Self-Deployment, Self-Configuration: Critical Future Paradigms for Wireless Access Networks

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Abstract. To combat the increasing significance of deployment and configuration costs, the concept of a self-deploying, self-configuring radio access network is discussed. It is proposed that the basic sciences of complex systems (cellular automata, game theory, ecology modeling) can be exploited to design algorithms for such a system. An example, taken from the field of cellular automata, is presented for a network capable of self-adaptation to achieve universal radio coverage in a simplified environment.

Key-words: Radio access networks; auto-configuration; self-deployment; self-organization; cognizant networks; complexity theory; game theory; cellular automata; ecology modeling.

1 Introduction

A number of trends for wireless access networks are clearly emerging: (a) reductions in equipment costs, (b) reduced cell sizes (with a commensurate increase in the total number of cells), and (c) additional complexity as interoperability between heterogeneous systems becomes economically critical. These all will increase the relative cost of deployment and configuration of the radio access nodes (base stations, access points, etc.), perhaps to the point where additional innovations will be difficult to introduce. Self-configuring radio access nodes help, but there is a strong need for the additional, novel concept of a *self-deploying* network. Such a network would, from experience of past traffic, be able to decide autonomously the changes needed in both the location and configuration of its wireless access nodes, and suggest locations for new nodes. Thus, this would be an innovative self-aware network that designs its own layout and configuration, adapting and expanding according to changes in user demand.

This vision differs from traditional ad-hoc networking concepts in that ad-hoc networks seek the optimal configuration, given the current location of nodes. Here the access network is allowed more freedom: the freedom to choose the location and nature of the nodes needed. This also contrasts even more with the current state-of-the-art where either such planning is done (e.g. in cellular networks) in a quasi-manual

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manner with a mixture of off-line planning tools, expensive drive-testing and economic rules-of-thumb; or is done not at all (e.g. in WLANs – wireless local area networks) and low efficiency results. To move beyond this, the main algorithmic challenges are with respect to the expensive resources such as spectrum and back-haul capability. The algorithms used must be simple, distributed, robust to changing user demand and to heterogeneity in the underlying technology, and, above all, financially viable in a multi-operator environment.

The key theoretical frameworks that should be exploited to design such algorithms are complexity theory, small-world theory, cellular automata, game theory, microeconomic modeling, and ecology/population growth modeling. Some of these frameworks (e.g. game theory) will give insights into the algorithms to be used at the individual access nodes, while others (e.g. ecology modeling) will be critical in assessing the technical robustness and the financial viability of the resulting solutions. It is only through proving the robustness and economic viability that one can have confidence that the resulting network be able to drive its own design in a manner that meets the needs of its owners.

In this paper, the expected future developments in next-generation networks and the resulting drivers for self-deploying and self-configuring networks are explored in more detail in section 2. Section 3 discusses the various applicable basic sciences that may be used to achieve such solutions. A useful case study involving the application of concepts from cellular automata for achieving coverage in a simplified propagation environment is given in section 4. Conclusions are drawn in section 5.

2 Problem Statement

Figure 1 shown below is indicative of many of today's wireless access networks: These are vertically integrated to provide tightly controlled services like voice and as such are (a) extremely centralized in terms of control, (b) hierarchical in terms of architecture, (c) isolated with respect to other systems, and (d) very inflexible as far as adapting to new services and traffic demands.

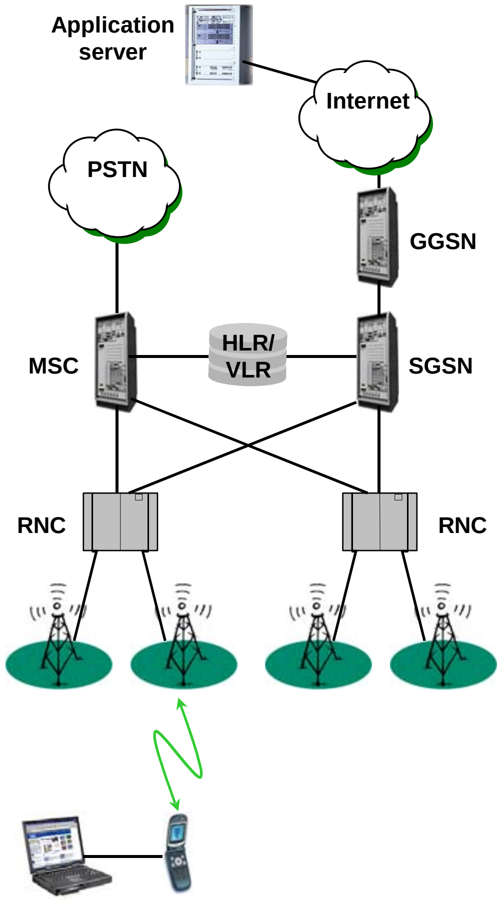

Fig. 1. Typical hierarchical, centralized, inflexible cellular network of today.

