at a global level to optimize network–wide metrics, while localized schedulers based on standards-based MAC protocols manage bandwidth over small time scales. The carrier initiates vertical handoffs that might reflect load balancing or cost optimization.

The centralized scheduler has to make decisions that not only increase overall system throughput, but that also maintains some level of fairness among all serviced users. At one extreme is the Hungarian algorithm approach where any user that can make the best use of a given resource should be assigned that resource [42]. Implementing this approach to decide the allocation of all the available resources will lead to an optimal solution in terms of overall achieved system throughput. But there is no guarantee in terms of achieved fairness. On the other extreme is the max-min approach where the goal is to maximize throughput experienced by the user that is experiencing the worst conditions. This allocation scheme would result in maximum fairness across all equally deserving users, but might not result in an optimal allocation scheme that maximizes overall system throughput. Proportional Fairness, which would allocate bandwidth to all users including those experiencing poor link connections, is an accepted fairness policy that has been deployed in current 3G networks [43, 44].

This paper is organized as follows. Section II presents and relates the relevant background and provides motivations for the work. We describe the system model and the research methodology in Section III. We discuss the results in Section IV. Section V provides further insight into the results and identifies limitations of the work.

II. Background

Significant advances have been made in the last decade in radio technology. Recent work in cross-layer optimization has shown that breaking the rigid OSI layered stack model can enhance both spectral efficiency and application performance [2],[3]. Increased efficiency can be obtained through the use of transmit diversity methods such as multiple input, multiple output (MIMO) techniques [4],[5]. It has been shown that further improvements are obtained when wireless nodes cooperate using techniques such as relays and other forms of MAC/PHY layer cooperative communications [6]-[8]. Dynamic spectrum access (DSA) is another form of cooperation that is likely to be a foundation of future wireless systems [9]-[11]. DSA requires devices to be frequency agile giving rise to software defined radios (SDR) and cognitive radios (CR) as possible implementations. While SDRs and CRs have been under development for many years, they are limited to relatively narrowband systems due to multiple issues including power consumption and available computing cycles [12]-[14]. The challenge in handset design is managing the tradeoff between flexibility in how spectrum is used and in space/power requirements of the platform.

An extension to CR is cognitive networking which is defined in [19] as "a network with a cognitive process that can perceive current network conditions, and then plan, decide, and act on those conditions" [19]-[21]. One step further, symbiotic networking observes that current wireless networks tries to achieve the best performance within their own network and generally neglects the impact on co-located wireless networks [22]. In other words, radio behaviors are generally selfish and based only on information observed locally. Symbiotic networks extend the scope of cooperation across all layers and network boundaries.

While SDRs, CRs, cognitive networking and symbiotic networking focus on improving efficiency from the bottom up, heterogeneous wireless networks represent methods for cooperation driven from the top down. The IEEE 802.21 standard provides a framework to support seamless mobility through networks based on different radio access technologies (RATs) without the need to restart the radio connection every time the mobile moves to a new network [23]. Another relevant standard, IEEE P1900.4, defines building blocks for enabling coordinated network-device distributed decision making which will aid in the optimization of radio resource usage, including spectrum access control, in heterogeneous wireless access networks [24].

A number of architectures to support heterogeneous wireless networks have been proposed in the literature. Hierarchical resource managers have been proposed by the Common Radio Resource Management, Joint Radio Resource Management and Multi-access Radio Resource Management schemes studied by the 3GPP group [25]-[29]. The overhead associated with a centralized hierarchical wireless system is studied in [30]. In these hierarchical schemes, and also in our proposed system, the local resource managers of different wireless technologies interact with a centralized entity to jointly optimize the process of resource allocation.

The work in [44] confirms our observation that there has been minimal research published that considers resource allocation in wireless networks taking into account global fairness. To the best of our knowledge, we have found that the work in [28] is the only work that involves a global resource controller issuing reconfiguration commands to radios.

III. SYSTEM DESCRIPTION

A. System Model

Figure 1 illustrates the system model. The system consists of devices (also referred to as nodes) that have connectivity to one or more AWSs. Each AWS will have a controller (referred to as an AWSC) that represents all nodes in the AWS and that serves as a gateway connecting the AWS with other AWSs or external networks. A global resource controller (GRC) manages resources in a manner that supplements decisions made by local AWSs.

Users are presented with a unified network. Depending on node capabilities, users can operate over more than one AWS at any given time. A node's TCP/IP stack sees a single IP link. The wireless virtual link layer (WVLL) handles packet scheduling over one or more radio links. Packet resequencing, error recovery using ARQ and/or FEC can optionally be implemented over the tunnel. The radio link block pictured in Figure 1 represents the MAC and physical layer that operates over a portion of the spectrum. A radio would be implemented using a combination of custom hardware along with programmable hardware based on technologies such as field programmable gate arrays (FPGAs) or digital signal processors (DSPs). User data is tunneled over the unified network cloud. The GRC (or another entity located in the backend network) represents the termination point for the tunnel. Nodes must maintain periodic contact with the GRC by sending status update information periodically. The GRC sends network level status and/or resource management control information periodically to the AWSC (and possibly to individual devices). The unified network provides a best effort datagram service specified. Based on tiered services, users would specify a downstream and upstream service rate. The network could define more complex data services such as a differentiated service offering, however, this is out of the scope of our current exploratory work.

