Improving Quality of Data User Experience in 4G Distributed Telecommunication Systems

Omar Alsaleh, Bechir Hamdaoui, and Ammar Rayes[†]
Oregon State University, Corvallis, OR 97331
alsaleh,hamdaoui@eecs.oregonstate.edu
[†] Cisco Systems, San Jose, CA 95134
[†] rayes@cisco.com

***Abstract*— We propose an efficient service management technique that enhances the quality of experience (QoE) of 4G users by enabling them to locate the best available network service provider (NSP) among many existing NSPs. We also propose a practical method that 4G users can use to implement the proposed technique in a purely distributed manner. Using simulations, we show that the proposed technique $i)$ increases network service availability by allowing 4G users to quickly find available NSPs, $ii)$ are very scalable by performing well regardless of the number of users in the system, and $iii)$ are implementable in decentralized fashion by relying on information that can be observed locally and without any cooperation.**

***Index Terms*—Distributed service management; data traffic; scalable techniques; 4G networks.**

I. Introduction

The fast-growing popularity of wireless mobile applications and devices has generated explosively increasing demands for network resources. New mobile applications, ranging from watching live games via real-time streaming to delivering important healthcare information to practitioners and from locating your favorite restaurant via GPS to keeping up with your friends via Facebook, are emerging and quickly reaching millions and millions of users. Existing, traditional wireless services also continue to blossom at dramatic rates, creating extra demands for network resources. The proliferation of these wireless mobile services and applications is fundamentally reshaping how resources and services ought to be allocated and managed. As new enabling technologies, such as cognitive radios [1, 2], are on the horizon, we anticipate a shift from the traditional subscription business model, where users subscribe to and receive service from one network service provider (NSP) at all time, to more liberal models, where users can freely seek and trade service dynamically and in real-time from multiple, different NSPs. This new mobility trend calls for new network management techniques, where resources are allocated only when needed, and services are managed and controlled dynamically by end-user devices themselves with little to no involvement from any centralized NSPs. With this in mind, the focus of this paper is on developing dynamic management techniques that can meet, and effectively cope with, these expected high service demands.

The key challenge of the management task at hand arises from the highly dynamic and complex nature of this emerging network environment, which is expected to handle potentially large numbers of heterogenous devices/users, each possibly having different quality of experience (QoE) desires. This environment gives rise to unique characteristics, which make it too difficult for users to model/predict its dynamics and behaviors [3–7]. As such, learning-based techniques that do not require prediction models, but can still manage well the network resources by learning through their interactions with the environment are particularly well suited to this type of environment, whose behavior is, by nature, too complex to predict, but the QoE to be achieved as a result of using the environment can easily be assessed/observed [8–14]. Instead of using prediction models, these techniques rely on learning algorithms, such as reinforcement learners [15, 16], to learn from past and present interaction experience to decide what to do best in the future. For example, albeit it may be difficult to predict which NSP is going to offer the best service in the near future (e.g., less congested, has more available resources, etc.), the QoE can easily be quantified once the user subscribes to an NSP. In essence, learning techniques enable 4G users to learn from interaction experience and use the acquired knowledge to choose the proper actions that lead to the maximization of their own/intrinsic objectives, thereby "hopefully" maximizing their QoE to be received in the long run.

One interesting observation came from our initial study is that when users aim to maximize their intrinsic objectives, their collective behavior as a whole often leads to making each other's QoE worse. That is, when the users' private objectives are not so carefully chosen/designed, the learning based techniques may lead to poor performances.

In this paper, we propose efficient management techniques that indeed allow 4G users to maximize their received QoE levels through careful design, coordination and alignment of the users' objectives. Specifically, we propose user objective functions that are aligned with system objective, so that when users go after them, their behavior as a whole also results in increasing each user's long-term received QoE. The proposed techniques enhance the users' QoE by allowing them to quickly locate the best available NSP. Furthermore, we propose a distributed/practical function computation method that 4G users can use to compute their objectives. Using Matlab simulations, we show that the proposed management techniques $i)$ enhance network service availability in that they allow 4G users to quickly find available NSPs, $ii)$ scale well with the number of users in the system, and $iii)$ are implementable in decentralized fashion by relying on information that can be observed locally and without any cooperation.

