IEEE Access
The journal for rapid open access publishing

Received July 2, 2015, accepted July 17, 2015, date of publication August 11, 2015, date of current version August 28, 2015.

Digital Object Identifier 10.1109/ACCESS.2015.2467174

Artificial Intelligence-Based Techniques for Emerging Heterogeneous Network: State of the Arts, Opportunities, and Challenges

XIAOFEI WANG, (Member, IEEE), XIUHUA LI, (Student Member, IEEE), AND VICTOR C. M. LEUNG, (Fellow, IEEE)
Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, BC V6T 1Z4, Canada

Corresponding author: X. Wang (xfwang@ece.ubc.ca)

This work was supported in part by the Canadian Natural Sciences and Engineering Research Council under Grant RGPIN-2014-06119 and Grant RGPAS-462031-2014, in part by the Chinese Scholarship Council through the Four-Year Post-Graduate Scholarship, and in part by the National Natural Science Foundation of China under Project 61271182.

ABSTRACT Recently, mobile networking systems have been designed with more complexity of infrastructure and higher diversity of associated devices and resources, as well as more dynamical formations of networks, due to the fast development of current Internet and mobile communication industry. In such emerging mobile heterogeneous networks (HetNets), there are a large number of technical challenges focusing on the efficient organization, management, maintenance, and optimization, over the complicated system resources. In particular, HetNets have attracted great interest from academia and industry in deploying more effective solutions based on artificial intelligence (AI) techniques, e.g., machine learning, bio-inspired algorithms, fuzzy neural network, and so on, because AI techniques can naturally handle the problems of large-scale complex systems, such as HetNets towards more intelligent and automatic-evolving ones. In this paper, we discuss the state-of-the-art AI-based techniques for evolving the smarter HetNets infrastructure and systems, focusing on the research issues of self-configuration, self-healing, and self-optimization, respectively. A detailed taxonomy of the related AI-based techniques of HetNets is also shown by discussing the pros and cons for various AI-based techniques for different problems in HetNets. Opening research issues and pending challenges are concluded as well, which can provide guidelines for future research work.

INDEX TERMS Artificial intelligence, genetic algorithms, ant colony optimization, self-organization networks, heterogeneous networks.

I. INTRODUCTION

Due to the fast development of current Internet and Mobile Communication industry, the mobile traffic load has experienced an explosive growth during the last few years as well. Accordingly, the systems of mobile network operators (MNOs) have been designed and improved with more complexity of infrastructure, higher diversity of associated devices and resources, and more dynamical formations of networks [1], and they are evolving towards the promising future mobile networking paradigm, the heterogeneous networks (HetNets).

In HetNets, there are various types of cells with different transmission power, coverage, and working mechanisms, as shown in Fig. 1, e.g., macrocell, base station (BS) in Worldwide Interoperability for Microwave Access (WiMAX), and enhanced NodeBs (eNBs) in Long-Term Evolution (LTE), which is with the largest transmission power and thus coverage (up to several kilometres outdoor), picocell which has relatively less coverage mainly targeting indoor coverage enrollment, femtocell which has relatively small-size low-cost low-power user-deployed access points in offices and homes, relay which is an MNO-deployed access point that only routes signals between the macro cell and end users in poor coverage areas and dead spots. Therefore, the complicated network infrastructure is facing to troubles for effectively organizing, managing and optimizing the network resources, while the skyrocketing mobile traffic demand is generating more pressure. Although there have been many proposed techniques for directly improving HetNets performance, how to automatically deal with the HetNets' complexity via other evolutionary techniques and algorithms becomes a hot research topic.

"Brains exist because the distribution of resources necessary for survival and the hazards that threaten survival vary in space and time [2]. The similar concept of bringing intelligence has been greatly expected in research areas on HetNets, which are increasingly dynamic, heterogeneous, large-scale, and complex. For a long time, researchers have been sparing no effort in deploying novel solutions by adopting Artificial Intelligence (AI) techniques for the automatic management and optimization of HetNets.

AI techniques include multi-disciplinary techniques from machine learning, bio-inspired algorithms, fuzzy neural network and so on, and they have been extensively studied and applied to optimize computer systems and networks in diverse scenarios and complicated environments. It has been proved that AI techniques can achieve outstanding performance [3]–[5], as most of them are inspired from nature findings or motivated by the ways of thinking of human beings. They have relatively lower complexity enabled by recursive feedback-based learning and local interactions, and hence faster speed of finding sub-optimal solutions compared to conventional techniques [3], [4]. Therefore, the integration of AI techniques into the design of smart infrastructure becomes one promising trend for effectively solving problems in HetNets. e.g., cell planning, fault-tolerance, resource management and optimization etc.

From the aspect of reducing the operational and capital expenditure (O/CAPEX) of MNOs, AI-based techniques can substantially diminish human involvement in operational tasks, and optimize network capacity, coverage, and Quality of Service (QoS) in HetNets, according to the advanced features discussed in Self-Organizing Networks (SONs) along following directions [3], [4], [6]: **1) self-configuration**, where newly deployed high variety of cells are automatically configured and updated before entering operation tasks, **2) self-healing**, where cells and networks can automatically detect and recover from failure and even execute compensation mechanisms whenever failures occur, and **3) self-optimization**, where cellular systems can measure the network conditions and optimize the settings to improve the performance in terms of coverage, bandwidth, interference avoidance, and QoS, while the corresponding issues of system scalability and energy conservation are also considered.