However, it is clear that mobile communication systems will become richer in features and capability, and the isolation between systems will have to decrease [1]. Within systems, the need for rapidly deployable systems in areas of high-traffic density has pushed architectures towards flatter designs (e.g. 802.11b WLANs). Economic necessity will force operators and service providers to use more flexibility in their systems so as to keep up with changes in user needs and terminal capabilities. Figure 2 below shows the potential future vision. It is also significant that to increase capacity, average cell sizes are decreasing: witness the shrinking cell sizes of cellular systems in going from second- to third-generation technology and the introduction of WLANs and PANs (personal area networks).

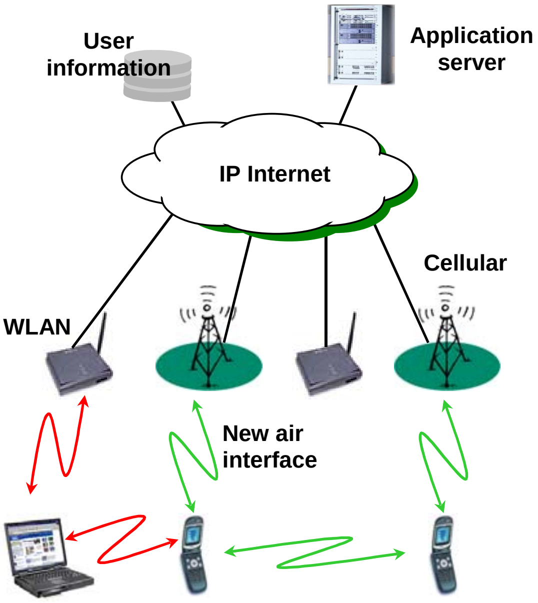

Fig. 2. Future vision of a distributed, flexible wireless access network.

All of the above inevitably will lead to exploding complexity in the management, construction, and configuration of these networks. Manual decision making and optimization will prove to be exorbitantly expensive and will end up dominating the total network costs, particularly as the capital expenses are reduced over time through improvements in hardware and software technologies. More fundamentally, the increases in complexity may exceed the capabilities of manual planning and configuration entirely, resulting in reductions in reliability and end-user trust of the system.

Thus, if future wireless communications networks are to be viable financially and are to command the confidence of end users then the expected ad-hoc, dynamic architectures need to be highly robust, self-deploying and self-healing, with nodes that are auto-configurable and flexible. A *self-deploying* radio access network is one that is able to learn from its current performance, both technically (in terms of coverage and capacity) and economically (i.e. is the network profitable?) and then is able to determine what changes, additions, and removals of access nodes are needed[2] as user demands and the competitive environment changes over the long term, say weeks to years. *Self-configuration* is more of a short-term activity over tens of minutes to days: A node dropped into a coverage area must be able to integrate itself into an existing network quickly and reliably. The removal of a node from the network (e.g. through node failure) should also trigger a sequence of auto-configuration among the remaining nodes. Fundamentally, the nodes need to work together to adapt the instantaneous network configuration to short-term variations in the user traffic, readjusting to opti-

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[2] While this network can determine what changes are needed, it is expected that it will still generally require human intervention to implement the actual physical relocations! However, exceptions to this may occur in the fields of military and emergency communications.

mize the radio coverage, the traffic-bearing capacity, and also connectivity among the nodes in the network. The result should be a network that inspires end-user trust and confidence in its ability to provide, on demand, network transport over a wide range of conditions.

These objectives are critical enablers of economical deployment of complex communications systems, particularly in the following areas:

- Without the automation implied in the above vision, operators and wireless service providers will be very reluctant to exploit the potential advantages of heterogeneous air interface access and dynamic, demand-adaptive network architectures if the deployment costs and running costs explode as a result of the associated complexity.
- The situation is even more critical for small- to medium-sized businesses and non-profit organizations. The technology proposed here will allow them to overcome their inability to afford the highly specialized staff needed for manual deployment and configuration. Hence, they will be able to more easily deploy and exploit state-of-the-art internal wireless communication infrastructures within their premises and beyond.
- Automatic deployment and recovery is of extreme importance for flexible, quickly deployable emergency communication systems – a recognized key component for modern health and civil defense services.