The rest of the paper is organized as follows. In Section II, we describe our system model. Section III states the studied problem. In Section IV, we present our proposed management techniques. We evaluate the performance of the proposed techniques in Section V, and finally conclude the paper in Section VI.

II. 4G Network Model

We consider a 4G data/IP network, as shown in Fig. 1, that consists of m NSPs all providing real-time services (e.g., Internet access, real-time online gaming, streamed multimedia, IP telephony, etc.) to n 4G users (e.g., smartphones, tablets, e-readers, iPads, and other IP-enabled devices). In this work, we assume a free-subscription service model, where users are free to seek and trade service dynamically and in real-time from multiple, different NSPs. That is, 4G users do not have to be subscribed to one NSP all the time, rather they can switch to and receive service from any NSP at anytime. For example, a user can have multiple accounts with multiple different NSPs, and depending on the user's perceived/desired QoE (including, quality, price, policy, etc.), a user can decide to switch to any other NSP. Once a user subscribes to and receives service from an NSP for a period of time, the user can easily quantify the QoE of the service offered by the NSP. Data rates can for e.g. be a way of quantifying the amount/quality of service that the NSP offers the 4G user. Other examples of quality metrics are the signal reliability and the data packet success rate of the communication carried on the NSP's network. Here, we assume that once a 4G user switches/subscribes to a particular NSP, the user can easily quantify the QoE of the service received from the NSP. Hereafter, let V_j represent the total amount of service NSP j offers.

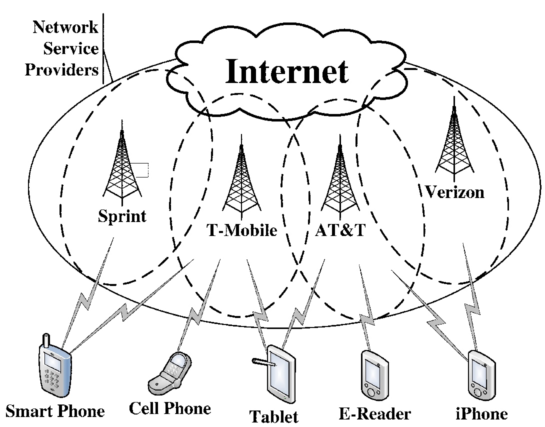

Fig. 1. 4G network access model.

In this paper, we are interested in data traffic, such as web browsing, file downloading, and emailing. That is, we assume that all 4G users want to connect to the 4G network to receive data services. Unlike the case of voice traffic, a user's QoE for data traffic generally increases proportionally to the amount of data service/rate the user receives. This is reasonable when the amount of service is not too low or, more formally, when it is above a certain required threshold ϖ. But when the amount of received service is below ϖ, the user's QoE decreases exponentially with the received service. Here, the higher the amount of received service, the better the QoE perceived by the user. But when the user's amount of received service is less than the required threshold, ϖ, the QoE is unacceptable. Formally, the QoE, $q_i(t)$, of 4G user i subscribed to NSP j at time step t can be written as:

$$q_i(t) = \begin{cases} r(t) & \text{if} \quad r(t) \geq \varpi \\ \varpi e^{-\beta(\varpi/r(t)-1)} & \text{otherwise} \end{cases} \tag{1}$$

where $r(t)$ is the amount of service received by 4G user i at time episode t, and β is a design parameter that captures the sensitivity of the user's QoE to the amount of received service when the amount becomes less than the required threshold, ϖ; the higher the β value, the faster the QoE goes to zero. For illustration, we show in Fig. 2 the QoE user i receives from NSP j as a function of $r(t)$ for $\beta = 10$ and $\varpi = 2$.

