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INTRODUCTION

1.1 THE FOURTH INDUSTRIAL REVOLUTION

The *fourth industrial revolution*, which is denoted by the term "Industry 4.0," is in its early stages. The hallmarks of the former three industrial revolutions are as follows:

- Deployment of mechanical production facilities
- Use of electric power for mass production and communications
- The digital revolution

The distinct feature of Industry 4.0, which distinguishes it from its three predecessors, is the fact that it has been predicted a priori instead of being observed by postanalysis. This prediction opens a window of opportunity for futurists as well as visionary individuals and institutes to actively participate and play key roles in engineering the future. Industry 4.0 is built upon the following four pillars [1]:

- *Cyber-physical systems* (*CPS*), which include *smart products* as their subcomponents
- *Internet of things* (*IoT*), which relies on *machine-to-machine* (*M2M*) *communication* as an enabling technology
- *Internet of services* (*IoS*), which is exemplified by *cloud computing* as a model for allowing Internet-enabled devices to access a shared pool of configurable computing resources according to their needs
- *Smart factories*.

Fundamentals of Cognitive Radio, First Edition. Peyman Setoodeh and Simon Haykin.

Industry 4.0 will produce *massive* amounts of data. Portions of the produced data that are associated with high volume, variety, and velocity (3 Vs) are referred to as *big data*. Each one of the above pillars will be briefly described in what follows [2–7].

By definition, the integration of digital computing and a physical environment results in a cyber-physical system. Therefore, many applications can be collected under the umbrella of such systems [8]. A cyber-physical system usually includes a distributed set of different sensors, where the number of sensors depends on the scale of the system. Data gathered by these sensors are used to form a representation of the environment, which is then used for decision-making. Only portions of the gathered data will be useful (i.e., relevant to) the decision-making task. Hence, in accordance with the task at hand, the information extracted from the available data can be divided into two sets: relevant and irrelevant. The former provides the *actionable information* [9].

In order to perform a task with an acceptable level of risk, a specific amount of information is required, which is called sufficient information. If the actionable information does not meet the information sufficiency criteria from the decision-making perspective, the decision-maker will face an *information gap*. In Ref. [10], *cognitive control* was proposed to reduce this gap between the actionable and sufficient information sets by controlling the directed flow of information:

> Given a probabilistic dynamic system that includes a perception–action cycle, and ideally mimics the human brain, the function of cognitive control is to adapt the directed flow of information from the perceptual part of the system to its executive part so as to reduce the information gap, which is equivalent to reducing a properly defined risk functional for the task at hand, the reduction being with a probability close to one.

In a cyber-physical system, cognitive and physical controllers play complementary roles. Cognitive complementary actions can influence different parts of the system:

- Cognitive actions may be applied to the environment in order to indirectly affect the perception process.
- Cognitive actions may also be applied to the system itself in order to reconfigure the sensors and/or actuators.
- In addition, cognitive actions may also be subsumed in physical-control actions. In such a case, a physical action is applied to the system but with the goal of decreasing the information gap (with or without other goals).

In other words, in large-scale CPS with the requirement of critical decision-making, cognitive control will enhance reliability of the decision-making process. Final decisions (i.e., outputs of the decision-making process) are then sent as a set of commands to different actuators, which are also distributed in the system. As a result, CPS have been significantly transforming the way our modern society perceives the physical world and interacts with it.

The word “thing” in the Internet of Things refers to different entities, such as radio-frequency identification (RFID), sensors, actuators, computers, and mobile wireless devices, which may all be smart products that communicate with each other using a specific addressing scheme and cooperate toward a common goal. "Thing" can also be interpreted as cyber-physical entities and in effect, therefore, IoT can be viewed as a network of CPS [1].

Adopting a systematic viewpoint on organizations has led to the idea of *value chain*, which refers to activities that are performed by an organization in order to deliver a valuable product or service to market [11]. Regarding the fact that CPS have made the fusion of physical and virtual worlds possible [1], a combination of both physical and virtual value chains must be taken into account. Hence, a service-oriented architecture can be created that promotes distributed production control, which is built on modular assembly stations that are connected by automated guided vehicles. This provides customers with special production technologies and gives them a degree of freedom to somehow custom design the product that they need. Customers can use the assembly stations and the associated automated transportation system through the IoS.

A factory is said to be smart if in a context-aware manner it can help both employees and machines to execute the tasks that are assigned to them. The operation of such factories would be demand-driven. As proposed in [12], what distinguishes a smart factory from an ordinary one is the existence of the so-called *calm systems* that operate in the background and are able to communicate and interact with their environments. A smart factory can be viewed as a factory, in which CPS communicate over the IoT to facilitate execution of assigned tasks to employees and machines [1]. The idea of calm systems is very similar to the notion of *cognitive dynamic systems* (CDS) [13], which can play the role of the central nervous system for the smart factory.

It is obvious that all the mentioned pillars of Industry 4.0 rely on communications and networking in one way or another. In this regard, *cognitive radio* as a smart product will be part and parcel of each one of the pillars. Therefore, it can be expected that cognitive radio networks will play essential roles in the years to come far beyond the initially set mission for improving spectral efficiency. In order to exploit the full potential of cognitive radio networks in light of the fourth industrial revolution, such networks must be studied as *intelligent sociotechnical systems* [14]. Therefore, the socioeconomic principles for self-organizing institutions [15] provide guidelines for design and analysis of cognitive radio networks, where decentralized control, competition for limited resources, and vulnerability to both intentional and unintentional errors, are the main characteristics. In such an environment, the emphasis should be on the endurance of the resource-distribution mechanism rather than on its optimality. According to [16], eight design principles must be considered for endurance of self-management of common-pool resources:

1. Clearly defined boundaries for determining who has the right to use which portion of the resources.
2. Congruence between appropriation and provision rules and the state of the prevailing local environment.
3. Collective-choice arrangements.
4. Monitoring of both state conditions and users' behavior.

5. A flexible scale of punishment for users that violate communal rules.
6. Access to fast, cheap conflict-resolution mechanisms.
7. Existence of and control over their own institutions without intervention by external authorities.
8. Systems of systems as layered or encapsulated common-pool resources, with local resources at the base level.

Regarding the potentials of cognitive radio networks to play key roles in Industry 4.0 especially, in implementing intelligent sociotechnical systems, the primary objective of this book is to introduce a relatively new way of thinking about such networks. With this objective in mind, we find it instructive to start the discussion with the spectrum-supply chain paradigm, which may not be that well known in the signal-processing and communication-systems communities.