In this article, we survey the state-of-the-art AI-based techniques for evolving the smarter HetNets infrastructure and systems. Discussions on how researchers have been trying to adopt Machine Learning, Genetic Algorithms, Ant Colony Optimization Artificial Neural Networks, Fuzzy System, Markov Models and Bayesian Models for improving the smartness, efficiency, performance and QoS of HetNets will be carried out, followed by a comprehensive taxonomy of AI-based techniques used for evolving HetNets. Note that we will not penetrate into technical details of each algorithms and schemes, but will try to introduce and summarize up-to-date research issues in related areas with sufficient breadth and proper depth.

The remainder of this article is organized as following: We first introduce why intelligence is demanded for evolving the emerging HetNets in Sec. II. Then we describe issues of HetNets that can benefit from AI-based techniques in Sec. III. The taxonomy of the AI-based techniques for supporting HetNets is summarized in Sec. IV. New challenges and opportunities are discussed in Sec. V, and Sec. VI concludes the paper.

II. THE EMERGING HetNets

The emerging mobile networks are becoming increasingly dynamic, heterogeneous, large-scale, and systematically complex, and hence the infrastructure consists of various wireless access technologies with various capabilities, constraints, and operating functions towards the emerging HetNet.

More specifically, in the multi-tier infrastructure of the newest release of LTE-Advanced [7], macro-cells, pico-cells, femto-cells, as well as relay stations and Remote Radio Heads (RRHs), are envisaged. **Macro-cell base stations** use dedicated backhaul, for providing guaranteed bandwidth. **Pico-cells** and **femto-cells** are with significant popularity recently, and are small-size low-cost low-power user-deployed access points in buildings and houses, offloading data traffic locally. **Relays** are just MNO-deployed access points routing only signals from the macro cell to end users and vice versa in poor coverage areas and dead spots. **RRHs** are compact-size, high-power, and low-weight units, mounted outside the conventional macro BS and connected to it generally through a fiber optic cable for creating a distributed BS. The associated centre macro BS is in charge of control and baseband signal processing, and some radio circuitry is moved into RRHs. Details of each types times of cells and stations are discussed and shown in Fig. 1 as well.

Deploying various types of cells aims at offloading the traffic load via different requirements on coverage, locations, environment characteristics and user dynamics, for boosting the spectrum re-usage effectively. Therefore, HetNets can drastically reduce the O/CAPEX of MNOs. However, the complexity of HetNets brings substantial design challenges and problems, where the integration of AI-based and the framework of "Self-Organization Networks" (SON) with the HetNets can be one effective way towards smart future mobile networks.

III. "SELF-EVOLUTION" IN HetNets

During the last few years, the technology of SONs has experienced an explosive growth in its study. SONs are to effectuate substantial reductions of operation cost by diminishing human involvement. The essential idea of SONs is to integrate network planning, configuration, and optimization into a single and mostly automated process requiring minimal

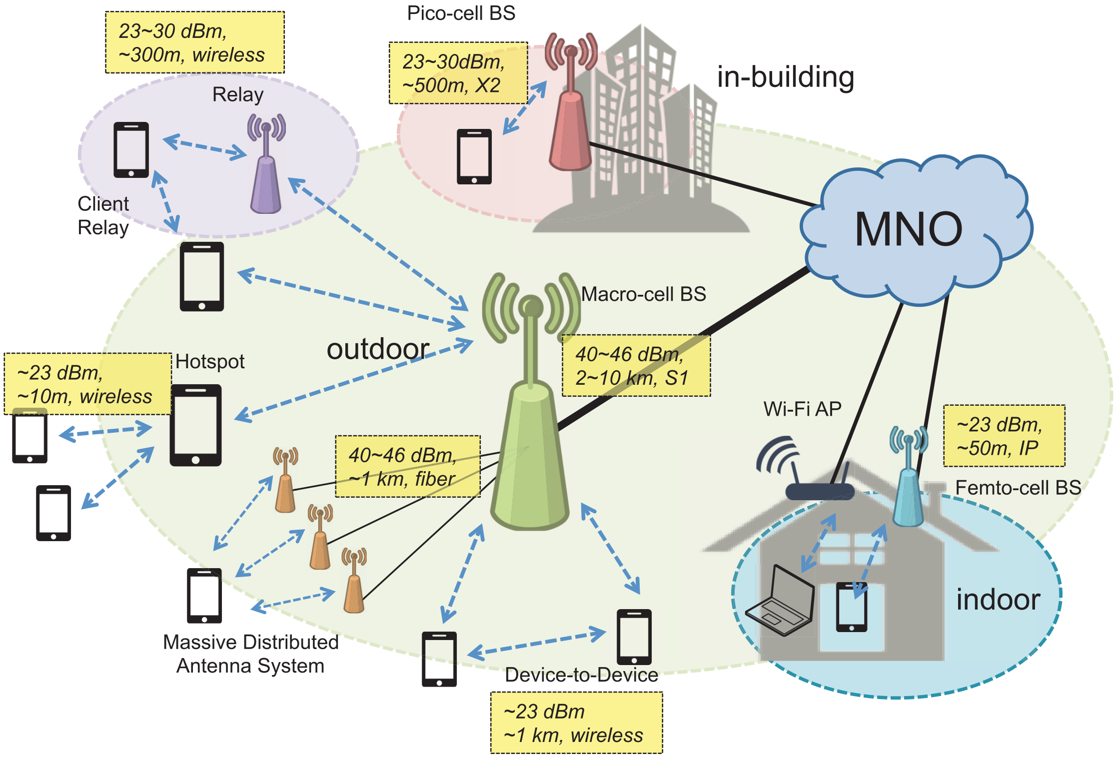

FIGURE 1. Infrastructure of heterogeneous networks.