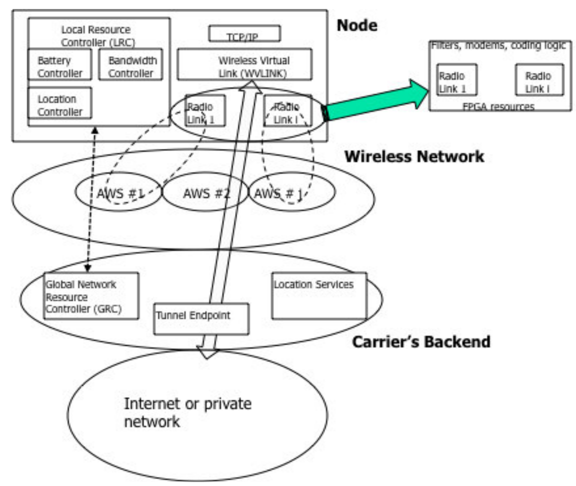

Figure 1 System Model

B. Radio Capabilities

Radios are either static or capable of reconfiguration. Static radios are equipped with one or more non-reconfigurable radios. A non-reconfigurable radio supports a limited level of adaptive capability, but provides the lowest power consumption due to its custom nature. The position of mobile devices will be tracked by the GRC as location-based management is required. An AWS will likely consist of multiple wireless networks, generally of the same radio access technology. For example, a particular 3G network or a campus-wide 802.11 network would be considered an AWS. The GRC is necessary to facilitate cooperation across AWSs. For example, a node that concurrently supports 802.11 and 3G might be told by the GRC to use the 3G link as the control channel and the 802.11 network as the data channel. Alternatively, if the same node moves to a location that has 802.16e coverage, the GRC might initiate a 'reconfiguration handoff'. For example, as the node moves out of coverage of the 802.11 network and the GRC determines that the node is in coverage of the 802.16e network, the network could issue a reconfiguration command to the node instructing it to reconfigure the radio to 802.16e. A reconfiguration handoff is a vertical handoff that requires a radio to reconfigure itself. The implicit assumption here is that due to the multimodal nature required, radios will support reconfiguration rather than have several chipsets, each dedicated to a specific standard.

Reconfigurable architectures span the gamut from general purpose processors to multi-core DSPs, with application specific instruction set processors presenting a good compromise between processing power and computational resources. Chip integration densities allow integrating a large number of cores on a single die, however, the issue of programming and managing these multi-cores in an efficient manner that meets real time processing requirements is still an open research issue. On the other hand, having dedicated chipsets for each individual standard becomes both cost and power prohibitive when the number of supported standards increases. An alternative approach that is gaining momentum due to the massive integration of transistors in advanced technology nodes is the potential use of FPGAs as programmable mobile platforms. Reconfiguration of the FPGA fabric allows for multi-modal support, while real-time performance metrics are easy to achieve due to the hardware acceleration of computational intensive tasks, as well as the massive parallelism achievable by the FPGA architecture. In fact, several FPGA manufacturers are already proposing low power versions of their current FPGA platforms specifically for that reason. Furthermore, Xilinx which is a leading FPGA vendor has released hardware platforms and tools that support partial reconfiguration of individual portions of the FPGA while the remaining sections continue processing, thus allowing fine grain reconfiguration.

In the remainder of the paper, we will assume an FPGA platform is used as the technology for reconfigurable radios. While currently available FPGA's are still considered too power hungry to be used as mobile chips, the preceding argument indicates that there is strong push towards making this a reality in the near future. The intention is not to argue that FPGAs are the best platform for reconfigurable computing, but rather to use them as an exemplar to demonstrate the impact of reconfiguration in terms of network performance improvement, as well as estimate the impact on throughput and power consumption. Table 1 presents implementation and performance statistics for common access technologies. The table is by no means representative of the vast amount of architectures available in literature but is intended to extract a measure of the complexity in terms of area (measured in Kilo gate equivalents of a simple 2 input, drive one, NAND gate), as well as power consumption. The power consumption is categorized as dynamic power consumption (P_{dyn}), which is consumed during regular circuit operation, and reconfiguration power (P_{rec}) which is consumed when the circuit is reconfigured to a new standard. The reconfiguration power and time (T_{rec}) are estimated based on the complexity of the standard, where the minimum reconfigurable block is defined as a data path container (DPC~13.5 Kilo gates). Based on [32], the average reconfiguration power for each DPC (for a Xilinx Virtex II solution) is 234 mW and the average reconfiguration time is 0.63 ms, while the dynamic power is estimated from [33]. Thus, the average total power can be calculated as follows:

$$P_{total} = \propto_{run} P_{dyn} + \propto_{rec} P_{rec} \qquad (1)$$

where P_{dyn} and P_{rec} represent the running and reconfiguration power respectively, and $\propto_{run}$ and $\propto_{rec}$ represent the percentage of time the system operates in regular operation versus reconfiguration mode.

Table 1 Implementation statistics for current representative access technologies

	802.11a	**Mobile WiMAX**	**LTE**	**HSDPA**	**EVDO (est. from UMTS)**
Reference	[34]	[35]	[36]	[37]	[38]
No of Kgates	416	728	270	723 (est. from area and technology)	684
No of DPCs	31	53	20	53	50
P_{dyn} *(W) @ 100 MHZ*	1.76	3	1.13	3	2.83
P_{rec} *(W) @ 50 MHZ rec*	7.25	12.4	4.68	12.4	11.7
T_{rec} *(ms)*	19.53	33.4	12.6	33.4	31.5

C. *Use-Case Scenarios*

Two ways to increase the coverage and capabilities of a wireless network are to use more spectrum and to increase the efficiency of how allocated spectrum is utilized. Government regulations usually dictate the spectrum that is available in a given geographic area. Increasing spectral efficiency is possible under two conditions: (i) the cellular carrier deploys significant amount of higher throughput, lower cell radius access technologies (such as 4G and Wi-Fi); (ii) the mobile terminals are capable of reconfiguration which allows them to access additional resources through roaming agreements between cellular carriers. We formulate two use cases based on these conditions, both of which assume that two cellular wireless providers (we refer to each as Carrier 1 and Carrier 2) provide coverage within the same geographic area. The two use cases differ in the level of cooperation that exists between the two carriers. Use case 1 involves *x* mobile nodes that can connect only to Carrier 1's cellular network and *x'* nomadic nodes that can connect to Carrier 1's cellular and Wi-Fi network. Use case 1 also has *y* nodes that can connect only to Carrier 2's cellular network and *y'* nomadic nodes that can connect to Carrier 2's cellular and Wi-Fi network. Use case 2 allows any mobile node to make use of the other carrier's cellular network and allows any nomadic node to make use of the other carrier's cellular and Wi-Fi network if there is excess capacity on other carrier's networks. The two use cases are designed to reflect current generation wireless capabilities and next generation technology respectively.