The notion of a *supply chain* may be viewed as follows: A supply chain is made up of different entities, the role of which is to fulfill the request of a specific customer. In addition to manufacturers, suppliers, and customers, a supply chain includes transporters, warehouses, brokers, and retailers. A supply chain also includes all functions of each party such as new product development, marketing, operations, distribution, finance, and customer service. Supply chains have been gradually evolving to complex structures known as *supply chain networks*, which are characterized by their dynamic nature due to continuous flow of information, product, and funds between different parties [17].

Supply chain networks including energy networks, food and water-resource networks, transportation networks, and communication networks play critical roles in shaping and survival of our modern-day society. Hence, it is significantly important to understand how an efficient supply chain must be designed and managed, how weaknesses can be improved, and how each party should plan and operate in order to achieve a competitive advantage [18].

Both urban and rural environments have been transforming by new emerging technologies. Even social relevance has been affected by these technologies. One of these transforming technologies is the wireless technology, which has manifested itself as a revolutionary paradigm shift through applications that have already gone far beyond our imagination. The applications include, but not limited to, multimedia communications, telemedicine, sensor networks, smart spaces (e.g., homes, offices), and recently smart cities [19]. This book revisits wireless communications in the light of recent understandings of supply chain networks.

1.2 COGNITIVE RADIO

The second great unification in physics is attributed to Maxwell for integrating electricity, magnetism, and optics under one unifying umbrella, collectively named the theory of classic electromagnetism [20].[1] However, the original formulation, which was published in 1865, included a set of 20 equations instead of the celebrated 4 partial differential equations known as Maxwell's equations [21]. Later on, in 1873, Maxwell presented his theory in its final form in a two-volume book [22].[2]

In 1887, Hertz experimentally demonstrated the physical existence of radio waves, which had been predicted by Maxwell about 20 years earlier [24, 25]. This historical achievement confirms the following statement: Theory and experiment must go hand in hand to flourish in their own respective ways. After his successful experiment, Hertz said:

> I do not think that the wireless waves I have discovered will have any practical application.

Despite this prediction, mobile communications and the broadband Internet access have been playing two key roles in the development of our society in recent years: (1) The increasing number of users of Internet-enabled wireless devices illustrates the shift away from traditional application-specific radio technology to service-oriented information delivery systems. (2) Regarding the ever-increasing demand for more advanced applications that require transferring higher volumes of data, communication technologies are progressing toward providing secure and seamless connectivity of mobile devices to any network, anytime, and anywhere [26, 27].

In this regard, to allocate the spectrum dynamically and openly, future wireless devices need to be service-oriented terminals, which are compatible with computer systems and support the unlocked and multiple wireless standards [28]:

> Spectrum is like air; we need to keep it clean, open, and green for our environment.

A significant emerging approach to improve spectrum utilization is through *temporal spectrum reuse*. *Cognitive radio* offers a novel way for improving the efficiency of spectrum utilization [29–31]. Deployment of scaled-down wireless base stations (i.e., *femtocells*), which use licensed spectrum belonging to an operator improves capacity and coverage through *spatial reuse of spectrum* [32]. However, conventional small cells put no new spectrum into play. Hence, a new paradigm for wireless communications that can harness the potential possibilities offered by these two different approaches and unify them under one umbrella would be appealing. Small-cell networks equipped with cognition (*cognitive small-cell networks*) will pave the way for efficient spectrum sharing across networks via *spatiotemporal reuse of spectrum* [33].

Interest in a new generation of engineering systems enabled with cognition, started with *cognitive radar* [34] followed by *cognitive radio*, a term that was coined by

[1] Newton's theory of classic mechanics is considered to be the first great unification in physics, which unified terrestrial and celestial mechanics [20].

[2] Heaviside takes credit for reducing the number of Maxwell's equations to make the theory more understandable for his contemporary scientists so that its importance could be appreciated [23].

Mitola and Maguire [35]. A cognitive system is built on five pillars: perception–action cycle, memory, attention, intelligence, and language [13, 36]. In [35], the idea of cognitive radio was introduced within the software-defined radio (SDR) community. Subsequently, Mitola elaborated on a so-called "radio knowledge representation language" in his own doctoral dissertation [29].

Furthermore, in a short section entitled "Research Issues" at the end of his doctoral dissertation, Mitola went on to say the following [29]:

> How do cognitive radios learn best? merits attention. The exploration of learning in cognitive radio includes the internal tuning of parameters and the external structuring of the environment to enhance machine learning. Since many aspects of wireless networks are artificial, they may be adjusted to enhance machine learning. This thesis did not attempt to answer these questions, but it frames them for future research.

Haykin in his seminal journal paper on cognitive radio, proposed the following definition [30]:

> Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming radio frequency (RF) stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:
>
> - highly reliable communications whenever and wherever needed;
> - efficient utilization of the radio spectrum.

Then, he provided a detailed exposition of signal processing, control, learning and adaptive processes, and game-theoretic ideas that lie at the heart of cognitive radio [30]. As shown in Figure 1.1, three fundamental cognitive tasks, embodying the perception–action cycle of cognitive radio, were identified in that 2005 paper [30]:

- Radio-scene analysis (RSA) of the radio environment performed in the receiver
- Transmit-power control and dynamic spectrum management (DSM), both performed in the transmitter
- Global feedback, enabling the transmitter to act and, therefore, control data transmission across the forward wireless (data) channel in light of information about the radio environment fed back to the transmitter by the receiver. In other words, information on spectrum holes (i.e., underutilized subbands) and the forward channel's condition, extracted by the scene analyzer at the receiver, is sent to the transmitter via a feedback channel.

In effect, the emphasis in that 2005 paper was placed on cognitive radio as a "closed-loop feedback control system" with practical benefits and the need for precautionary measures, recognizing that feedback is a "double-edged sword".