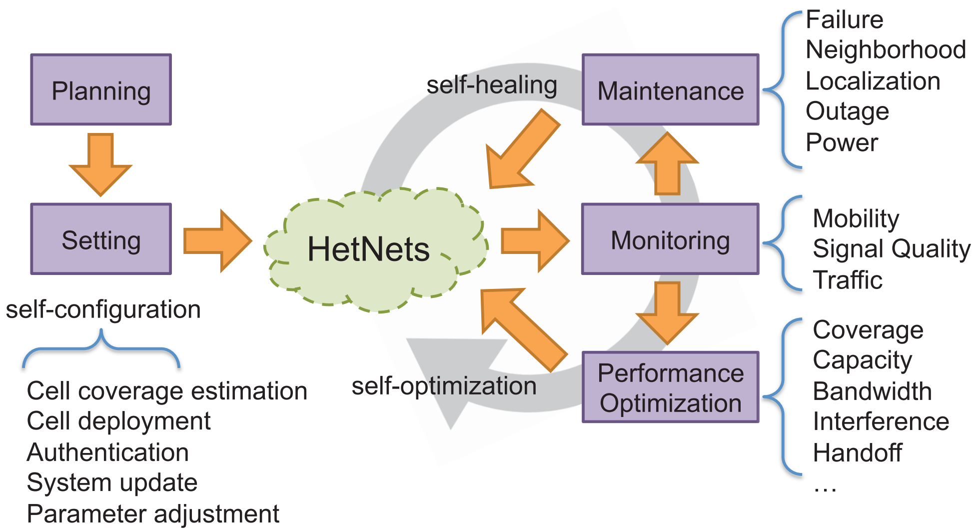

FIGURE 2. Illustration of AI-based techniques for self-organization on HetNets.

manual intervention; particularly AI-based techniques may offer efficient solutions for SONs in HetNets. Main features in SONs in HetNets include self-configuration, self-optimization, and self-healing, which designs HetNets with the ability of "self-evolution" [5], [8]. The abilities of "self-planning" and "self-organisation" are sometime discussed separately from self-configuration, but in this article we consider them as one essential automatic pre-operational starting phase. In following subsections, we will introduce related AI-techniques for SONs in HetNets with regards to the aforementioned three features. And features of SONs for HetNets are illustrated in Fig. 2.

Note there are already several studies focusing on proposals of the three main features of SONs comprehensively. The study in [8] has proposed SONs for Radio Access Networks (RANs) in HetNets with centralized annealing approach for coverage and capacity optimization, a hybrid neighbourhood based approach for cell outage detection, and a centralized greedy approach for cell outage compensation. The study in [3] also surveys different aspects of swarm intelligence inspired mechanisms as well as their designing principles, and examines various optimization algorithms that have been applied to artificial SON systems for HetNets. And we will detail most up-to-date related literature for improving the self-"X" ability of HetNets in following sections.

A. SELF-CONFIGURATION

In the planning phase of HetNets, the locations of base stations (or other types of cell stations), links between base stations, and associated various network devices as well as the corresponding parameters (output power, antenna angle, etc.) should be determined before all equipments are practically installed. However, because of the coexistence of multiple types of cells in the HetNets and high dynamics of users and services, an ever increasing number of parameters need to be managed and optimized. A better planning can shape the cell coverage optimally and prevent severe propagation losses at the cell edge. Therefore, it is important to derive optimal parameter settings automatically so that the amount of human-beings' labor is minimized in HetNets [9].

AI-based techniques (e.g., Genetic Algorithm) can be easily utilized to evolve **cell planning and coverage** optimization with pilot power adjustment [10]. And the most initialisation phase is the automatic **physical cell identifier assignment** and **radio resource configuration** in HetNets [9]. Ant then in the configuration phase after the planning and placement phase, newly deployed cell base stations (and related hardware) should be able to get automatically configured, throughly tested, and autonomously authenticated by downloading and running firmware/software before entering the operational state, which is called **"plug-and-play"** mode. There have been a certain number of studies focusing on the self-configuration in HetNets, mostly on the methodology for deriving appropriate parameters for specific HetNets scenarios. For example, the study in [11] addresses the issues of smart low-power node deployment in 5G HetNets, and proposes to associate appropriate sectorization with radio resource allocation during the adaptive SON by integrating cognitive radio with inter-cell interference coordination. Also relay placement requires sophisticated modeling and configurations as researched in [12] for determining the parameters of interfere-limited relay channel management to maximize capacity without committing to protracted system simulation studies.

Some other studies focus on the **distributed beamforming configuration** in HetNets to achieve some breakthrough for optimal coverage and signal quality. Compared with conventional beamforming techniques that require priori knowledge of channel conditions at transmitters, the bio-inspired robust adaptive random search algorithm (BioRARSA) [13] is proposed to enable a convergence time that scales linearly with the number of distributed transmitters, as inspired by a heuristic random search mechanism that mimics the foraging strategy and life cycles of E. coli bacteria [14]. Since the convergence time of BioRARSA is insensitive to the initial sampling step-size of the algorithm, it exhibits a robustness against all initial parameters and the dynamic nature of distributed HetNets.

B. SELF-HEALING

Robustness is one of the most critical issues for commercial HetNets, MNOs need to stably support a large number of various devices and diverse users. SON functionality in HetNets provides the essential self-healing ability based on active tracking, passive monitoring, proper measurement for faults, and appropriate consequent remedial actions, such as restarting, falling back to backup system, switching to compensation equipment and so on. SONs also offer some means for automatically upgrading the software of network equipments to fix legacy bugs and problems, as well as adjusting parameters adaptively to avoid problematic situations. Self-healing saves huge amount of human intervention for networking system maintenance, and recovers the network failures as much autonomously as possible.

Therefore, AI techniques can be adopted conveniently for the self-healing feature to ensure services and resources availability. As one representative work of **cell outage compensation**, the proposal in [15] proposes an autonomic particle swarm compensation algorithm to generate a centralized cell outage compensation management scheme in LTE HetNets, in order to mitigate the performance degradation induced by the cell outage.