D. *Simulation Description*

We have developed a MATLAB-based simulation model with sufficient fidelity to demonstrate the possible benefits of the proposed wireless system. We base the analysis methodology loosely on that used in [39] which demonstrates the potential increase in spectral efficiency when femtocells augment the reach of a wireless provider's macrocell network. While our underlying assumptions allow us to consider more complex heterogeneous wireless systems, our methodology is similar. We use simulation to model an approach for managing resources taking into account the benefits and possible costs of reconfiguration. As in [39], we are interested in showing the improvements observed by each node and also at the global network-wide level.

The simulation topology that was used for the results reported in this paper consists of a 2 * 2 km^2 grid. Any number of wireless access technologies can be used for connectivity within the grid. The AWS model is parameterized by transmit power, a propagation model, and a mapping between effective receive power at a given location and effective data rate. The latter capability allows, for example, the modulation and coding scheme (MCS) of specific radio access technologies (e.g., WiMAX16e, 802.11g) to be taken into account. An example simulation configuration involving three AWSs per carrier is illustrated in Figure 2. Depending on the location of the user with respect to the AP/BS of any given AWS under consideration, the user can operate at corresponding MCS of that specific radio access technology. The closer the user is to an AP/BS, the better the signal reception the user experiences at that location. This translates into a better MCS mapping for the specific radio access technology under consideration. The different color shades in Figure 2 represents an example MCS mapping for various AWSs, where the darker the MCS, the higher the order of MCS any user can use in a given location.

Using the topology in Figure 2, a simulation involves any number of nodes, each of which can be assigned a maximum of three radios. Further, each radio might be reconfigurable (i.e., can be instructed to operate over any of the AWSs) or non-reconfigurable (statically set to one AWS). For use case 1 described in Section C, since a node can only connect using technologies of its own carrier, the three radios on each node are statically set to support each node's corresponding carrier technologies. For use case 2, the three radios on each node are reconfigurable since the three radios should be capable of supporting up to six radio access technologies (three corresponding to its own carrier and three corresponding to the other carrier).

We present simulation results from a scenario involving two wireless providers, each of which has three RATs: EVDO Rev 0 (3G Carrier 1), HSPA (3G Carrier 2), IEEE 802.16e (4G Carrier 1), LTE (4G Carrier 2) and IEEE 802.11g (Wi-Fi Carrier 1 and Carrier 2). For the cellular based AWSs (3G/4G AWS) we assume that a single base station serves all nodes in the simulation topology. These base stations are located near the center of the grid. The 3G base stations have a coverage radius of 1.25 km and the 4G base stations have a coverage radius of 0.75 km. The IEEE 802.11g APs are spread throughput the topology as illustrated in Figure 2. There are two Wi-Fi AWSs, each having three APs, and each AWS belongs to a different carrier. The coverage radius of each Wi-Fi AP is 0.15 km. Based on the location of a subscriber node in the topology, the node can connect to these RATs using one of the corresponding MCSs provided in Appendix Tables [A-1, A-5]. The scenario is based on an urban location that has two large service providers in the area and is designed to show the possible tradeoffs surrounding varying levels of device reconfiguration and varying levels of sharing between the two wireless providers.

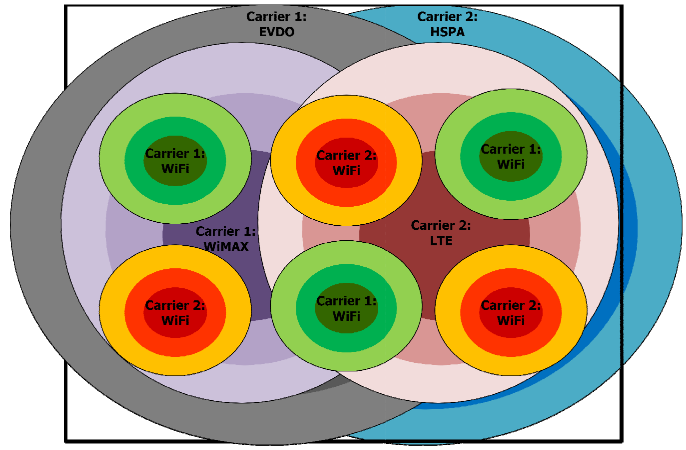

Figure 2: Coverage of an example simulation topology

The simulation involves 100 mobile nodes that are initially positioned randomly within the grid. 50 nodes represent users subscribed to Carrier 1 and the other 50 represent users subscribed to Carrier 2. 75 percent of the total users are mobile users and the remaining 25 percent are nomadic users, and the mobile and nomadic users are split evenly among both carriers. So, 37 users for Carrier 1 are mobile users and 13 of them are nomadic users. 38 users for Carrier 2 are mobile users and 12 of them are nomadic users. Mobile users are allowed to move freely in the entire 2 * 2 km^2 grid, whereas the nomadic users are confined to move in an inner 1 * 1 km^2 grid that encompasses all Wi-Fi APs. Mobile users move using a random walk mobility model at a constant speed of 20 mph. Nomadic users move using a random walk mobility model at a constant speed of 2 mph. Due to these movement patterns, link performance varies over time depending on the node's location in the grid and scheduling decisions. To strike a balance between update frequency and overhead, the mobile and nomadic nodes sends its connectivity parameters for each access technology to the Global Resource Controller every one second.