At one level, these are problems of network architectures, interfaces, network protocols, and software and hardware architectures. There already exist substantial research efforts in these areas, e.g. [2], particularly in the field of self-configuration. However, there are also serious algorithmic problems in a few key areas: namely those where there are significant resource bottlenecks: e.g. air interface capacity and coverage, back-haul capabilities. Fundamentally, both the wired and wireless links of access networks are both costly and resource-limited and matching these resources to dynamic user demand is a non-trivial problem – on any timescale. This is exacerbated by the trend towards more distributed, heterogeneous networks.

3 Synthesis and Analysis of Solutions

The sciences of complex systems have much potential for providing solutions to the above challenges of self-deploying and -configuring radio access networks. In terms of synthesizing algorithms for implementation primarily at the node level, the following areas are promising candidates:

- *Cellular automata (CA).* A network operating on self-organizing behavior would have many characteristics that are similar to cellular automata [6] – particularly if the algorithms used at individual nodes are relatively simple. (Indeed, one can argue that given the limited, local knowledge available to a given node that complex algorithms, such those from modern control theory, will yield little by way of performance improvements. The other alternative, global knowledge, implies centralized control, which is inimical to the network architectures here.) The field of cellular automata studies how the overall system evolves given particular node behaviors within a discrete space-time system. One potentially useful aspect of the

field of cellular automata, apart from self-organizing behavior, is that fairly sophisticated, coordinated global behavior can arise from these highly simplistic, locally interacting nodes [7], and the behaviors can be changed according to the network status simply by changing the CA (cellular automata) rules. A network coordinated by these global behaviors have the scalability and robustness that would otherwise be difficult to achieve in more centralized approaches. An example of the application of cellular automata to a related problem (the operation of location based services in a mobile network) is given in [8].
- *Swarm intelligence*. Biological swarms (e.g. ant colonies) are a good example of self-organized systems based on distributed processing. As such investigations into the mechanisms used to regulate their operations may provide useful templates for wireless networks. For example, consider the principle of stigmergy [9], a mechanism of coordinated behavior within a swarm whereby modifications of the environment by one member of the swarm results in changes in the behavior of other members. This has direct analogies with the adjustments needed among radio access nodes with limited direct intercommunication: often a change in the configuration of one access node may be only perceived by other access points by its impact on the radio environment and associated mobiles.
- *Microeconomics of oligopolies and game theory*. This is one of the best-known paradigms for the design of distributed systems competing for resources, due to the recognized optimizing properties of free market scenarios [3]. Examples of distributed algorithms using the concept of an *abstract* “market price” for a given resource include those given in [4] for call routing and in [5] for wireless ad-hoc networks. However, further work is needed to use such concepts in a more holistic approach, taking account of the *actual* economic drivers.

It should be noted that there are close interrelationships between the above frameworks, but they do provide distinctly different perspectives that should be explored. For example, there are equivalences between auctions in free-market economics and response threshold models in swarm theory [9] and yet a competitive market environment has different drivers from those in the collaborative structure of a social ant swarm. Both sets of drivers are to be seen in radio access networks – collaboration is needed within a network; competition, between the networks of different operators.

While the above theories can be used both for algorithm design and for the analyzing the resulting performance, there are yet other areas that can be used for analyzing the resulting behavior and performance:

- *Spatiotemporal models of population growth* [10]. The deployment of a wireless network in the presence of competition from other operators (using the same or different technologies) is directly analogous to the growth of a population of a particular species competing with others for limited resources. In this case, the resources are not spectrum but end-users. Therefore, mathematical models of ecologies should have direct relevance for the prediction of network growth. In particular, niche theory, with its concept of partially overlapping niches [11], can be seen as excellent framework for analyzing the impact of competition of systems using different technologies (e.g. third-generation cellular versus WLAN) specializing in different, but overlapping, ranges of service types
- *Entropy-based complexity measures*. Such measures [12], [13] can be used to characterize behavior, and hence performance, in complex systems. This type of

approach was recently used in [14] to control the configuration of transmit power levels in wireless networks and as such, represents a good example of how an analysis technique can be then used to drive the system design. Furthermore, the global behaviors of the complex systems considered here are prone to instability due to phase transitions [15], [16]. Hence, for a network operating with distributed, interacting and autonomous nodes to be used with confidence, there is also a need for a mechanism to detect and avoid such critical points within the network: an entropy-based complexity measurement is one such mechanism.