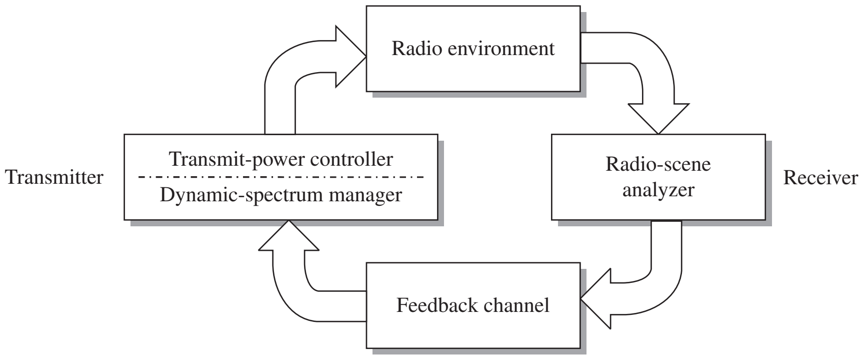

FIGURE 1.1 The cognitive information-processing cycle in cognitive radio. A cognitive radio transceiver is built on a perception–action cycle. Radio-scene analyzer in the receiver plays the role of the perceptor. Dynamic spectrum manager and transmit power controller in the transmitter play the role of the executive part. The perceptual and executive parts together with the feedforward and feedback channels form a closed-loop system. Source: Haykin and Setoodeh (2015) [37]. Reproduced with the permission of IEEE.

Since its inception over a decade ago, interest in cognitive radio, its theory and applications has grown exponentially. The driving force behind this exponential growth is summed up as follows [13]:

> Cognitive radio has the potential to mitigate the radio-spectrum underutilization problem in today's wireless communications.

With this engineering challenge in mind, we begin the study of cognitive radio with this critical issue as our starting point.

1.3 THE SPECTRUM-UNDERUTILIZATION PROBLEM

The electromagnetic *radio spectrum* is a natural resource, the use of which by transmitters and receivers is licensed by governments. In November 2002, the Federal Communications Commission (FCC) published a report prepared by the Spectrum-Policy Task Force aimed at improving the way in which this precious resource is managed in the United States [38]. The task force was made up of a team of high-level, multidisciplinary professional FCC staff: economists, engineers, and attorneys – from across the commission's bureaus and offices. Among the task force's major findings and recommendations, the second finding on page 3 of the report is rather revealing in the context of spectrum utilization [38]:

> In many bands, spectrum access is a more significant problem than physical scarcity of spectrum, in large part due to legacy command-and-control regulation that limits the ability of potential spectrum users to obtain such access.

Indeed, if we were to scan portions of the radio spectrum including the revenue-rich urban areas, we would find that

- some frequency bands in the spectrum are largely unoccupied most of the time;
- some other frequency bands are only partially occupied; and
- the remaining frequency bands are heavily used.

The underutilization of the electromagnetic spectrum leads us to think of a new term commonly called *spectrum holes*, for which we offer the following definition [13, 30]:

> A spectrum hole is a band of frequencies assigned to a primary (licensed) user, but, at a particular point in time and specific geographic location, the band is not being utilized by that user.

Spectrum utilization can be improved significantly by making it possible for a secondary (cognitive radio) user (who is not being serviced) to access a spectrum hole unoccupied by the primary (legacy) user at the right location and time in question.

Cognitive radio offers a new way of thinking on how to promote efficient use of the radio spectrum by exploiting the existence of spectrum holes. In a related context, the *spectrum-utilization efficiency* of cognitive radio is assessed in the context of four practical system issues [13]:

1. *Accuracy and reliability*, with which the spectrum holes are identified.
2. *Computational speed*, with which the spectrum-hole identification is accomplished.
3. *Management of resources*, which involves the allocation of spectrum holes among competing secondary users in the cognitive radio network, effectively and reliably.
4. *Coexistence of the cognitive radio network alongside the legacy radio network*, which will have to be accomplished in a harmonious manner for the good of all users, both secondary and primary.

Requirements (1) and (2) are responsibilities of receivers in the cognitive radio network, while the transmitters in the network are responsible for requirement (3). As for requirement (4), with the legacy radio network having paid for using the spectrum and legally approved by regulatory agencies, the responsibility for this last requirement rests with the cognitive radio network, viewed as a system of systems [13].

1.4 COUNTRYWIDE MEASUREMENTS OF SPECTRUM UTILIZATION

According to predictions made by the International Telecommunications Union as well as the Organization for Economic Cooperation and Development, unless serious actions are taken toward smart, efficient, and dynamic management of the electromagnetic spectrum, the worldwide mobile communication network would face serious problems in the near future [28].

In this context, several measurement studies have been conducted in different countries around the world, as summarized in Table 1.1.

In the United States, measurements have shown that from January 2004 to August 2005, on average, only 5.2% of the radio spectrum was actually in use [39]. Measurements over a period of 2 days in November 2005 showed that the average spectrum occupancy in the band 30–3000 MHz was 13.1% and 17.4% for New York and Chicago, respectively [40]. In [42], the spectrum occupancy in the band 400–7200 MHz was compared for an urban area (Atlanta, Georgia) and a rural area (North Carolina); the respective measurements were 6.5% and 0.8%. At the Loring Commerce Centre, Limestone, Maine, USA, measurements over a period of 3 days in the band 30–3000 MHz, showed that the average spectrum usage was 1.7%; occupancy varied from less than 1–24.65% in different subbands. The maximum occupancy of 24.65% was reported for the band 470–512 MHz [41].

In Auckland, New Zealand, the spectrum occupancy was reported to be 6.2% over the frequency band 806–2750 MHz [43].

In Singapore, the average spectrum occupancy in the band 80–5850 MHz, based on measurements over a period of 12 days, was reported to be 4.54% [44].

In Doha, Qatar, measurements performed over a period of 3 days in the 700–3000 MHz frequency band showed that the spectrum utilization was 1% for indoor environments and 15.3% for outdoor environments [45].

It is worth mentioning that the results just mentioned highly depend on sensing locations, the spectrum sensing method, and the chosen threshold used to distinguish idle bands from occupied bands.

1.5 WHY BE INTERESTED IN COGNITIVE RADIO NETWORKS?

A significant emerging approach to improve spectrum utilization is through *temporal spectrum reuse*. *Cognitive radio* offers a novel way for improving the efficiency of spectrum utilization. Mitola's main idea described in [35] and [29] was to equip wireless personal digital assistants (PDAs) and related networks with a level of computational intelligence that they can detect users' communication needs and provide them with appropriate radio resources and wireless services. Haykin identified the basic building blocks of cognitive radio and developed a framework based on signal processing, communications, information theory, control theory, and game theory, which provides guidelines for implementing cognitive radio [30]. In this framework, the use of cognitive radio addresses the spectrum-utilization issue by identifying the underutilized subbands of the electromagnetic spectrum and then, providing the means for making those subbands available for employment by secondary users, who do not hold a license for using those subbands. Typically, the subbands allocated for wireless communications are the property of legally license owners, which, in turn, make them available to their own customers: the primary users. Naturally, the entire

TABLE 1.1 Sample Measurement Studies Regarding Spectrum Utilization in Different Countries

Country	Region in the Country	Frequency Range (MHz)	Usage (%)	Time	References
USA	–	–	5.2	January 2004–August 2005	[39]
	New York	30–3000	13.1	2 days in November 2005	[40]
	Chicago		17.4		
	Limestone	30–3000	1.7	3 days	[41]
	Atlanta	400–7200	6.5	–	[42]
	North Carolina (a rural area)	400–7200	0.8		
New Zealand	Auckland	806–2750	6.2	–	[43]
Singapore	Singapore	80–5850	4.54	12 weekdays	[44]
Qatar	Doha	700–3000	15.3	–	[45]

operation of cognitive radio hinges on the availability of spectrum holes that can be used for communication in an opportunistic manner. Moreover, the operation of cognitive radio is compounded further by the fact that the spectrum holes come and go in a rather stochastic manner, making the design of cognitive radio networks much more challenging.