The Global Resource Controller implements a scheduler that assigns each node's radio the most efficient access technology and that allocates bandwidth in a manner that seeks fairness while maximizing total system throughput. Pseudo-code for the scheduler is provided in Figure A-1 of the Appendix. The scheduler assigns resources for Wi-Fi and the cellular technologies in a separate manner. For assigning Wi-Fi resources, the scheduler checks the number of nomadic users that are in range of a Wi-Fi AP. It assigns equal number of Wi-Fi slots to all nomadic users that can connect using a particular Wi-Fi AP by dividing the total number of Wi-Fi slots the AP possesses by the total number of users that can connect to it. For assigning cellular technology resources, the scheduler follows a two step approach. In the first step, the scheduler allocates a minimum required throughput of 100 kbps to each node using its best cellular (3G/4G) radios. In the second step, the scheduler distributes unused cellular access technology resources to a window of 10 mobile nodes with best connectivity parameters in increments of 100 kbps. The overall order of allocation follows technologies that have the most allocation resources (supported throughput) to the technologies that have the least allocation resources. So, the scheduler assigns resources in the following order: Wi-Fi, 4G and then 3G technologies. All the nodes are limited to a maximum allocation of 1 Mbps during the cellular technology allocation phase. Any node that reaches 1 Mbps or is already above 1 Mbps (for example, any nomadic node that was assigned more than 1 Mbps by Wi-Fi) is not assigned any additional resources.

Our scheduler is clearly different from Proportional Fairness. The next phase of our work will focus on the scheduling problem in the proposed system. The current scheduler is meant to optimize bandwidth by favoring the better connected nodes. The analysis methodology assumes that random movement patterns will prevent any particular node from starvation over large timescales thus ensuring fairness. This approach to scheduling was sufficient to show the tradeoffs when reconfiguration is considered

Each node uses radios according to the decisions made by the GRC. When the GRC instructs a node to switch/reconfigure the radio to be used, there is a cost associated with this operation in terms of temporary downtime and an increase in power consumption. The number of switch/reconfigurations is related to a parameter referred to as *'network outage'*. Network outage represents the percentage of time the network is unavailable to the users. An outage might occur as a result of a number of situations including congestion due to increased network load, increased RF interference levels, AP/BS malfunction/software upgrades, or even network attacks such as Denial of Service. The network outage is an experimental parameter that controls the percentage of slots of a channel that are effectively not used. The outage percentage ranges from 0% to 25% in increments of 5% in our simulation. Each AWS suffers independent random outages with the probability determined by the network outage percentage. In previous work [41], we studied the effect of increasing mobile user speed to the number of switch/reconfigurations. We found that the number of switch/reconfigurations remained relatively constant as the speed was increased in the range [2 mph, 40 mph] in increments of 2 mph. For the results presented in this paper, a small percentage of reconfigurations are due to roaming. The majority are induced by the network outages.

During a switch/reconfiguration, the node switches from one static radio to the other for use case 1. In essence, it has to turn the current radio off and has to turn one of the other radios on. For use case 2, the node either switches from one radio to the other or it performs a reconfiguration by instructing the radio to switch its software components to support the new radio access technology. We treat cost values associated with a switch or a reconfiguration to be the same. The reference time and power cost values are presented in Table 1. The reference power estimates from the table are used in the simulation. Because the scheduler operates on a 1 second allocation basis, we approximate the communication downtime cost by not allocating any bandwidth to the radio for 1 second. This significantly exceeds the reconfiguration times shown in Table 1. However if we assume that downtime also includes the time required to establish the new physical and logical link connections, a downtime cost of 1 second seems reasonable. To better understand the impact of the cost, we multiply the cost of reconfiguration by a scalar in the range [0, 1] which we define as the '*impact of reconfiguration*'. The scalar value of 0 implies there is no switch/reconfiguration cost. The scalar value of 1 represents the reconfiguration power costs provided in Table 1 and the reconfiguration time cost of 1 second.

IV. RESULTS AND ANALYSIS

Each simulation is run for 10,000 seconds. The results from the simulations include the rate of reconfiguration, spectral efficiency and the average power consumption per node that were observed as the two experimental parameters (network outage and the relative impact of reconfiguration) were varied. We compute the spectral efficiency at the end of a simulation run by summing the throughput achieved by each node and dividing the sum by the total spectrum bandwidth (48.25 MHz) managed by all AWSs. The total power consumption of each node is calculated using Equation (1). At the end of the simulation, the aggregate power of all nodes is divided by the number of nodes and the simulation time resulting in the average power consumption per node. We then present results that demonstrate the properties of our scheduler. We analyze the cumulative distribution function of average throughput experienced by mobile and nomadic users for both use cases presented in Section C. Finally, we assess the fairness achieved by the scheduler using Jain's fairness index [40].

The results are dependent on node mobility, access technology coverage range, allocation resources of each access technology and scheduler implementation. The scheduler implemented in this study attempts to maximize network efficiency and maintain fairness across users. Other forms of schedulers might result in different results. We will explore in detail the scheduling problem in future work. For the purposes of this study, our objective was a simple allocation strategy that is sufficient to illustrate the potential benefits of the proposed ideas. In the remainder of this section, we present results related to spectral efficiency, to battery power consumption, and then to the fairness of the scheduler.

A. *Spectral Efficiency*

The spectral efficiency observed in the simulations is visualized in Figure 3. As expected, use case 2 utilizes the spectrum more efficiently than in use case 1. Reconfiguration allows the global and local controllers to use the most efficient RAT and modulation and coding scheme. To provide lower bounds, for no network outage and no impact of reconfiguration, the spectral efficiency gain for use case 2 (1.84 bits/sec/Hz) when compared to use case 1 (1.61 bits/sec/Hz) is around 14.30%. The spectral efficiency decreases as the network outage increases as can be observed from Figure 3. This phenomenon is intuitive since network outage results in loss of resources that could have been used to improve overall network throughput. Also as expected, the rate of decline for use case 1 where there is no carrier collaboration (static radios) is much steeper than use case 2 where carrier collaboration (reconfigurable radios) does exist as the experimental parameters, network outage and impact of reconfiguration, increase. The maximum spectral efficiency gain for use case 2 (1.58 bits/sec/Hz) when compared to use case 1 (0.90 bits/sec/Hz) is around 75.50% when there is 25% network outage and the impact of reconfiguration is 1.