Autonomous re-configuration is considered as one key feature of self-healing of SON in HetNets. By observing changes of users and network conditions, HetNets requires necessary re-configurations in a real-time manner without termination of mobile services. This has been studied in [16], which has proposed an adaptive policy-based dynamic reconfiguration framework, by creating and updating policies dynamically in response to changing reconfiguration requirements. Through the use of Reinforcement Learning methodology, already-deployed policies are updated dynamically within the two-layer policy based framework. However, adaptability of the network control mechanisms and on-the-fly derivation of new policy rules is not taken into consideration.

C. SELF-OPTIMIZATION

Much emphasis in this article is put to the self-optimization techniques in HetNets. Due to the running of HetNets, the performance should keep being improved from a large number of aspects, such as load balancing, power adaptation, neighbourhood maintenance, mobility management and so on, taking into account radio characteristics, traffic dynamics, and user demands in the service area. However, practically applying real-time optimization is difficult, because it typically entails heavy work load for comprehensive measurement, statistics learning, optimization problem solving, and decision making over the parameters.

a) Automatic coverage optimization and load balancing can be achieved by adjusting the antenna settings and thus shaping the radio coverage, and by adjusting the handover parameters to logically change the cell size. Automatic coverage optimization also aims to maximize the system capacity and ensure an appropriate overlapping area between neighbor cells based on cooperatively adjusting antenna tilt and pilot power among the related cells. For instance, the study in [17] proposes self-optimization of antenna tilt and power by using a fuzzy neural network optimization method based on cooperative reinforcement learning in HetNets.

b) Mobility optimization is to eliminate unnecessary handover and to provide appropriate handover timing, by automatically adjusting the thresholds related to cell re-selection and handover. And its target is also to load balancing optimization, which can automatically force special users covered by the edge of a congested cell to reselect or handover to some neighbor cells which are less congested by adjusting the parameter thresholds. Mobility optimization highly relies on the support of efficient neighbourhood maintenance, the users can automatically refresh and reconfigures the neighbourhood list for holding the minimum set of cells necessary for roaming based on measurements.

c) Link quality estimation must be always performed with a high reliability to facilitate a secure transmission with robustness in HetNets. Rather than conventional static link-quality aware routing metrics that adopt simple moving-average estimators, bio-inspired estimator based on the neural network paradigm can be utilized to improve the effectiveness of link-quality estimation [18].

d) Device-to-Device communications supply HetNets with higher scalability and large capacity, by utilizing the organized device-to-device links owing to the effective interference management. The desired resource allocation can benefit much from the AI-based techniques. For instance, the study in [19] proposes Ant Colony Optimization base intelligent management, by which D2D pairs can effectively, autonomously, and jointly select the suitable resource blocks and adjust power to guarantee signal quality of all users.

e) Relay-based multi-hop transmission can effectively extend the service coverage and strengthen the sustainability of HetNets by leveraging intermediate relay nodes, so that the transmission can cross over multiple hops, while the link interference and multi-hop path formation become quite challenging. One study in [20] presents a traffic-light-related approach to autonomous self-optimization of tradeoff performance indicators (i.e., coverage and capacity) in LTE HetNets, where by introducing a low-complexity interference approximation model, the related optimization problem is formulated as a mixed-integer linear program and is embedded into a self-organized network operation and optimization framework. The hierarchical cooperative relay-based HetNets are discussed in [21] for providing cost-effective coverage extension based on the convergence of heterogeneous radio networks. GA can be also used to optimize the relaying topology based on the awareness of the intercell interference and the spatial traffic distribution dynamics, where the topologies are encoded as a set of chromosomes, and special crossover and mutation operations are proposed to search for the optimum. The aforementioned study in [12] presents closed-form capacity expressions for interfere-limited relays as well as the deployment parameters that may maximize the capacity practically.

f) Virtical Handoff (VHO) in HetNets [22] plays an important role in fulfilling seamless mobile service when users cross different cells with different link layer technologies for RANs. Current VHO algorithms mainly focus on when to trigger and what connection QoS to improve, but neglect the synthetical consideration of all currently available candidate networks, where AI-based techniques can help to get optimal decisions on parameters by overall evaluation of the complicated conditions. For instance, the study in [23] addresses the VHO problem for user QoS enhancement and system performance improvement in HetNets, and proposes an adaptive parameter adjustment algorithm based on neural network model. Similar studies can be discovered in [24] and [25].

Note that practical design of SON features into HetNets systems and networks requires necessary deployment of monitoring and maintenance systems into core networks mostly. The study in [17] designs a dedicated SON server installed in HetNets with communication functions for distributed SON modules at each network devices and cells, integrated with database for storing collected information. The server periodically executes optimization algorithms on the basis of the analysis results, and SON features can be realized without having a large impact on existing systems.

IV. TAXONOMY OF AI-RELATED SON TECHNIQUES IN HetNets

In this section, we survey and discuss the AI-related SON techniques in HetNets by classifying them based on the types of AI techniques, while discussing their correlation and benefits with SONs in HetNets in detail. Note that all discussed studies are clearly listed in Table 1.

A. MACHINE LEARNING

Machine learning (ML) is evolved from the study of pattern recognition and computational learning theory in AI areas [26]. It effectively learns the way of human brains, explores the construction and study of algorithms, and makes data-driven predictions or decisions [6]. Among many ML techniques, the reinforcement learning (RL) is one particular learning algorithm inspired by behaviorist psychology, concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative rewards [27]. From the illustration in Fig. 3, RL aims at finding a policy that maximizes the observed rewards (i.e., payoffs) over a certain time period, and it is often used for channel access and transmit power allocation in networking systems. One representative work is the study in [28]

TABLE 1. Taxnomony of AI-based techniques for smart infrastructure of HetNets.