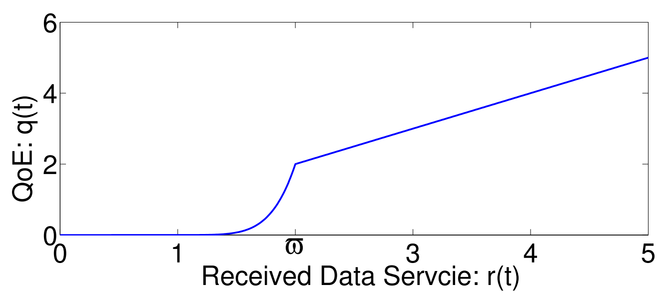

Fig. 2. QoE function: $\beta = 10$ and $\varpi = 2$.

Let c_j represent the maximum number of users that NSP j can support while satisfying all 4G users' required QoE thresholds. Here, $c_j = V_j/\varpi$, where V_j denotes the total amount of service that NSP j can offer. If we assume that all users subscribed to a particular NSP receive equal shares of service, then when the number of users, $n_j(t)$, subscribed to NSP j exceeds the capacity c_j, the amount of received service each user receives becomes less than ϖ. Therefore, as $n_j(t)$ increases beyond c_j, users' QoE decreases exponentially, meaning that all 4G users subscribed to NSP j will be unsatisfied with the amount of service they receive when the number of users exceeds the capacity.

III. Problem Statement

The aim of this work is to develop efficient network management techniques for 4G systems. Specifically, we focus on proposing objective functions that are $i)$ efficient in that they lead to the maximization of 4G users' long-term received QoE levels, $ii)$ scalable in that they maintain high performances even when the number of 4G users is large, and $iii)$ distributed in that 4G users can implement them in a decentralized manner. 4G users will implement the proposed techniques via existing learning algorithms to enable them to efficiently find good service opportunities by locating the best available NSPs, thus increasing the QoE level that each 4G user receives in the long run.

The challenge lies in that we want to propose distributed techniques that enable 4G users to learn and locate good NSPs without requiring any collaboration from other users or from the NSPs themselves. Techniques that learn through system interaction are particularly well suitable for such a 4G environment, whose behavior is too complex to predict. These techniques allow users to learn from experience by interacting with the environment, and rely on their gathered knowledge to select the proper actions that maximize their own/intrinsic service objectives, so as to maximize their long term received QoE. With this in mind, the question that arises here and that we want to answer in this paper is: which objective function g_i should each 4G user aim at maximizing so that its received QoE level is maximized by finding the best available NSP?

Although the techniques that we propose in this paper are designed for any learning algorithms, we use in this work the ϵ-greedy Q-learner [15] (with a discount rate of 0 and an ϵ value of 0.05). Therefore, at each episode (or time step) t, each user i aims at maximizing its own objective function $g_i(t)$ using its own Q-learner; that is, at the end of each time episode, each user takes the action with the highest entry value with probability $1-\epsilon$, and takes a random action (among all possible actions) with probability ϵ. After taking an action, the user computes then its QoE that it receives as a result of taking such an action (i.e., as a result of subscribing to the selected NSP), and uses it to update its Q-table. A table entry $Q(a)$ corresponding to action a is updated via $Q(a) \leftarrow (1-\alpha)Q(a) + \alpha u$, where α (set to 0.5 in this work) is the learning rate, and u is the received service from taking action a. All the results presented in this paper are based on this Q-learner (more details on the Q-learner can be found in [15]).

IV. Distributed Service Management

In this section, we first begin by presenting the proposed efficient objective functions that maximize the users' QoE levels, and then develop distributed computation methods that 4G users can use to implement these proposed functions.