The overall average throughput achieved by each user is around 710 kbps for use case 1 and 910 kbps for use case 2. The overall average throughput achieved by each user is high because of the nomadic users achieving much greater throughput than mobile users. In reality, a better comparison is the throughput achieved by mobile users and nomadic users separately for both use cases. We perform a case study by observing the average throughput achieved by mobile and nomadic users separately for both use cases for a network outage probability of 10 percent and the impact of reconfiguration value of 0. The results are presented in Table 2. Each result is the average throughput of users belonging to both carriers. As expected, use case 2 shows users were allocated higher throughput than users in use case 1. The increase from use case 1 to use case 2 was 22.5% and 31.5% for mobile and nomadic users respectively.

Table 2: Average throughput experienced by each user

	Use Case 1	Use Case 2
Mobile User	310 kbps	380 kbps
Nomadic User	1.90 Mbps	2.50 Mbps

The reconfiguration rate is presented as a function of network outage probability in Figure 4. Since each node has three radios in the simulation, the reconfiguration rate values can range between [0, 3]. We see that the actual values of reconfiguration rate lie between 0.18 and 1.2 which spans quite a broad range. For smaller network outage percentage, the reconfiguration rate for use case 2 is much higher in comparison to use case 1. This is justified since more reconfigurations are performed because better resources become available to nodes as they move according to their movement pattern and not because of the network outage. Network outage has lesser effect than the number of available resources in this case. Since nodes in use case 2 have access to more resources, it experiences a greater level of reconfiguration than use case 1 nodes. But as the network outage approaches 20%, reconfigurations for use case 1 and use case 2 converge as the rate of on/off switches equals (and actually surpasses) the rate of true radio reconfigurations. The results of Figure 4 also help explain the trend seen in spectral efficiency observed in Figure 3. For lower values of network outage, the impact of reconfiguration does not have a significant influence on spectral efficiency since the number of reconfigurations are relatively low. But as the value of network outage increases, the spectral efficiency declines noticeably as the impact of reconfiguration becomes significant.

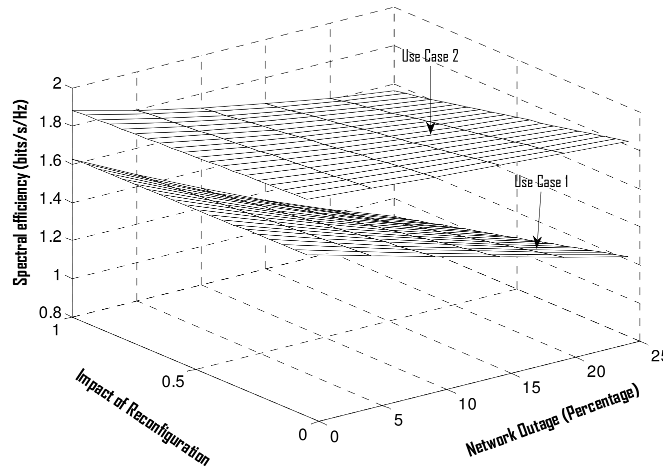

Figure 3: Spectral Efficiency

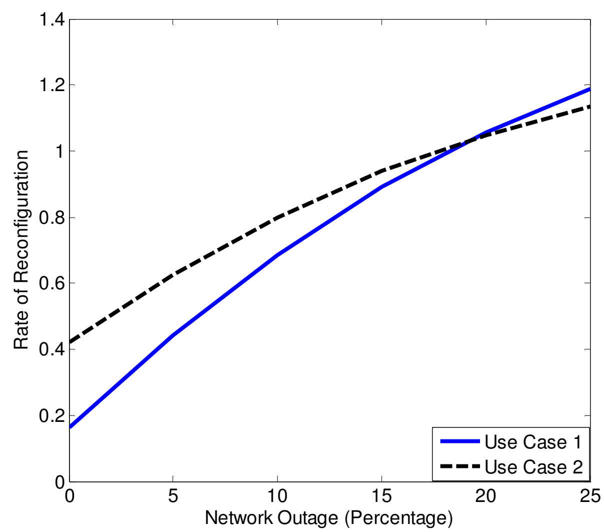

Figure 4: Reconfiguration Rate

B. *Power Consumption*

The average power consumption depicted in Figure 5 again follows a pattern that can be explained using the rate of reconfiguration presented in Figure 4. The impact of reconfiguration has a far greater effect on average power consumption for higher values of network outage as compared to the lower values of network outage since the reconfiguration rate is significantly higher for higher values of network outage. For use-case 2, since the reconfiguration rate is significantly high compared to use-case 1, the power consumption for use case 2 is affected more than that of use case 1 as the impact of reconfiguration increases from 0 to 1. In the worst case, for use case 2, the power consumption almost doubles (from 3 Watts to 6 Watts) with the reference power reconfiguration specs used from Table 1 at impact of reconfiguration value of 1. This suggests that the power cost needs to be carefully examined before the GRC issues a reconfiguration command. For an average power consumption of 6 Watts as compared to 3 Watts, a mobile battery powering a mobile device such as an iPhone 4G would last 1 hour 35 minutes in comparison to 3 hours 10 minutes. This decreases the battery life of a mobile terminal by half. But as better hardware innovations are made, the actual battery life reduction is going to decrease since the impact of reconfiguration is going to move farther away from 1 and move closer towards 0.