		Machine Learning	Genetic Algorithms	ACO & Swarm Intelligence	Artificial Neural Networks	Fuzzy Logic System	Markov & Bayesian
Self-Configuration	Coverage Planning	[33], [34], [36]		[54], [56]	[17]	[17], [37], [62], [63]	[69]
	System Configration	[33], [36]		[54]			
Self-Healing	Fault Identification			[15]		[37], [62]	
	Re-configuration	[16]	[43]			[37], [62]	[69]
Self-Optimization	Load Balancing	[17], [35], [36]		[56]	[17]	[17], [37], [38], [62], [63]	[71]
	Mobility	[32]					[67], [68]
	Link Quality & Beamforming	[28], [31], [36]	[47]	[15], [51]–[53], [55]	[17]	[17], [62], [64], [41], [61], [63]	
	D2D & Multi-hop Relay	[35], [82], [83]	[47], [48]	[51], [92], [52], [55]		[38], [64]	
	Virtical Handoff	[28], [30]	[47]		[23], [24]	[24], [25], [61], [62]	[68], [70]

which presents game dynamics and performance analysis of RL schemes for 4G HetNets where users try to learn their own optimal payoff and their optimal strategy simultaneously with limited information, and shows the advantages when dealing with imperfect, noisy and delayed measurement and randomly changing environment.

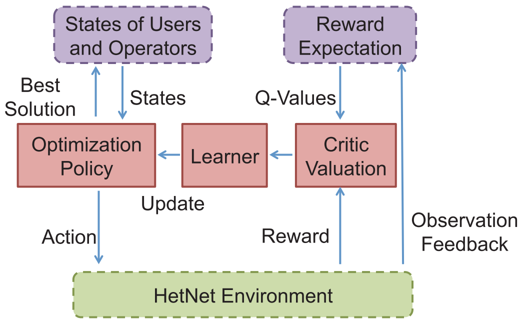

FIGURE 3. Illustration of learning-based optimization in HetNets.

Q-learning is a form of RL, which is a model-free RL technique to find an optimal Quality Value (Q-Value) of action-selection policy for any given (finite) Markov decision process [29]. And thus it can be utilized for most of the self-optimization objectives in HetNets, e.g., Q-learning based dynamical resource allocation with positioning information during carrier aggregation in semi-and uncoordinated deployment of HetNets in [30] and [31]. Also RL can facilitate the coordination-based context-aware mobility management [32], as well as the autonomous and adaptive reconfiguration management in HetNets efficiently, as researched in [16].

Due to the substantial amount of devices with various types in HetNets, interference management strategies in HetNets can benefit from distributed Q-learning as discussed in [33], where each cell reinforces the learning collaboratively with others, in order to achieve time-domain-adaptive enhanced inter-cell interference coordination. Similar interference optimization study with distributed self-organizing functions is also studied in [34]. Another similar approach is applied to improve spectral efficiency and energy efficiency of antenna tilting in HetNets in [35], where BSs do not need knowledge of location information. Also the study in [36] uses a regret-learning based algorithm to improve the interference coordination in closed-loop spatial multiplexing Multi-Input-Multi-Output HetNets, where cells jointly estimate own utility and learn strategies locally in a decentralized manner. Note that optimal solution cannot be always obtained by distributed methods, but near-optimal one can be achieved rapidly.

Fuzzy-reinforcement learning is one further step of RL techniques by integrating fuzzy state representations and fuzzy goals for uncertain environments in HetNets. Therefore, its target mostly falls into the optimization on dynamical resource management with SON-enabled fractional power control in HetNets [37]. The Fuzzy Q-learning can also be decentralized for HetNets, as studied in [38], which focuses on cross-layer interference mitigation in an OFDMA based HetNet deployment [39], [40]. By the comprehensive comparison among decentralized Q-learning, fuzzy Q-learning, improved Q-learning and expertness-based Q-learning methods, the study in [41] delves into the challenges of interference management solutions.

B. GENETIC ALGORITHMS

Among many popular evolutionary algorithms discovered and designed for optimizing complex systems, the Genetic Algorithm (GA) must be the representative one [42], [43]. The GA adopts the gene evolution procedure, including two main tasks, *crossover*, which facilitates the obtainment of optimal solution, and *mutation*, which prevents falling to regional optimal solutions. The offspring inherits the gene of superior chromosome in crossover operation, and eliminates poor chromosomes through competition. Fig. 4 illustrates the procedure using GA for HetNets.

Proved by years of studies, GA is efficient for solving problems where the potential solution scope is too high to be searched exhaustively in reasonable time, and it can appropriately converge to optimal (or suboptimal) results, in shorter

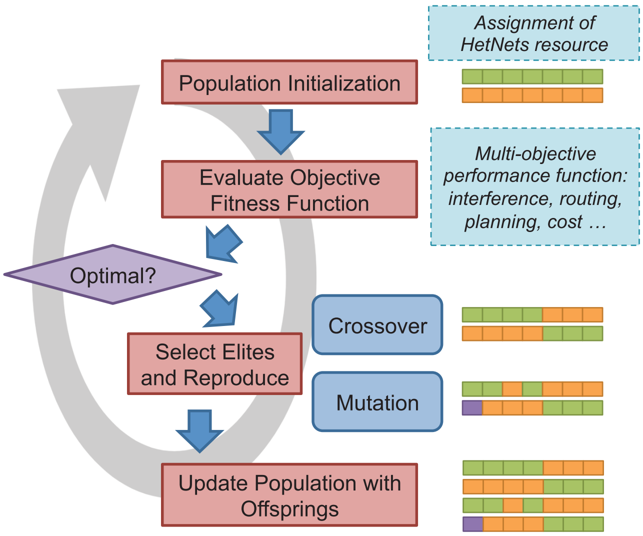

FIGURE 4. Illustration of GA optimization flow for HetNets.

time in most cases compared with other bio-inspired methods [44]–[46]. Particularly, GA can solve multi-objective optimization problems easily. Therefore, GAs are popularly used to facilitate HetNets, mostly focusing on the issues of cell planning and node placement optimization when a great number of parameters need to be evaluated.