A. Learnability and Alignedness

Let g_i denote the QoE objective function that user i aims to go after so as to maximize its QoE. Now, let $z(t)$ represent the joint move of all users in the system at time t, and $-i$ represent all users other than user i. $z_i(t)$ and $z_{-i}(t)$ are then used to specify the parts of the system state controlled respectively by user i and users $-i$ at time t, and $z(t)$ can be written as $z(t) = (z_i(t), z_{-i}(t))$. Here, the QoE function, q_i, is a function of $z(t)$, and hence, $q_i(t)$ can precisely be written as $q_i(z(t))$. For simplicity of notation, we often omit throughout this paper the dependency of these states on time t. For example, $z(t)$ will often simply be written as z.

For the joint actions of multiple 4G users to lead to good overall received QoE level, two requirements must be met. First, we must ensure that a user aiming to maximize its own QoE objective also leads to maximizing the system QoE level, defined as the sum of all users' QoE levels, so that each user's long-term average received QoE level is indeed maximized. This means that the users' objective functions ($g_i(z)$ for user i) need to be "aligned" with the system QoE level function for a given system state z. Intuitively, the higher the degree of alignedness of a user's objective function g_i, the more likely it is that a change of state will have the same impact on both the user's and the system's received QoE level.

Second, we must ensure that each user is able to discern the impact of its own actions on its own objective, so that a proper action selection allows it to quickly learn about good service opportunities. This means that the user's objective function should be learnable; i.e., more sensitive to its own actions than the actions of other users. For a given state z, the higher the learnability, the more dependent $g_i(z)$ is on user i's moves.

The alignedness and learnability requirements are unfortunately in conflict with one another [17], and therefore, the challenge in designing efficient objective functions for 4G users lies in finding the best balance between these two requirements. This balance guarantees that 4G users can learn to maximize their own objectives while their collective behavior does not make each other's received QoE worse.

B. Difference Objective Functions

In general, a highly aligned objective function will experience low learnability rate, and a highly learnable function will have low alignedness degree [18]. We propose to use for our 4G system the difference objective functions [19], which are shown to provide a good balance between alignedness and learnability. These difference functions have been shown to perform well in various domains, such as multi-robot coordination [20], air traffic control [21], and dynamic spectrum access [13, 22]. Formally, the difference objective function $d_i(z(t))$ (or simply $d_i(t)$) for a 4G user i subscribed to NSP j can be written as

$$\begin{aligned} d_i(t) &= \sum_{k=1}^{n} q_k(z(t)) - \sum_{k=1,k\neq i}^{n} q_k(z_{-i}(t)) \\ &= n_j(z(t))q_i(z(t)) - n_j(z_{-i}(t))q_i(z_{-i}(t)) \end{aligned} \quad (2)$$

where again $z(t)$ represents the full system state (i.e., joint move of all users in the system), and $z_{-i}(t)$ specifies the parts of the system state controlled by all users other than user i; i.e., $z_{-i}(t)$ represents the parts of the state on which user i has no effect. Note that these difference functions are aligned with one another, because the second term of Eq. (2) does not depend on user i's actions. But they do have a good learnability level, because subtracting the second term from the first term removes most of other users' effects from user i's objective function. Intuitively, since the second term evaluates the value of the system without user i, subtracting it provides an objective function that essentially measures user i's contribution to the overall achievable system QoE level, making it more learnable without compromising its alignedness quality.

C. Distributed Function Computation Method

We now propose a computation method that can be implemented by users to compute the objective functions in a distributed manner in spite of the large number of interacting users and the high dynamics of the network environment.

Formally, the full system state z can be decomposed into two components: z^{o_i}, a component observable by user i; and z^{h_i}, a component hidden from user i. Basically, the observable component, z^{o_i}, represents all what user i knows about the system state. The question now is that given the observable component z^{o_i} only, can each user i compute its objective function accurately enough?