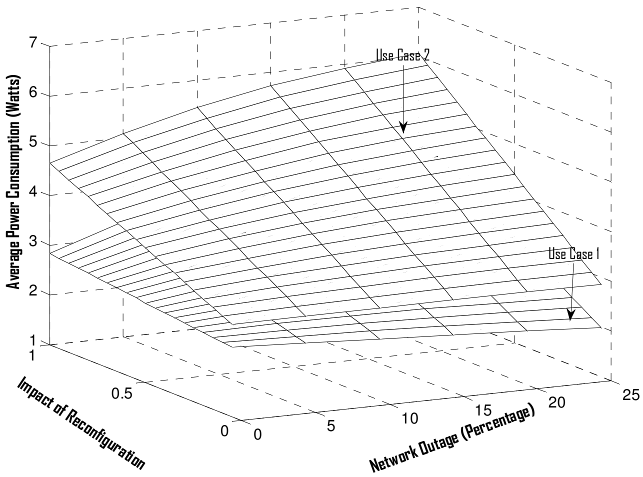

Figure 5: Average Power Consumption

C. Fairness Properties

We now present an analysis that confirms the scheduler achieves fairness over large timescales. We have to consider fairness metric for mobile users and nomadic users for both use cases separately. The metric for nomadic users will not result in fairness since Wi-Fi resources are just distributed evenly without caring for assignment of equal throughput. The throughput for nomadic users is also much greater than any cellular user as seen in Table 2, so fairness for nomadic users is not as much of a concern when compared to mobile users. We first compute the fairness metric for mobile users and then estimate the fairness metric for nomadic users. We also examine the cumulative distribution function of average throughput experienced by both mobile and nomadic users. We use Jain's fairness index equation to compute our fairness metric as follows[40]:

$$Fairness\ Index = \frac{\sum_{i=1}^{N}[Normalization\ Metric *\ x_{i,1} + x_{i,2}]^2}{N * [\left(Normalization\ Metric * x_{i,1}\right)^2 +\ (x_{i,2})^2]} \quad (2)$$

where N is the total number of users, $x_{i,1}$ is the average throughput experienced by user i belonging to Carrier 1 and $x_{i,2}$ is the average throughput experienced by user i belonging to Carrier 2. The normalization metric determines the ratio of resources users of Carrier 2 can access as compared to users of Carrier 1.

We have 2 Carriers, Carrier 1 and Carrier 2 respectively. We are interested in determining the normalization metric for mobile users for both use cases. For use case 1, the amount of available resources for each carrier determines this ratio. For use case 2, since a user can use resources from both carriers without any discrimination, customers of each carrier have access to equal resources and the normalization metric is equal to 1. Mobile users can only use cellular technology for connectivity. Carrier 1 has deployed WiMAX as its 4G technology and EVDO as its 3G technology. Carrier 2 has deployed LTE as its 4G technology and HSPA as its 3G technology. So, the expected average cellular throughput for Carrier 1 is the summation of average (middle) MCS throughput values of WiMAX and EVDO, and the expected average cellular throughput for Carrier 2 is the summation of average MCS throughput values of LTE and HSPA. Using the average MCS throughput values of cellular technologies from Tables [A-1, A-5] in Appendix A, the average cellular throughput for Carrier 1 and Carrier 2 is as follows:

Carrier 1 Average Throughput: 14.49 + 0.61 = 15.30 Mbps
Carrier 2 Average Throughput: 17.60 + 4.50 = 22.10 Mbps

If the network outage probability were different for Carrier 1 and Carrier 2, we would have to account for that in Carrier 1 and Carrier 2 Average Throughput respectively. Also, if the number of users for each carrier were different, we would have to account for that in calculating how many resources a Carrier 2 customer could access on average in comparison to Carrier 1 customer. But since we have the same network outage probability and the number of customers that use cellular access technologies for both carriers is the same, the ratio between average throughput experienced by Carrier 2 customers as compared to Carrier 1 customers is as follows:

$$\text{Normalization Metric} = \frac{\text{Carrier 2 Average Throughput}}{\text{Carrier 1 Average Throughput}} = \frac{22.10}{15.30} = 1.44$$

Using this normalization metric for use case 1 and number of mobile users which is equal to 75, we can use Equation (2) to determine the fairness metric for our scheduler. We obtain the fairness metric of 0.98 for mobile users for use case 1. For use case 2, the normalization metric is equal to 1. Again, using Equation (2), we obtain the fairness metric of 0.99 for mobile users for use case 2. The fairness metric suggests that the ratio of mean throughput squared to the second moment of throughput experienced by all users is 0.98 and 0.99 for use case 1 and use case 2 respectively. This means that our scheduler is fair to 98% and 99% of the users and no user gets starved of resources. To confirm this, the cumulative distribution function of average throughput experienced by all mobile nodes is plotted in Figure 6. For use case 1, since Carrier 2 users have access to more resources, the average value of throughput experienced by all Carrier 2 users is 1.44 times greater than that of Carrier 1 users. The average throughput value of Carrier 2 users is (22.10*0.9)/50 = 0.39

Mbps, and the average throughput value of Carrier 1 users is (15.30*0.9)/50 = 0.27 Mbps. As can be seen from Figure 6, the distribution of average throughput values lay around these numbers for Carrier 1 and Carrier 2 users respectively for use case 1. For use case 2, users of both carriers are equally favored, and their throughput distribution should lie close to ((22.10+15.30)*0.9)/100 = 0.34 Mbps. Again, Figure 6 verifies that this is indeed the case.