For example, the study in [47] proposes a multi-objective GA to address a multi-objective communication nodes (e.g., antennas and relays) placement problem in HetNets, aiming at maximizing the communication coverage as well as the total capacity bandwidth, and minimizing the placement cost. By adaptively adjusting the pilot power, GA can be also used to evolve cell coverage optimization as studied in [10]. And the detailed research work in [48] presents a novel sequential GA to optimize the relaying topology in multi-hop HetNets with awareness of the intercell interference and the spatial traffic distribution dynamics, where the topologies are encoded as a set of chromosomes, and special crossover and mutation operations are proposed to search for the optimum topology.

C. SWARM INTELLIGENCE AND ANT COLONY

Ant colony optimization (ACO) is one popular algorithm of swarm intelligence [49]. In the ant colony, a huge amount of ants are discovering optimal routes to food based on previously accumulated but dismissing pheromones. Because of the similarity between networking systems and ant colony (an ant corresponding to a data packet, and a path corresponding to the networking route), ACO is widely discussed in studies on HetNets as an effective methodology for approaching the optimal performance [3] with regard to interference management, routing, and coverage [5], [50], as shown in Fig. 5.

For mitigating inter-cell and cross-tier interference coordination, the study in [51] explores ant colony optimization for dynamic sub-channel allocation by utilizing ACO for channel allocation. The study in [52] employs quantum particle swarm optimization (QPSO) to propose a sub-optimal energy-efficient user association scheme in HetNets where cells can be switched off (cell sleeping) along with the dynamic traffic load. ACO has automatic self-healing capability, and thus Li *et al.* [15] proposed an autonomic particle swarm compensation algorithm (APSCA) for cell outage compensation management scheme, in order to mitigate the performance degradation induced by the cell outage.

Network routing in HetNets can obtain huge gain of swarm intelligence due to their inherent path optimization strategies

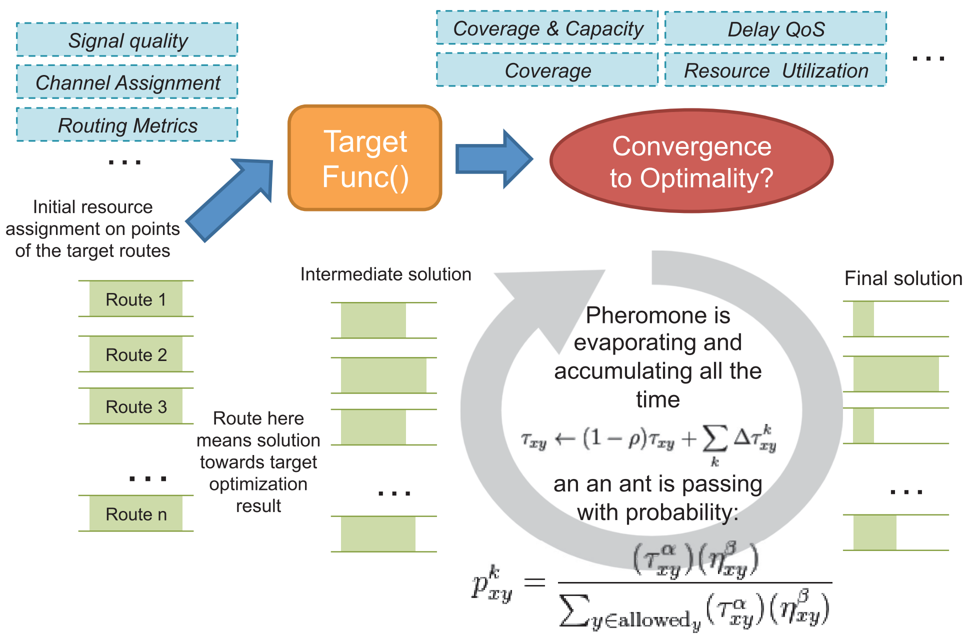

FIGURE 5. Illustration of ACO for HetNets.

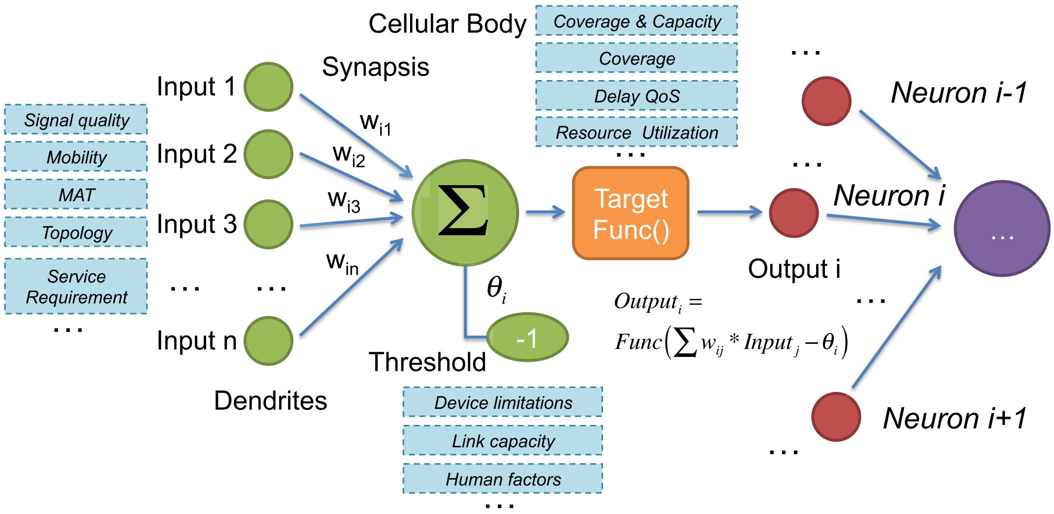

FIGURE 6. Illustration of artificial neural networks for HetNets.

of entities (i.e., ants) [53]. Most of the routing issues in HetNets take place in multi-hop transmissions where the ACO algorithm can address a multi-objective routing optimization problem that uses network performance measures such as delay, hop distance, load, cost and reliability [54].