Fundamentally, wireless systems are rapidly approaching the complexity of natural systems and have similar drivers of competition, collaboration, limited resources, etc. Hence, the design of the algorithms for their configuration and deployment should co-opt any insights available from the bodies of science already available from the worlds of biology, automata, and economics. However, for the particular application space here, namely the design of algorithms for a self-deploying, self-configuring wireless access network, advances are needed in the basic sciences. In particular these are far from maturity on the synthesis side. Analytical techniques yield important information regarding existing systems, but it is synthesis that is a key requirement for the ability to engineer solutions.

4 Cellular Automata: A Case Study

Recent work [14, 17] shows an example of the use of a two-stage, CA-like algorithm for the auto-configuration of base stations' pilot transmit power levels. By adjusting these, the method aims to achieve the best coverage in an area, but using a distributed algorithm at each base station and only localized information of neighboring base stations within its range. The base station is given several states, where at each state, the base station will perform certain functions. Which state the base station is in is determined by a set of CA-like transition rules, which changes the state of the base station depending on the states of its neighbors. In Figure 3, there are 100 base stations, placed roughly 2500 meters apart in a region with uniform radio propagation conditions, and deployed at random times. The base stations would, upon deployment, enter a state when seeks out its surrounding neighbors and approximate their distances, and sets its cell size accordingly by adjusting its power levels.

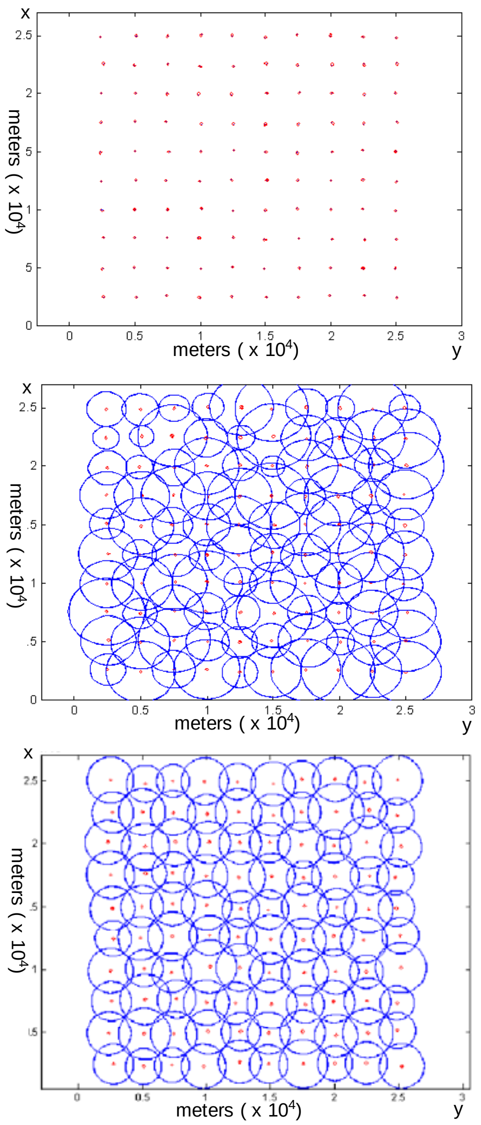

Fig. 3. Graphical representation of the coverage areas of a set of base stations (from top to bottom) before deployment, during deployment, and after deployment.

Once that state is done, the base stations enter a second stage when it uses feedback from the mobiles to make minor adjustments to the cell sizes to fill up the smaller gaps in the coverage, before eventually settling into a stable, static state. During this second stage, the base station keeps track of the mobiles that are connected to it. Each mobile monitors the signal it receives from the base station that it is connected to. When the signal begins to go below a predetermined threshold and the mobile cannot find a signal from a neighboring base station, the mobile sends out a signal to the base station to which it is connected to indicate a possible gap in coverage. When a mobile reports a possible gap in coverage, the base station to which it is connected increases its cell size by an increment. Periodically, the base station checks the status of the mobiles in its cell and increases its cell size by an amount that depends on how many mobiles have reported gaps in coverage. The cell size is increased by a factor of F:

$$F = ne^{-2d}$$

where n is the number of mobiles that have reported coverage gaps and d is the difference between the current cell size and the cell size that was established during the initial deployment stage. This factor ensures that a given base station does not increase its cell size too much and that both the base station and its neighbors increase their cell sizes evenly to cover the gap. Figure 4 shows the number of mobiles that were dropped due to gaps in coverage from the start of the second stage, which is reduced over time as the gaps are eventually covered.