For nomadic users, the average throughput experienced by users of both carrier 1 and carrier 2 is much greater than that of mobile users. The average throughput experienced by nomadic users for use case 1 is 1.90 Mbps and 2.50 Mbps for use case 2 as seen from Table 2 as compared to 310 kbps for use case 1 and 380 kbps for use case 2 for mobile users. This result is verified in Figure 7 which plots the cumulative distribution function plot of average throughput experienced by nomadic users of both carriers. The increase in throughput is mainly a result of access to Wi-Fi resources that the mobile users cannot use. Wi-Fi resources are the dominant source of expected achieved throughput for nomadic users, and as a result the cellular resources can be omitted in the calculation of our fairness metric. For use case 1, each nomadic user can access up to 3 Wi-Fi APs and users of each carrier can access equal amount of Wi-Fi resources. For use case 2, each nomadic user can access up to 6 Wi-Fi APs and again users of each carrier can access equal amount of Wi-Fi resources. So, for both use cases, the normalization metric is equal to 1. The number of nomadic users in both use cases is 25. Using Equation (2) again, we obtain the fairness metric for use case 1 to be 0.93 and for use case 2 to be 0.92. The achieved fairness can also be assessed by observing the variation in average throughput experienced by each nomadic user depicted in Figure 7. No user is starved and each user experiences average throughput in the range of [0.9, 3.1] Mbps for use case 1 and in the range of [1.4, 4.5] Mbps for use case 2. This variation is quite significant as was expected since Wi-Fi does not distribute resources in an equal manner in terms of throughput in our scheduler. But as the simulation is run for longer periods of time, each node becomes more likely to have travelled through the same locations in the topology and this results in increased likeliness of equal allocation of resources to all nodes. As the simulation time approaches infinity, we expect the fairness index for both mobile and nomadic users to approach 1.

We summarize the results as follows:

- Based on Figure 3, we see that reconfiguration increases the average spectral efficiency achieved by each node at least by 14.3% and as much as 75.5%.
- Additional power consumed by reconfiguration reduces the battery life of a mobile terminal by almost half.
- The scheduler implementation is fair over large time scales and results in a fairness index of 0.98 for mobile users, and 0.92 for nomadic users on a scale of [0, 1] with 1 being most fair.

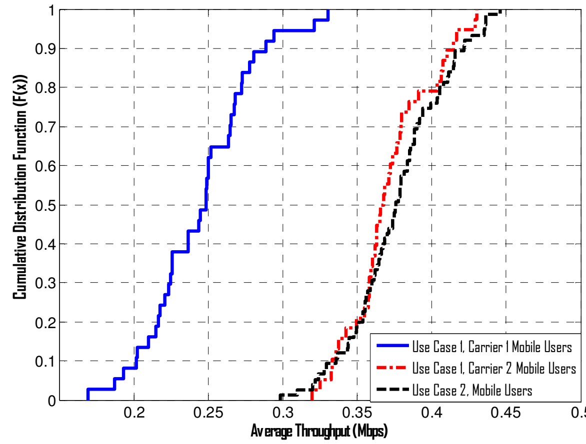

Figure 6: Distribution of Mobile User Throughput

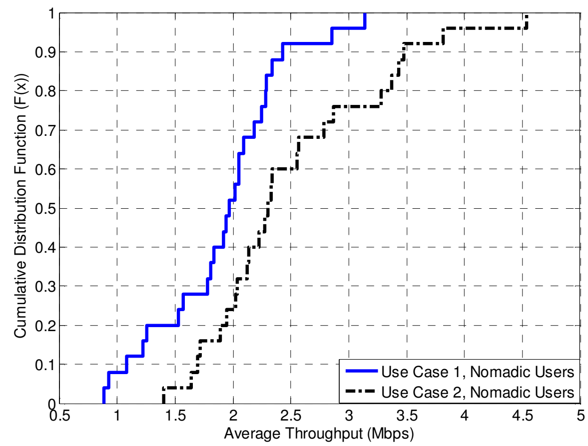

Figure 7: Distribution of Nomadic User Throughput

V. CONCLUSIONS AND FUTURE WORK

In spite of recent advances in wireless technology, wireless networks continue to be designed as independent networks that make resource decisions without considering co-located networks. Cognitive radio, and the more recent idea of cognitive networks, addresses the layer from the perspective of the physical layer (and up the stack). The system we have described builds upon the vast amount of related work in the area of cooperative and heterogeneous wireless networks. The contribution of the work presented in this paper is the insight provided to the motivating questions. Our results provide a data point that suggests that the benefits of highly reconfigurable devices can outweigh the costs.

Our results suggest that spectrum efficiency is indeed increased if independent wireless networks cooperate and if devices are sufficiently agile to take advantage of the different RATs that are available. Our main result suggests that nomadic users benefit the most from the ability to route traffic over 'hotspot' type of RATs that tend to have high data rates at reduced coverage. For the scenarios presented, the simulation results suggest the spectral efficiency can be increased by at least 14% for each node. The aggregate improvements at the network level are therefore tremendous as the network gain in spectrum efficiency is the sum of that experienced by all nodes in the system. In future work we will focus on the scheduler adding a control knob that determines the level of sharing that exists between two AWSs. For example, a wireless carrier would require a scheme that limits the amount of traffic it would support from another carrier.

The increase in spectral efficiency that is possible with reconfigurable hardware would increase as the number of AWSs in a given area increases. As wireless carriers deploy 4G systems, they will have to support legacy devices. It is not unreasonable to expect a dozen or more RATs in an urban environment.

Our analysis estimated the cost of reconfiguration based on modern FPGA technology. While current FPGA is not necessarily low power, the objective was to use the technology as an exemplar to demonstrate the impact of reconfiguration in terms of network performance improvement, as well as estimate the impact on throughput and power consumption. The results also suggest that based on current power costs for FPGA-based reconfigurable hardware, and in particular, if we look at the rate at which power consumption of FPGA technology is dropping, highly reconfigurable devices that fit into modern handheld device form factors is likely to become available over the next decade. The larger obstacle to our ‘beyond 4G’ vision is the paradigm shift that must occur before wireless carriers would ever consider sharing wireless resources with their competitors.

We acknowledge the following limitations of this work:

- We limited the analysis to a small set of scenarios and network configurations.
- The impacts of messaging overhead required for network-wide coordination were not considered.
- Realistic path loss, signal fading and interference were not taken into account.
- The impacts of congestion caused by time varying traffic patterns were also not taken into account.