The approach we propose for computing these proposed objective functions assumes no cooperation among users. Essentially, we propose a method that estimates the full system state given the observable component of the system state only, and then use these estimates (of the full state) to estimate the objective functions. Specifically, the user's estimated function that we propose for the function d_i (given in Eq. (2)) is

$$\hat{d}_i(t) = \hat{n}_j(z(t))\hat{q}_i(z(t)) - \hat{n}_j(z_{-i}(t))\hat{q}_i(z_{-i}(t)) \quad (3)$$

where $\hat{q}_i(z) \equiv E[q_i(z)|z^{o_i}]$, $\hat{q}_i(z_{-i}) \equiv E[q_i(z_{-i})|z^{o_i}]$, $\hat{n}_j(z) \equiv E[n_j(z)|z^{o_i}]$, and $\hat{n}_j(z_{-i}) \equiv E[n_j(z_{-i})|z^{o_i}]$. Here, $E[\cdot]$ can be the expectation operator or any estimation function.

Now, assuming that the total amount of service V_j each NSP offers is known, and that all users subscribed to the same NSP will receive roughly the same amount of service, the number $\hat{n}_j(z(t))$ can be estimated to $V_j/r_i(t)$ and the number $\hat{n}_j(z_{-i}(t))$ can be estimated to $V_j/r_i(t) - 1$. Likewise, the function values $\hat{q}_i(z(t))$ and $\hat{q}_i(z_{-i}(t))$ can respectively be estimated to $q_i(r_i(t))$ and $q_i(\frac{r_i(t)V_j}{V_j - r_i(t)})$ (the function q_i is given in Eq. (1). Thus, $d_i(t)$ can be estimated to

$$\hat{d}_i(t) = \frac{V_j}{r_i(t)}q_i(r_i(t)) - (\frac{V_j}{r_i(t)} - 1)q_i(\frac{r_i(t)V_j}{V_j - r_i(t)}) \quad (4)$$

Note that $\hat{d}_i(t)$ depends on $r_i(t)$ only (assuming V_j is known), an information that can be observed locally without any cooperation. Hence, the proposed functions can be implemented/computed in a fully decentralized manner.

V. Simulation Results

In this section, we evaluate the effectiveness of the difference objective functions in terms of their ability to find the best available NSP. Specifically, we assess their ability to 1) easily find/locate available data services, and 2) scale well with the number of 4G users. We evaluate these two performance metrics of the proposed functions and compare them with those of the intrinsic/greedy function q_i.

For this, we consider a 4G system consisting of m NSP, and a large number, n, of 4G users, all independently and distributively seeking to receive data service from the system. Each 4G user is allowed to freely choose any NSP, and users are allowed to switch between NSPs at any time. In our simulations, we set the average value of NSP's offered services to 20, the threshold ϖ to 4, and the number of NSPs to 10.

A. Impact of Network Load

We measure and compare the performances of the proposed difference and the intrinsic functions in terms of their ability to find an NSP that satisfies/meets the required data service threshold. For this, we plot in Fig. 3 the percentage of satisfied 4G users for various network loads, where a user is considered to be satisfied when its received QoE is above the required threshold, ϖ. Here, we plot the performances against the normalized network overload, which is defined as the ratio of the total number of users minus the system capacity (in number of users) to the system capacity, where the system capacity is $\sum_{k=1}^{m} V_k/\varpi$. The figure clearly shows that the

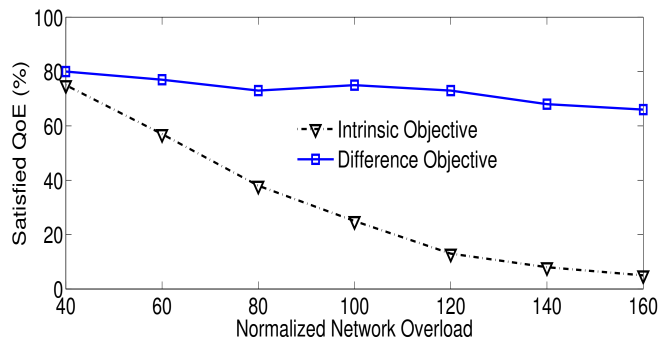

Fig. 3. Network availability: $\varpi = 4$, $\beta = 20$, $V_k = 20$ for all k.