1.6 DIRECTED INFORMATION FLOW

As described in [13], for a dynamic system to be cognitive, it has to embody four distinct processes: perception–action cycle, memory, attention, and intelligence. Every cognitive dynamic system has its own characteristic perception–action cycle, so does cognitive radio. However, before proceeding to address this issue, it is instructive to come up with a definition for what we mean by a "user" in a radio network. To this end, we first recognize that at each end of a wireless communication channel we have a *transceiver*, which embodies a transmitter and a receiver combined together as one whole unit. So, when we speak of a radio user, we offer the following definition [13]:

> A user refers to a communication link that connects the transmitter of a transceiver at one end of the link that is in communication with the receiver of another transceiver at the other end of the link. Moreover, the term "secondary user" is adopted for a cognitive radio, so as to distinguish it from the term "primary user", which is reserved for a legacy (i.e., licensed) radio unit.

Note the terms "primary user" and "secondary user" were used in the previous sections, ahead of this definition.

Referring to Figure 1.2, we see that on the right-hand side of the figure we have a receiver unit in the transceiver of cognitive radio (RX-CR) whose cognitive function is RSA, where CR stands for cognitive radio. On the left-hand side of the figure, at some remote location, we have a transmitter unit in the transceiver of cognitive radio (TX-CR) whose cognitive function is DSM and transmit power control (TPC) [47]. The RSA of the RX-CR unit senses the radio environment with the objective of identifying spectrum holes. This information is passed onto the TX-CR unit via the feedback channel. At the same time, through its own RSA, the TX-CR unit will have identified the spectrum holes in its own specific neighborhood. The combined function of the DSM and TPC in the TX-CR unit is to identify a spectrum hole that is common to it as well as the RX-CR unit, through which transmission over a data channel in the radio environment can be carried out. In this way, directed information flow across the cognitive radio is established on a cycle-by-cycle basis.

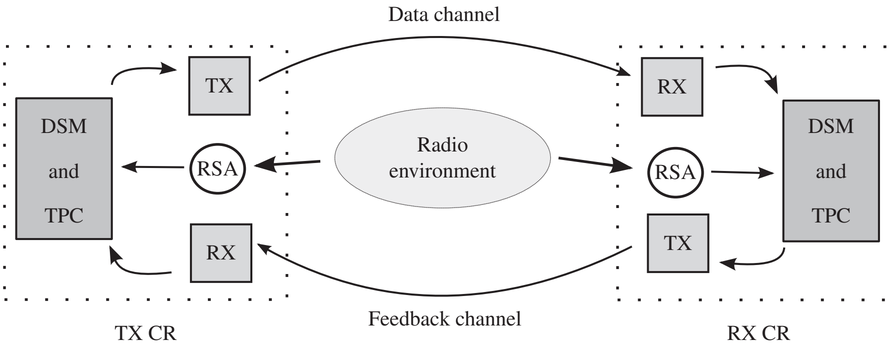

FIGURE 1.2 Directed-information flow in cognitive radio. DSM: dynamic spectrum manager; TPC: transmit-power controller; RSA: radio-scene analyzer; RX: receiver; TX: transmitter; TX CR: transmitter unit in the transceiver of cognitive radio; RX CR: receiver unit in the transceiver of cognitive radio. Source: Khozeimeh and Haykin (2009) [46]. Reproduced with the permission of John Wiley and Sons.

What we have just described is the very essence of the perception–action cycle for a communication link in cognitive radio. To add more specificity to the notion of RSA, "nonparametric spectrum estimation" is used in the receiver.

On the basis of Figure 1.2, we now address how the basic four processes of cognition are indeed satisfied, one by one. In so doing, we will have not only justified the rationale for radio cognition but also paved the way for the material to be covered in subsequent parts of the book [13].

1. *Perception–action cycle*: By using nonparametric spectrum estimation for perception in the receiver, the task of finding spectrum holes is achieved without having to formulate a "model" of the radio environment; hence, in effect, bypassing the need for perceptual memory. Spectrum estimation is an ill-posed inverse problem, which, therefore, requires the use of regularization. As will be explained later, the *multitaper method* (MTM) satisfies this requirement. Moreover, through the use of time-space processing, MTM provides the means for identifying the spectrum holes at a particular point in time as well as location in space. It is for these two reasons and a few others to be elaborated later on that we view the MTM as a method of choice for perception (i.e., spectrum sensing) of the radio environment.
2. *Learning and memory*: The task of DSM, to be discussed later, relies on the use of a learning process called *Hebbian learning*, inspired by the human brain [48]. An important characteristic of Hebbian learning is the inherent capability of self-organization. Thus, the dynamic spectrum manager has the practical means to dynamically choose and assign a set of appropriate links for communication to each cognitive radio user by learning the underlying environmental communication patterns. Knowledge thus learned about the communication patterns of the primary users in a radio network and, to some extent, those of

other secondary users in the local neighborhood is stored in memory. Moreover, the "synaptic" weights of a self-organized feature map are adaptively updated in response to new inputs, on a cycle-by-cycle basis.

Looking at Figure 1.2, we see the *coupling* between dynamic spectrum manager and the transmit-power controller. Specifically, through the use of *game-theoretic ideas*, also to be discussed later, and by virtue of information received from the nonparametric spectrum estimator through the feedback channel about interference levels in chosen feedforward communication channels, the transmit-power controller is enabled to *adaptively* adjust the transmitted radio signal, subject to prescribed constraints. In this *resource-allocation game*, the cognitive radio acquires the ability to reach equilibrium fast enough.