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Appendix

MCS	Data Rate (Bits/slot)	Slots/Sec	Throughput (Mbps)
BPSK 1/11	91	9000	0.82
QPSK 1/11	182	9000	1.64
BPSK 1/2	500	9000	4.50
BPSK 3/4	750	9000	6.75
QPSK 1/2	1000	9000	9.00
QPSK 3/4	1500	9000	13.50
16-QAM ½	2000	9000	18.00
16-QAM 3/4	3000	9000	27.00
64-QAM 2/3	4000	9000	36.00
64-QAM 3/4	4500	9000	40.50

Table A-1: Simulation Parameters for IEEE 802.11g

MCS	Data Rate (Bits/slot)	Slots/Sec	Throughput (Mbps)
QPSK ½	48	102000	4.90
QPSK ¾	72	102000	7.34
16-QAM ½	96	102000	9.79
16-QAM ¾	144	102000	14.69
64-QAM ½	144	102000	14.69
64-QAM 2/3	192	102000	19.58
64-QAM ¾	216	102000	22.03
64-QAM 5/6	240	102000	24.48

Table A-2: Simulation Parameters for IEEE 802.16e

MCS	Data Rate (Bits/slot)	Slots/Sec	Throughput (Mbps)
QPSK ½	36	163000	5.89
QPSK ¾	54	163000	8.80
16-QAM ½	72	163000	11.74
16-QAM ¾	108	163000	17.60
64-QAM ½	108	163000	17.60
64-QAM 2/3	144	163000	23.47
64-QAM ¾	162	163000	26.41
64-QAM 5/6	180	163000	29.34

Table A-3: Simulation Parameters for LTE

MCS	Data Rate (Bits/slot)	Slots/Sec	Throughput (Mbps)
QPSK ¼	2.34375	384000	0.90
QPSK ½	4.6875	384000	1.80
QPSK ¾	7.03125	384000	2.70
16-QAM ½	9.375	384000	3.60
64-QAM ¾	14.0625	384000	5.40
64-QAM 4/4	18.75	384000	7.20
64-QAM ¾	22.9167	384000	8.80
64-QAM 5/6	27.47395	384000	10.55

Table A-4: Simulation Parameters for HSPA

MCS/ Spreading Factor (Chips/bit)	Data Rate (Bits/slot)	Slots/Sec	Throughput (Mbps)
QPSK 1/5/32	64	600	0.04
QPSK 1/5/16	128	600	0.08
QPSK 1/5/8	256	600	0.15
QPSK 1/5/4	512	600	0.31
QPSK 1/5/4	512	600	0.31
QPSK 1/3/2	1024	600	0.61
QPSK 1/3/2	1024	600	0.61
8-PSK 1/3/1.33	1536	600	0.92
QPSK 2/3/1	2048	600	1.23
16-QAM 1/3/1	2048	600	1.23
8-PSK 2/3/0.67	3072	600	1.84
16-QAM 2/3/0.5	4096	600	2.46
64-QAM 3/4/0.5	5120	600	3.07

Table A-5: Simulation Parameters for EVDO

Technology	Spectrum Used (MHz)
Wi-Fi	22
WiMAX	10
LTE	10
HSPA	5
EVDO	1.25
Total	48.25

Table A-6: Spectrum Usage

```
for each time unit
    for each node j
        for each radio i
            node(j).radio(i).mcs =     function(node(j).radio(i).distance_from_BS);
            node(j).radio(i).rate = function(node(j).radio(i).mcs);
        end for i
    end for j

    for each technology i
        for each node j
            node(j).radio(i).rank = Sort(node.radio(i).mcs) % Descending order
        end for j
    end for i

    %  Assign Wi-Fi AP resources to all nodes that can connect to it
    for each Wi-Fi AP i
        node(j).radio(i).assigned_bw(time_unit) = total_APslots(i)/num_conn_users;
    end for

     % Cellular Step 1 – Assign each node 100K with its best radio(s)
    for each node j
        for each cellular radio i
            sorted_radio_rank[num_technologies] = Sort(node(j).radio(i).rank);
        end for i

        for each cellular radio i
            if (node(j).assigned_bw(time_unit) < 100K &&
                            remaining_slots(sorted_radio_rank(i) >= 0)
                if (remaining_slots(sorted_radio_rank(i)) >=
                                        slots_required_to_reach_100K)
                    node(j).radio(sorted_radio_rank(i)).slots =
                                            slots_required_to_reach_100K;
                else
                    node(j).radio(sorted_radio_rank(i)).slots =
                                        remaining_slots(sorted_radio_rank(i));
                end if-else
            end if
        end for i
    end for j

    % Cellular Step 2 – Assign additional resources of each technology to 10 best
                    nodes in  increments of 100K until they reach a cap of 1M
    for each cellular technology i
        for each node j
            sorted_tech_rank[num_nodes] = Sort(node(j).radio(i).rank);
        end for j
    end for i

    for each cellular technology i
        while (remaining_slots(i) > 0)
            nodes_served = 0, unservable_node = 0;
            for each node j
                if (node(sorted_tech_rank(j)).assigned_bw(time_unit) < 1M &&
                                node(sorted_tech_rank(j)).radio(i).mcs > 0)
                    if (remaining_slots(sorted_radio_rank(i)) >=
                                        slots_required_for_additional_100K)
                        node(sorted_tech_rank(j)).radio(i).slots =
                                        slots_required_for_additional_100K;
                    else
                        node(sorted_tech_rank(j)).radio(i).slots = remaining_slots(i);
                    end if-else
                    nodes_served++;
                    if (nodes_served == 10)
                        break;
                    end if
                else
                    unservable_node++;
                end else
            end for
            if (unservable_node == num_nodes)
                break;
            end if
        end while
    end for i

end  for each time unit
```

Figure A-1: Pseudo-code for the scheduler implementation