proposed difference function d_i outperforms substantially the intrinsic function. That is, the proposed objective function leads to a much higher network service availability than the intrinsic function, and the availability of the network can reach up to 80% when compared with the ideal scenario. The proposed techniques can then be thought of as distributed management methods of network resources that result in a great enhancement of the users' QoE. Here, the percentage of satisfied users (or network availability) is normalized with respect to the ideal performance, which is used here as an upper bound. The ideal performance corresponds to when the users distribution among all NSPs is done in a centralized fashion with full knowledge of the system state.

Also, observe that as the network load increases, the proposed difference function maintains high performance, whereas the performance achievable under the intrinsic function drops rapidly. Therefore, we conclude that not only are the proposed functions practical in that they can be implemented in a decentralized manner, but they are also very scalable.

B. Impact of NSPs' Offered Service Variability

We also study the impact of the variability of the amount of service offered by the NSPs. For this, we show in Fig. 4 the percentage of satisfied users under each of the two studied objective functions when varying the coefficient of variations of V_j across all j's while keeping the average value to 20 ($\frac{1}{m}\sum_{k=1}^{m} V_j = 20$). Observe that the proposed technique outperforms the intrinsic technique regardless of the variability of the offered services across the NSPs. It can also be seen that

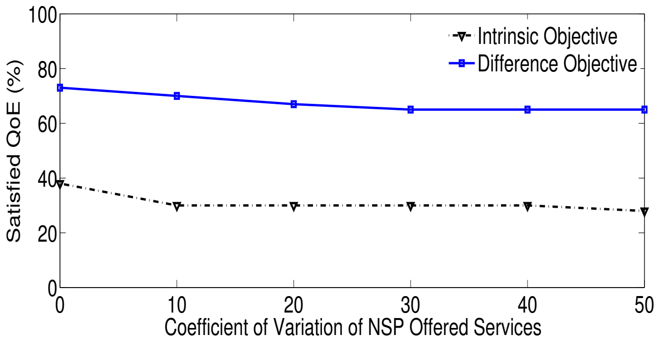

Fig. 4. Impact of Service Variability: $\varpi = 4$, $\beta = 20$, $\frac{1}{m}\sum_{k=1}^{m} V_j = 20$.

the proposed technique maintains relatively high performance independently of the coefficient of variations.

VI. Conclusion

This paper proposes distributed and scalable management techniques that improve 4G users' QoE by enabling them to quickly find the best available NSP. They allow 4G users to maximize their received QoE levels through careful design, coordination and alignment of their objectives. More specifically, we propose objective functions that are aligned with system objective, so that when users maximize them, their collective behavior results in increasing the long-term received QoE of each user. We also propose a practical computation method that 4G users can use to compute the proposed objective functions. We show via simulations that the proposed techniques are capable of enhancing network service availability, are very scalable, and are implementable in a decentralized fashion by relying on local information only.

VII. Acknowledgment

The authors would like to thank Pavithra Venkatraman for her help with Matlab coding.

References

[1] J. Mitolla III and G. Maguire, "Cognitive radio: making software radios more personal," *IEEE Personal Communications*, August 1999.

[2] R. J. Lackey and D. W. Upmal, "Speakeasy: the military software radio," *IEEE Communications Magazine*, May 1995.

[3] X. Li, Q. C. Zhao, X. Guan, and L. Tong, "Optimal cognitive access of markovian channels under tight collision constraints," *IEEE Journal on Selected Areas in Communications, Special Issue on Advances in Cognitive Radio Networks and Communications*, To Appear 2011.