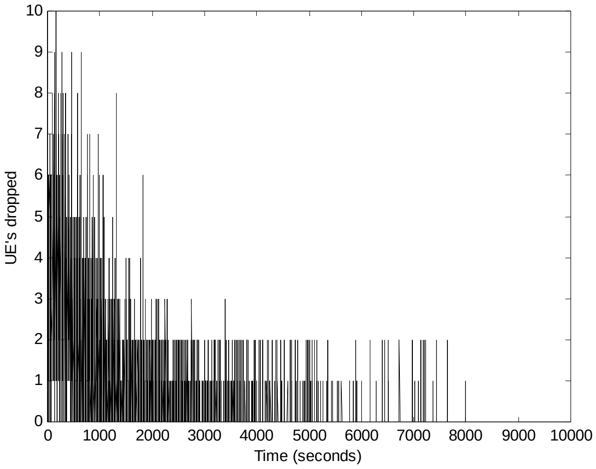

Fig. 4. Number of UEs dropped over time because of gaps in coverage.

This CA-like arrangement also enables reconfiguration whenever a base station is added or, as shown in Figure 5, removed. When changes are made to one part of the network, this would trigger state changes in neighboring base stations, and this change then propagates throughout the entire system, prompting every base station to readjust to compensate for the addition or removal of base stations. Figure 5 also shows the implementation of the algorithm's state transition rules in a more recognizable 2-dimensional CA, showing the state change propagation in CA form. The mapping of the system to the 2-dimensional CA is achieved by treating each base station as a CA cell, each having the same three states and transition rules as the base stations. The neighborhood list of each cell in the CA reflects the interactions between the base stations, and the size of the list is dependent on the maximum range of the base station. This illustrates the advantages of achieving flexible, decentralized control by using simple, localized CA rules, demonstrating the potential of this field within the application domain of wireless access networks.

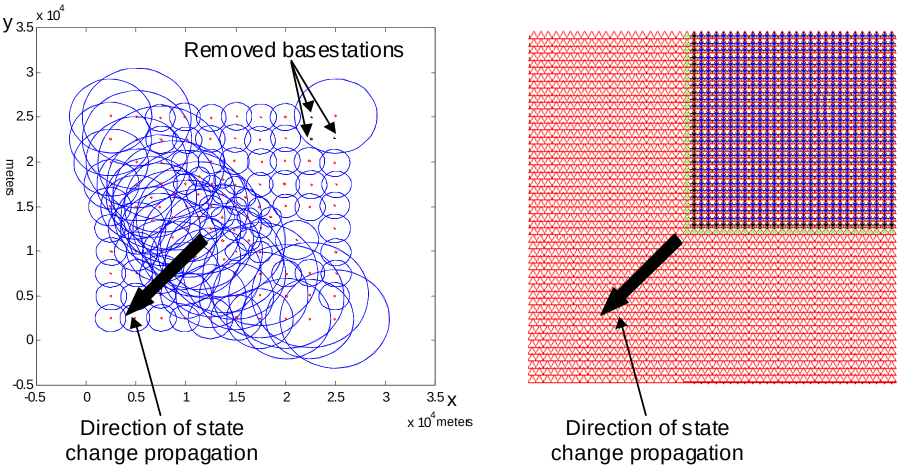

Fig. 4. Propagation of state changes in cell-boundary view (left) and 2-d CA view (right) when a number of base stations are removed.

5 Conclusions

This paper has examined the current and future trends in next-generation wireless access networks that will lead to the increasing significance of the costs associated with the deployment and configuration of such networks. To address this, the concept of a self-deploying, self-configuring radio access network was proposed. The sciences of complex systems, whether they come from economic theory, ecology/population growth models, or cellular automata should be capable of providing solutions for the required algorithms. An example, taken from the field of cellular automata for a radio network capable of self-adaptation to achieve universal coverage in a simplified environment, was examined.

While there are significant challenges posed by the vision here, if the appropriate robust, synthesis techniques can be found then self-aware, self-designing radio access networks will result. These will enable additional complexities at the radio-system level to be accommodated without overwhelming the system owner with an infeasible uphill struggle to find an efficient deployment. This could well be the difference between widespread adoption and economic non-viability of next-generation wireless access architectures.

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