3. *Attention*: To illustrate how the process of attention manifests itself in cognitive radio, consider the following example. A serious accident has occurred at some particular point in time and specific location in space, thereby resulting in a "surge" in wireless-communication traffic. By virtue of built-in space-time processing, the nonparametric spectrum estimator sends information to the transmit-power controller, identifying which particular subbands of the radio spectrum have become congested due to the accident. Furthermore, in response to input from the radio-scene analyzer, the dynamic spectrum manager itself focuses its attention on those remaining subbands with lower interference levels. In so doing, communication over the newly found cognitive radio link is maintained, bypassing the congested subbands.

   Moreover, through its own self-organized learning process, the dynamic spectrum manager builds a *predictive model* of the radio environment. Using this model, the cognitive radio is enabled to predict the availability duration of spectrum holes, which, in turn, determines the predicted horizon of the transmit-power control mechanism.

4. *Intelligence*: As it is with human cognition, intelligence in cognitive radio builds itself on the processes of perception, memory, and attention, just described under points (1), (2), and (3), respectively. To appreciate the importance of intelligence, consider a cognitive radio network with multiple secondary users whose communication needs would have to be accommodated in a satisfactory manner. Accordingly, the perception – action cycle of Figure 1.2 would have to be expanded in a corresponding way, such that the secondary users share:

   - the radio environment for their individual forward communication needs and
   - separate wireless channel for their individual feedback requirements.

   In such a scenario, intelligence manifests itself as follows [13]:

   > Through a decision-making mechanism involving intelligent choices, the available resources (i.e., bandwidth and power) are equitably assigned to the secondary users in accordance with a prescribed protocol in the face of environmental uncertainties, and in such a way that the interference in the radio environment does not exceed a prescribed limit.

The environmental uncertainties include the reality that spectrum holes come and go in some stochastic manner, which may, therefore, mandate *robustification* of the transmit-power controller, an issue that is discussed later.

From the rationale just presented under points (1)-(4), it is now apparent that the four basic processes of cognition involved in radio for communication are satisfied. Now that it has become clear how cognitive capabilities are built into the system, the next step is to study issues pertaining to networks of cognitive radios.

1.7 COGNITIVE RADIO NETWORKS

A cognitive radio network, which is a *system of systems*, is a *goal-seeking* network in the sense described in [49]. The following classes of problems are involved in developing a cognitive radio network [37]:

- Specifying the goal that the system is pursuing (i.e., efficient spectrum utilization and ubiquitous network connectivity).
- Discriminating between the available alternative scenarios is based on the meaning of a desirable decision.
- Choosing a desirable action is based on a decision-making process.

By the same token, every system in the network (i.e., every cognitive radio) is a goal-seeking system too. *Game theory* has been extensively used to model complex interactions among different types of users with different desired payoffs [50]. In this context, researchers have investigated a wide range of problems and issues including but not limited to the following: spectrum sharing [51–53], scheduling [54], and interference managing [55].

For spectrum sharing, three different paradigms have been suggested in the literature [31]:[3]

- In the *underlay* paradigm, the interference caused by secondary-user transmitters on primary-user receivers must be kept below a certain threshold.
- In the *overlay* paradigm, the secondary users must have perfect knowledge about both primary and secondary users as well as the communication channels between them [56]. Sophisticated radio architectures are needed to use this knowledge and try to keep the interference caused by the secondary network on the primary network at the minimum level possible. Such a scenario seems to be quite challenging.

[3]In what follows, the following terms should be noted:

- In the context of network providers, the notions of primary users and legacy users are used interchangeably.
- Correspondingly, in the context of cognitive radio networks, the notions of secondary users and cognitive radio users are used interchangeably.

- In the *interweave* paradigm, the secondary users must not interfere with the operation of active primary users. Hence, secondary users should be able to accurately detect active primary users and switch bands when it is necessary. This calls for spectrum agility and ability to transmit in different bands.

These three mentioned paradigms can be viewed from another perspective regarding the attitude of primary and secondary users toward each other. For the coexistence of both primary (legacy) users on the one hand and secondary (cognitive radio) users on the other hand in some specific subband in a harmonious manner, there are two spectrum-sharing schemes [57]:

- *Protective-spectrum sharing*, in which legacy owners do not allow the coexistence of secondary users in their nonidle subbands. In other words, when primary users are active and using certain subbands, secondary users should not transmit over those subbands. The interweave paradigm belongs to this category.
- *Aggressive-spectrum sharing*, in which coexistence of primary and secondary users in the same subbands is allowed on the condition that interference power experienced by the primary user's receiver remains below a specified threshold. Both underlay and overlay paradigms belong to this alternative category.

While the protective approach allows secondary users to use only white spaces, the aggressive approach allows them to use gray spaces as well. White spaces refer to subbands, in which only white noise resides. On the other hand, gray spaces refer to subbands that are partially occupied by primary users. Obviously, among the two, aggressive spectrum sharing is less conservative regarding the improvement of spectrum utilization. However, such an approach can only make sense from legacy owners' perspective if it is profitable for them to allow the coexistence of secondary users in their nonidle subbands. In other words, the aggressive approach can only be rationalized if some form of pricing is involved. Market-based models, in which pricing is involved, have been used to study spectrum sharing among one primary user and multiple secondary users as well as spectrum sharing among multiple primary users and one secondary user [58].

In this book, we propose a general framework based on the theory of supply chain networks to study the spectrum market. In the proposed framework, multiple primary users and multiple secondary users as well as multiple brokers are all involved, side by side [59]. Brokers are profit-maximizing entities that buy the right of using spectrum subbands from legacy owners and sell them to secondary users. In a way, they can be viewed as network distributors that are mainly concerned with promotion and sales [60]. In general, brokers are involved in a competitive game among themselves. We may therefore identify two regimes for *dynamic spectrum access* [37]:

- *Open-access regime*: This regime employs open sharing of spectrum among peer secondary users. In the open-spectrum regime, activities of cognitive radio users should not affect the performance of primary users. In other words, the existence of cognitive radio users in a legacy owner's band should not be noticed by the primary users that receive service from that legacy owner. While the legacy owners and their primary users do not need to know anything about the secondary users, secondary users would have to be quite cautious about activities of the primary users. In this regime, secondary users rely on spectrum sensing for identifying spectrum holes [61]. Sweeping the spectrum frequently in search of spectrum holes would be of critical importance for providing seamless secondary communication. In other words, secondary users should always be ready to jump from one subband to another, whenever primary users demand their subbands. Moreover, interference management is performed in a self-organized manner without or with minimum coordination between secondary users in order to maintain an acceptable level of quality of service (QoS) [32].