The study in [55] uses ant colony algorithm to solve the problem of coverage optimization for dense deployment of small cell in HetNets by finding the optimal pilot transmit power of each small cell through the minimization of the cost function. Also for HetNets with huge amount of wireless sensors [56] the efficient-energy coverage problem requires and motivates the design of a novel ACO algorithm by using three types of pheromone (i.e., local pheromone to help an ant organize its coverage set with fewer sensors, and two global pheromone for optimizing the number of required active sensors per Point of Interest (PoI) and forming a sensor set that has as many sensors as an ant has selected the number of active sensors) to find the solution efficiently.

D. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are one type of statistical learning models inspired from the biological neural networks of human brains [57]. ANNs are generally presented as systems consisting of interconnected "neurons" within numerically weighted values which can be tuned for making ANNs adaptive to inputs and capable of learning [58]. Therefore, the neural network paradigm assures the ability to learn from the unsupervised environments, and thus exhibits an effectiveness in applying to HetNets for estimating or approximating functions that depend on many unknown input conditions [3]. Note that the functionality and working flow are shown in Fig. 6.

The study in [17] proposes self-optimization of antenna tilt and power by using a fuzzy neural network optimization method based on RL, which is one of the most important tasks in the context of SON and can meet the need of practical applications of self-optimization in a dynamic environment because of its rapid convergence. ANNs can be also utilized for addressing the vertical handoff problem for user QoS enhancement and HetNets system performance improvement as research in [23], which proposes an adaptive parameter adjustment algorithm based on neural network model by which user parameters can be determined optimally.

E. FUZZY SYSTEM

A fuzzy system is a control system based on fuzzy logic, which mathematically analyzes analog input values in terms of logical variables that take on continuous values between 0 and 1 [59]. Fuzzy logic is able to create rules by inferring knowledge from imprecise, uncertain, or unreliable information [60]. And hence it can rapidly help to make decisions for what action to take, based on a set of "rules" over great amount information of physical and systematical resources with varying conditions and characteristics in HetNets. How to utilize Fuzzy System for improving HetNets is illustrated in Fig. 7. Fuzzy system techniques are mostly extended for handoff decision algorithms with certain adaptability to specific network environments, e.g., the adaptive neuro-fuzzy based VHO decision algorithm in [24].

In HetNets with vehicular users, multi-parameters handoff decisions should be made adaptively to user speed [25], where the type-2 fuzzy logic contributes significantly by naturally handling more uncertainty in vehicular HetNets. Vertical handoff algorithm can balance the flow load by the proposal in [61] based on determining the optimal flow-dividing ratio of the traffic delivered in HetNets.

Fuzzy logic provides easy understanding over complicated HetNets and has been discussed for improving performance (e.g., load balancing, coverage optimization, and energy efficiency) in commercial LTE [62] and WiMAX networks [63], respectively. More specifically, the intercell-interference coordination in HetNets can be addressed by employing fuzzy logic controllers as studied in [64].

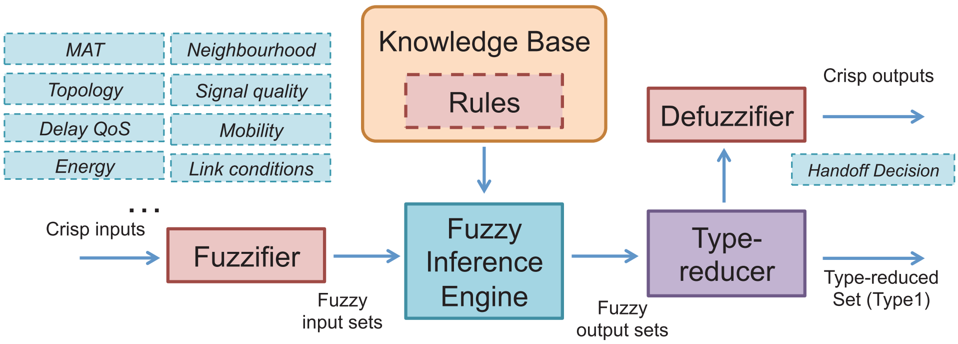

FIGURE 7. Illustration of fuzzy logic handoff in HetNets.

F. MARKOV MODELS AND BAYESIAN-BASED GAMES

Although Markov Models [65] and Bayesian Methods [66] are not exactly AI techniques, they still provide statistical solutions for HetNets with certain ability of automatic optimization. Along with the stochastically transitions among various states in Markov Models and the Bayesian-based learning, the localization and mobility issues in HetNets can be improved based on decision-tree based prediction.

Hidden Markov Models (HMM) are often used for modeling the signal strength history to achieve accurate localization as studied in [67]. Also the study in [68] proposes Preferred Route Indoor Mobility Model for indoor environments in HetNets, based on HMM as well to perform mobility modelling and learning. BS-cooperative power management with self-organized sleep mode in virtual cell-based HetNets [69] uses Semi-Markov stochastic process to derive detailed analytic formulas of average cumulative delay and interference time as well as the energy consumption.