[4] K. Liu, Q. Zhao, and B. Krishnamachari, "Dynamic multichannel access with imperfect channel state detection," *IEEE Trans. on Signal Processing*, vol. 58, no. 5, May 2010.

[5] M. Maskery, V. Krishnamurthy, and Q. Zhao, "Decentralized dynamic spectrum access for cognitive radios: cooperative design of a non-cooperative game," *IEEE Transactions on Communications*, vol. 57, no. 2, pp. 459–469, February 2009.

[6] S. H. A. Ahmad, M. Liu, T. Javidi, Q. Zhao, and B. Krishnamachari, "Optimality of myopic sensing in multi-channel opportunistic access," *IEEE Transactions on Information Theory*, 2009.

[7] B. Hamdaoui, "Adaptive spectrum assessment for opportunistic access in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 8, no. 2, pp. 922–930, Feb. 2009.

[8] U. Berthold, M. Van Der Schaar, and F. K. Jondral, "Detection of spectral resources in cognitive radios using reinforcement learning," in *Proceedings of IEEE DySPAN*, 2008, pp. 1–5.

[9] P. Venkatraman, B. Hamdaoui, and M. Guizani, "Opportunistic bandwidth sharing through reinforcement learning," *IEEE Tran. on Vehicular Technology*, vol. 59, no. 6, pp. 3148–3153, July 2010.

[10] J. Unnikrishnan and V. V. Veeravalli, "Algorithms for dynamic spectrum access with learning for cognitive radio," *IEEE Transactions on Signal Processing*, vol. 58, no. 2, August 2010.

[11] H. Liu, B. Krishnamachari, and Q. Zhao, "Cooperation and learning in multiuser opportunistic spectrum access," in *Proceedings of IEEE ICC*, 2008.

[12] K. Liu and Q. Zhao, "Distributed learning in cognitive radio networks: multi-armed brandit with distributed multiple players," in *Submitted to IEEE Int. Conf. on Acousitcs, Speech, and Signal Processing*, 2010.

[13] M. NoroozOliaee, B. Hamdaoui, and K. Tumer, "Efficient objective functions for coordinated learning in large-scale distributed osa systems," *IEEE Transactions on Mobile Computing*, to appear.

[14] O. Alsalah, P. Venkatraman, B. Hamdaoui, and A. Fern, "Enabling opportunistic and dynamic spectrum access through learning techniques," *Wireless Communications and Mobile Computing Journal*, to appear.

[15] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, MIT Press, Cambridge, MA, 1998.

[16] C. Watkins and P. Dayan, "Q-learning," *Machine Learning*, vol. 8, no. 3/4, pp. 279–292, 1992.

[17] K. Tumer and D. Wolpert, Eds., *Collectives and the Design of Complex Systems*, Springer, New York, 2004.

[18] A. K. Agogino and K. Tumer, "Analyzing and visualizing multiagent rewards in dynamic and stochastic environments," *Journal of Autonomous Agents and Multi Agent Systems*, vol. 17, no. 2, pp. 320–338, 2008.

[19] A. Agogino and K. Tumer, "Multi agent reward analysis for learning in noisy domains," in *Proc. of the Fourth Int'l Joint Conf. on Autonomous Agents and Multi-Agent Systems*, Utrecht, Netherlands, July 2005.

[20] A. K. Agogino and K. Tumer, "Efficient evaluation functions for evolving coordination," *Evolutionary Computation*, vol. 16, no. 2, pp. 257–288, 2008.

[21] K. Tumer and A. Agogino, "Distributed agent-based air traffic flow management," in *Proceedings of the Sixth International Joint Conference on Autonomous Agents and Multi-Agent Systems*, Honolulu, HI, May 2007, pp. 330–337.

[22] M. NoroozOliaee, B. Hamdaoui, and K. Tumer, "Achieving optimal elastic traffic rewards in dynamic multichannel access," in *Proceedings of IEEE Conference on High Performance Computing and Simulation*, July 2011.