- *Market-driven regime*: In this alternative regime, pricing is involved and legacy owners gain profit by leasing their idle and partially used subbands to secondary users. In particular, legacy owners are responsible for the probing and management of interference in their own bands. Taking account of maximum allowable interference that guarantees an acceptable level of QoS, legacy users advertise their available subbands for secondary usage. Accordingly, spectrum sensing is not considered as a critical functionality for secondary users' operation in the market-driven regime.

As different as they are, both regimes can be viewed as a spectrum-supply chain network. In addressing them in this manner, they represent two complementary approaches for solving underutilization of the radio spectrum. However, the nature of the games played between the different decision-makers in each one of them is entirely different. Other scenarios can be considered in addition to these two regimes. For instance, *bandwidth exchange* with emphasis on cooperative forwarding is an alternative scenario aimed at enhancing network connectivity and throughput [62]. In this framework, secondary users operate as relays for primary users and in return they get permission to use idle subbands of the corresponding legacy owner for their own data transmission [63].

In each regime, the associated game can be formulated as a *variational inequality (VI) problem*, whose solution is the equilibrium point of the game. The *Nash equilibrium* is commonly used as a standard notion of equilibrium in game theory especially in noncooperative games among selfish players. However, it is not robust against faulty or unexpected behavior, and it is also vulnerable to coalitions [64]. Although the latter sheds light on how to improve the quality of the solution, the former is troublesome. In some games, the equilibrium may not be a valid representation of the outcome of selfish behavior. In other words, instead of converging to an equilibrium point, selfish players may show nonconvergent cyclic behaviors. This may happen even when a unique equilibrium point exists [65]. In a cognitive radio network, spectrum holes can frequently appear or disappear and mobile users can freely start or stop communications. In such a dynamic environment, it is quite likely that we observe fluctuating patterns in users' behaviors [66].

Changes in the number of users as well as the available subbands may occur so fast that users cannot reach an equilibrium point between the time instants that those changes happen. Therefore, compared to the equilibrium point of the game that may not be even reached by the users, the *disequilibrium* behavior of the network, which is governed by its dynamics, more accurately describes the solution quality. Regarding the fact that focusing too much on equilibria, may lead to conclusions about the network behavior, which are qualitatively invalid, a shift of perspective on games from an equilibrium-based analysis toward natural dynamic-process-based description has been suggested [65]. Following this way of thinking, theory of the *projected dynamic systems* is used to derive dynamic models of the spectrum-supply chain for both regimes. These state-space models provide insight on the network disequilibrium behavior over the course of time and facilitate the stability analysis. Such a dynamic-process-based approach distinguishes the current work from other related works such as [67].

1.8 MATHEMATICAL TOOLBOX

A principled basis for the dynamic allocation and management of resources in a cognitive radio network is developed based on the fusion of ideas from game theory, control theory, and optimization.

1.8.1 Game Theory

Game theory provides an analytical toolbox for modeling and analyzing situations in which multiple decision-makers (players) with possibly conflicting interests interact. *Rationality* and *strategically reasoning* are two basic assumptions in game theory. These assumptions reflect that each decision-maker has a well-defined objective and acts based on its knowledge or expectation of other decision-makers' behaviors [68]. Game theory provides a framework for scientifically predicting the future and using this knowledge to engineer it [69].

James Waldegrave discovered the idea of *maxmin* in competitive games and provided the solution for a specific game in 1713. However, it seems that the name "game theory" was first used by Émile Borel in the 1920s. Later, John von Neumann provided proof for the *minimax theorem*. He and Oskar Morgenstern wrote the first book on game theory in 1944 [70]. In addition to discussing noncooperative games, they laid the groundwork for the study of cooperative games by presenting the concept of coalitional games with transferrable utility. A few years later in the beginning of the 1950s, the Nobel Laureate John Nash introduced the key concepts of *Nash Equilibrium* in noncooperative games and *Nash bargaining solution* in cooperative games. In the last few decades, game theory has been a very active field and has benefited from contributions of many researchers such as John Harsanyi and Reinhard Selten, who shared the 1994 Nobel prize in economics with John Nash, and Robert Aumann, who won the Nobel prize in economics in 1995. Harsanyi developed the theory of *Bayesian games*. Selten is well known for his work on *bounded rationality*, which was first proposed by Herbert Simon. Aumann introduced the concept of *correlated equilibrium*.

Coalitional games with nontransferable utilities were also introduced by Aumann and Bezalel Peleg. Although game theory was initially focused on economics, it has been successfully applied for solving problems in other disciplines such as biology. For instance, John Maynard Smith formalized the concept of *evolutionarily stable strategy* (ESS) in the 1970s.

In engineering, in many cases that deal with decentralized control systems, controllers are designed in a centralized manner and then implemented in a decentralized way [71, 72]. This method is not truly decentralized and may cause some problems in practice. Game theory provides a natural framework for analysis and design of truly decentralized control systems. John Nash's paper on "Parallel Control" is perhaps the pioneering work in this area [73]. Influenced by his earlier work on equilibria in noncooperative games [74, 75], Nash proposed to build computers in which components work in a more autonomous way. Başar and Olsder's book on dynamic noncooperative games [76] focuses more on control theoretic aspects and interprets optimal control problems as one-player games. Also, in [77], the robust control problem was interpreted as a zero-sum game in which the controller tries to maximize the system's utility while the environment is trying to minimize the system's utility.

In wireless networks, the radio communication channel is usually shared between different transmitter–receiver (transceiver) pairs. In such environment, multiple users compete for limited resources and the behavior of each user affects the performance of neighboring users. It is therefore not surprising that game theory has attracted the attention of many researchers in the field of communication networks, especially those who are working on cognitive radio.

Recently, several tutorials on game theory have been published for communication engineers. A nice survey on applications of game theory in wired communication systems is presented in [78]. The monograph [79] covers the noncooperative game theory and in the final chapter mentions some research areas in wireless communications and networking that can benefit from game theoretic approaches. The technical report [80] explains the terminology of noncooperative game theory using four simple examples from wireless communications. The concept of equilibria and the related theorems are presented in [81]. The tutorial paper [82] explains the cooperative game theory. In September 2008, *IEEE Journal on Selected Areas in Communications* published a special issue on game theory in communication systems and John Nash wrote a foreword for that. Also, in September 2009, *IEEE Signal Processing Magazine* published another special issue on game theory in signal processing and communications. The latter includes the mentioned tutorial papers on equilibria and cooperative games. Due to the key role that game theory plays in studying cognitive radio networks, the following chapter is dedicated to this topic.

1.8.2 Control Theory

Control engineering is an exciting and challenging field with a multidisciplinary nature and strong mathematical foundation. A control engineer's systematic insight can be easily extended to be utilized in other fields. The present challenge to control engineers is the modeling and control of modern, complex, and interrelated systems.

To face this challenge, we need something dramatically different from traditional control techniques possibly new control structures coming out of the neuroscience world.

Control systems are found throughout nature at the levels of genes, proteins, cells, and entire systems [83]. Some of the natural control systems have unequaled degrees of sophistication [84]. Increased understanding of the scientific and engineering principles behind the living organisms as well as the way they interact with the world and learn from it will lead to fantastic breakthroughs in the design and application of intelligent machines that are truly cognitive.

A living organism interacts with nature through observation and action. Inspired by the perception–action cycle in the brain, a cognitive radio transceiver is built as a closed-loop feedback system, which embodies the radio environment, radio-scene analyzer, feedback channel, and radio-environment actuator. Moreover, a cognitive radio network is a hybrid dynamic system with both continuous and discrete dynamics. Therefore, cognitive radio networks have the potential for presenting a rich spectrum of dynamic behaviors.

1.8.3 Optimization under Uncertainty

In a complex system such as a cognitive radio network, every decision-making process will be a multicriteria optimization problem with possibly conflicting objectives [85]. In order to make certain rational decisions, a user needs to gather information and process it. Data acquisition and computation capabilities of users are limited and they can only make the best decisions regarding their knowledge and resources. Also, real-life cognitive radios are subject to uncertainties that cannot necessarily be dealt with by statistical analysis. In this environment, robust optimization provides an essential tool for making decisions based on the worst-case conditions. According to the Institute of Electrical and Electronics Engineers (IEEE) [86]

> The robustness of a system is the degree to which a system or component can function correctly in the presence of invalid inputs or stressful conditions.

Much too often in the literature, optimality is considered as the driving force for obtaining the best performance possible. Such an objective may well work satisfactorily when considering small-scale applications or toy problems. However, when the application of interest is of a complex or large-scale kind, exemplified by a cognitive radio network, we find ourselves confronted with a much more pressing system requirement: robustness.

Most, if not all, control design strategies exemplified by transmit-power control, are based on the selection of a model for the plant. Selection of the model is influenced by mathematical tractability and prior knowledge that we may have about the plant, a generic term used to describe part of a dynamic system that is supposed to be controlled. Unfortunately, no matter how hard we try and irrespective of all the prior knowledge we may have about the system, there will always be some discrepancy between the actual physical behavior of the plant and the corresponding behavior of the hypothetical model. The response produced at the output of the plant due to a prescribed input signal is determined by the underlying physics of the plant. On the other hand, when the corresponding behavior of the plant is considered, the response of the model due to the same input signal deviates invariably from the actual response of the plant due to unavoidable model uncertainty. The challenge in designing the controller is to make sure that the errors are kept small enough to be acceptable from an operational viewpoint, regardless of all operating conditions that are likely to arise in practice. The following section reviews the dominant sources of uncertainty in cognitive radio networks.

1.9 DOMINANT SOURCES OF UNCERTAINTY IN COGNITIVE RADIO NETWORKS

There are two primary resources in a cognitive radio network: channel bandwidth and transmit power. The operation of the transmit-power controller is complicated by a phenomenon that is peculiar to cognitive radio communication, namely, the fact that spectrum holes come and go, depending on the availability of subbands as permitted by licensed users. To deal with this phenomenon and thereby provide the means for improved utilization of the radio spectrum, a cognitive radio system must have the ability to fill the spectrum holes rapidly and efficiently.

In spectrum sensing that constitutes a basic cognitive function in the receiver, the issue of prime interest is that of variance versus bias of estimation [87]. When we go on to consider the associated cognitive function of transmit-power control in the transmitter, the issue of prime interest is robustness versus optimality [66].

In the context of cognitive radio, the physical plant represents the communication channel between the transmitter and receiver, the radio-scene analyzer plays the role of the sensor, and the radio-environment actuator is the controller. Since the sensor and the actuator are not collocated, they have to be connected by a physical feedback channel and the controller receives the sensor measurements via the feedback channel. Due to the different uncertainty sources in a cognitive radio network, adjusting the transmit power of a cognitive radio requires solving an optimization problem under uncertainty.

The dominant sources of uncertainty in a cognitive radio network are as follows:

- *Primary users*: In a cognitive radio network, spectrum holes come and go, depending on the availability of idle subbands. Therefore, primary users' activities are the cause of *supply-side risk*. Communication patterns of primary users determine the availability and the duration of availability of resources. The availability of the spectrum holes determines the joint feasible set of the resource-allocation optimization problems that are solved by individual secondary users. In other words, it determines the joint set of the action spaces of all secondary users in the corresponding game. As mentioned before, the availability duration of spectrum holes determines the control horizon for the radio-environment actuators of secondary users. Depending on the subbands of interest and the dynamics of activities of primary users in those subbands, two different cases are observed:

a) The activities of the primary users and, therefore, their occupancy of the corresponding subbands are well defined. A good example for this case would be the use of TV bands for cognitive radios.

b) The activities of the primary users and, therefore, the appearance and disappearance of spectrum holes are more dynamic and far less predictable than the former case. A good example for this case would be the use of cellular bands for cognitive radios.

- *Secondary users*: Anytime users can leave the network and new users can join the network in a stochastic manner. This is the cause of *demand-side risk* in the network.
- *Mobility*: Users move all the time. Because of the mobility, the interference that a user causes on other users and mutually the interference that other users cause on that particular user in the network are time-varying.
- *Multiple-time-varying delays*: The feedback channel plays a fundamental role in the design and operation of cognitive radio. Feedback may naturally introduce delay in the control loop and different transmitters may receive statistics of noise and interference with different time delays. Moreover, the sporadic feedback causes users to use outdated statistics to update their power vectors. The time-varying delay in the control loop of each cognitive radio is another source of uncertainty that degrades the performance and may cause stability problems.
- *Noise*: The ambient noise depends on different activities in the environment and is caused by both natural and man-made phenomena.

During the time intervals that the activity of primary users does not change and the available spectrum holes are fixed, two approaches can be taken to deal with the uncertainty caused by joining and leaving of other cognitive radios as well as their mobility: *stochastic optimization* and *robust optimization* [88]. The pros and cons of these two approaches are discussed here.

If there is good knowledge about the probability distribution of the uncertainty sources, then the uncertainty can be dealt with by means of probability and related concepts. In this case, calculation of the expected value will not be an obstacle and, therefore, transmit-power control can be formulated as a stochastic optimization problem.

However, since in practice, little may be known about the probability distribution, the stochastic optimization approach that utilizes the expected value is not a suitable approach. In this case, robust optimization techniques that are based on the worst-case analysis, without involving probability theory, are more appropriate, although such techniques may well be overly conservative in practice. Suboptimality in performance is, in effect, traded in favor of robustness.

Stochastic optimization guarantees some level of performance on average, and sometimes the desired QoS may not be achieved, which means a lack of reliable communication. On the other hand, robust optimization guarantees an acceptable level of performance under the worst-case conditions. It is a conservative approach because real-life systems are not always in their worst behavior, but it can provide seamless communication even in the worst situations. Regarding the dynamic nature of the cognitive radio network and the delay introduced by the feedback channel, the statistics of interference that is used by the transmitter to adjust its power may not represent the current situation of the network. In these cases, robust optimization is equipped to prevent permissible interference power level violation by taking into account the worst-case uncertainty in the interference and noise. Therefore, sacrificing optimality for robustness seems to be a reasonable proposition. However, the use of a predictive model may make it possible for the user to choose the uncertainty set adaptively according to environmental conditions and, therefore, may lead to less conservative designs.

1.10 ISSUE OF TRUSTWORTHINESS

In addition to improving spectral efficiency, cognitive radio networks can lead to socioeconomic benefits due to their impact on competition, innovation, and investment. For instance, they allow for low-speed telemedicine care functions including telenursing and home monitoring through lightweight sparse networks for Internet access. The coalescence of such networks will provide low-cost ubiquitous connectivity and social networking using both fixed network infrastructures and mobile small-scale base stations [89]. Moreover, cognitive radio would be an efficient tool for building *disaster-response networks* [90] or *never-die networks* [91, 92], which should be able to quickly reconnect affected areas by disasters to the rest of the world.

1.11 VISION FOR THE BOOK

The rest of the book is organized as follows:

- Chapter 2 reviews the terminology of game theory with emphasis on noncooperative, cooperative, and minority games, which will be used in design and analysis of cognitive radio networks in the following chapters. The concept of Nash equilibrium is introduced. Reformulation of a noncooperative game as a variational inequality problem is also presented, which paves the way for building dynamic analytic models for networks.
- Chapter 3 discusses the structure of a cognitive radio transceiver and covers its three main functional blocks in detail. These building blocks are radio-scene analyzer, dynamic-spectrum manager, and transmit-power controller. The radio-scene analyzer allows the cognitive radio to perceive the radio ecosystem in order to identify the available spectrum subbands and measure the level of interference plus noise in those subbands. Then, based on the gathered information from the radio ecosystem, a cognitive radio solves the resource-allocation problem in two stages in a hierarchical manner. At the higher level of the

hierarchy, the dynamic spectrum manager selects a set of channels that are more suitable for communications, and then, at the lower level of the hierarchy, the transmit-power controller adjusts the transmit power over the selected channels in a dynamic manner according to the measured levels of interference in those channels. The MTM is discussed in detail as the method of choice for designing the radio-scene analyzer. The notion of cooperative games may be employed to form coalitions among groups of cognitive radios in order to implement a cooperative spectrum sensing mechanism. Two different approaches are suggested for designing the dynamic spectrum manager based on self-organized maps and minority games. These two methods are then compared with each other in terms of performance efficiency regarding different scenarios. The transmit-power controller is designed based on a robust formulation of the iterative waterfilling algorithm in a noncooperative game-theoretic framework.

- Chapter 4 is focused on networks of cognitive radios. It develops a framework based on viewing cognitive radio networks as spectrum-supply chain networks. Two complementary regimes (i.e., open access and market driven) are considered and analytic models for their governing dynamics are derived, which allow for studying both equilibrium and disequilibrium behaviors of the network under study. In the open-access regime, the spectrum-supply chain is a two-tier network consisting of network providers (i.e., legacy owners) and cognitive radio users (i.e., secondary users). On the other hand, in the market-driven regime, the spectrum-supply chain is a three-tier network consisting of network providers, spectrum brokers, and secondary users. In both of the mentioned regimes, a noncooperative game is played among peers in each tier of the network. Theory of variational inequalities is used to derive an equilibrium model for the network, which is the combined outcome of different games played in different tiers of the network. Then, theory of projected dynamic systems is used to derive a state-space model for the network, whose stationary points coincide with the solutions of the corresponding variational inequality (i.e., network equilibrium). This dynamic model allows for analysis of the transient behavior of the network before reaching an equilibrium or transitions between different equilibrium points, when the network is perturbed. Effects of uncertainties and time-varying delays on the behavior of the network are investigated using the analytical dynamic model, and conditions for guaranteeing the network stability are found. Subsequently, theories of evolutionary variational inequalities and projected dynamic systems in Hilbert space are used to extend the developed framework in order to capture the multi-time-scale nature of the network.
- Chapter 5 is dedicated to sustainability of the spectrum-supply chain network. In order to cope with the ever-increasing demand for bandwidth, improving the efficiency of spectrum utilization across licensed and unlicensed bands is of critical importance. For this purpose, an artificial economy is developed based on viewing the licensed and unlicensed bands as private goods and common-pool resources, respectively. The combined outcome of the games played in different tiers of the spectrum-supply chain is a Nash equilibrium, which may

not be Pareto optimal. Moreover, Nash equilibrium is not immune to coalition formation. In order to improve the sustainability of the spectrum-supply chain, the developed artificial economy aims for achieving a Pareto-optimal equilibrium, the so-called Lindahl equilibrium.

- Chapter 6 is focused on cognitive heterogeneous networks (HetNets) with emphasis on economic provisioning for resource sharing. HetNets are viewed as one of the enabling technologies for 5G. An economic model is developed based on decoupling of network infrastructure and spectrum, which facilitates horizontal merger of different networks. In the developed framework, networks merge and split in a dynamic manner to improve their utilities. When networks merge, they may share spectrum, infrastructure, or both depending on the situation in a specific time and location. By the same token, secondary networks may lease spectrum, infrastructure, or both from network providers. In light of merging and splitting of networks, the communication-supply chain network must be optimally designed and redesigned in a dynamic manner.