The study in [70] formulates the network selection problem in HetNets with incomplete information as a Bayesian game and uses Bayesian Nash equilibrium as the solution by applying the Bayesian best response dynamics and aggregating best response dynamics. The study in [71] investigates the application of sparse Bayesian methods for anomaly detection in HetNets, and constructs a detection system, which can provide human interpretability. More complicated studies based on game theories can be referred to [72].

V. FUTURE CHALLENGES

The paradigm of mobile networks has been shifted from traditional centralized infrastructure to distributed and hierarchical HetNets with more autonomous, cooperated, and intelligent rollouts. In the near future, cells (base stations) are equipped with certain automated mechanisms, and hence can reposition themselves optimally corresponding to traffic dynamics, user demands, and physical environment interference conditions.

Although till now AI-based self-evolutionary techniques for HetNets have been researched a lot, it is not yet clear how and when will HetNets work towards realistic deployment. AI-based techniques for HetNets can be seen as an excellent opportunity for enhancements, and also introduce challenges as well. Hence, HetNets may induce significant technical problems and raise substantial challenges.

A. OPTIMIZATION ON VIRTUAL RESOURCE IN THE DATA CENTER FOR CLOUD-BASED HetNets

One essential direction of 5G evolution is the resource virtualization based on cloud computing techniques for elastic and dynamic resource allocation according to the ever changing service requirements [73], [74]. Not only RRHs will cooperate with the virtual resource of cloud-based RAN, but also in HetNets, much of the computation load of the computation-intensive tasks for radio access and processing will be offloaded to the centralized cloud in MNOs' data centers.

For instance, the proposal in [75] has introduced a concept of **cloud cooperated heterogeneous cellular network (C-HetNet)** where femtocell and picocell overlaid on a macrocell are connected to cloud radio access network (C-RAN) to operate cooperatively. Also, the study in [76] develops a theoretic computation framework of the deployment cost of the HetNets (modelled using various spatial point processes) to explore whether heterogeneous C-RAN is cost-effective. These frameworks offer potential research models for how to utilize AI algorithms to improvement virtualized HetNets.

The heterogeneity in terms of cell types and RRHs will allow the MNOs to further enhance the performance with respect to co-channel interference management, cell coverage, traffic engineering, routing optimization as well as mobility and handoff, by sufficiently utilizing the **collaborative resources on virtual machines** according to the user demands and link conditions. Due to the convenient obtaining of status of all cells (virtualized devices in the same data center), many learning-based and bio-inspired algorithms can be effectively utilized for multi-objective optimization over virtual resource, but yet have not been exploited.

B. UTILIZING THE INTELLIGENCE OF SOFTWARE-DEFINED NETWORKS IN 5G HetNets

The Software-Defined Network (SDN) technology [77] is one important enabler for the evolution of current networks towards the intelligent 5G HetNets [78]. It offers real-time packet reporting and re-activity functions of traffic flow characteristics, and thus has been bringing basic intelligence to the networks. In addition, SDN's fine-grained packet classifier and decoupling of control plane from data plane of network hardware can offer central controllability and powerful programmability to enable an intelligent carrier cloud environment by allocating networking resources for better consolidation of heterogeneous hardware resource with high interoperability, andresilience.

Therefore, based on SDN's inherent packet classifier for traffic recognition and real-time programmability, there is a large potential of designing appropriate methods and algorithms for network failure recovery (self-healing) to ensure services and resources availability. For example, the study in [79] aims to simplify authentication handover by global management of HetNets through sharing of user-dependent security context information among SDN-assisted related access points.

Bio-inspired algorithms like ACO and GA, which are often used for route optimization, can accelerate the **flow optimization along with the programability of SDN**, e.g., the study in [80] presents an OpenFlow-based load balancing system with the GA but it does not consider the heterogeneity and complexity of the emerging HetNets, and hence we can expect a huge performance improvement in the near future.

C. DISTRIBUTED EDGE INTELLIGENCE IN HetNets

Decentralizing current mobile network is not as easy as virtualizing computation load into the cloud data center, but moving services toward the network edge will be put to a priority [81]. The significance of this trend is twofold: 1) it reduces latency for users, and service providers can enjoy more revenue opportunities in HetNets, e.g., local content, localized radio resource management, and value-added data processing at network edge; 2) it can significantly reduce network congestion in the core network, which is increasingly a risk due to the proliferation of media-intensive applications. Furthermore, some critical challenges in the emerging HetNets, i.e., the coordination and management of various types of devices, must be resolved with decentralized methods, by which we expect more service functions and management decisions can be made locally at the involved devices, rather than always gathering and processing in the center modules.

One emerging technical issue of edge intelligence is the **Base Station Caching** [81], [82], by which most of the content delivery can be locally achieved by caching at the base stations of small cells. The preliminary study in [83] proposes a transfer learning-based caching scheme for small cell base stations in HetNets by exploiting the rich contextual information (i.e., users' content viewing history, social ties, etc.), which can be further extended by exploring means of state-of-art ML and bio-inspired techniques in the future.

Thus according to the dynamical user demands and high diversity of contents, how to carry out more effective learning-based caching strategies for exploiting the spatial and social structure of HetNets, and how to formulate collaborative BS caching among various cells in distributed manner, by borrowing creative ideas from nature cooperative evolution of living organism systems (e.g., cooperation of bees in their hive as illustrated in Fig. 8) become critical but challenging. Research on BS caching just started but it unveils a new stage of edge computing and service, where more needs to be discovered. Also, how to integrate cognitive radio techniques [84], [85] with SON (e.g., game-based, learning-based, bio-inspired ones) becomes a promising research topic for cognitive edge intelligence of HetNets in the near future [86], [87].

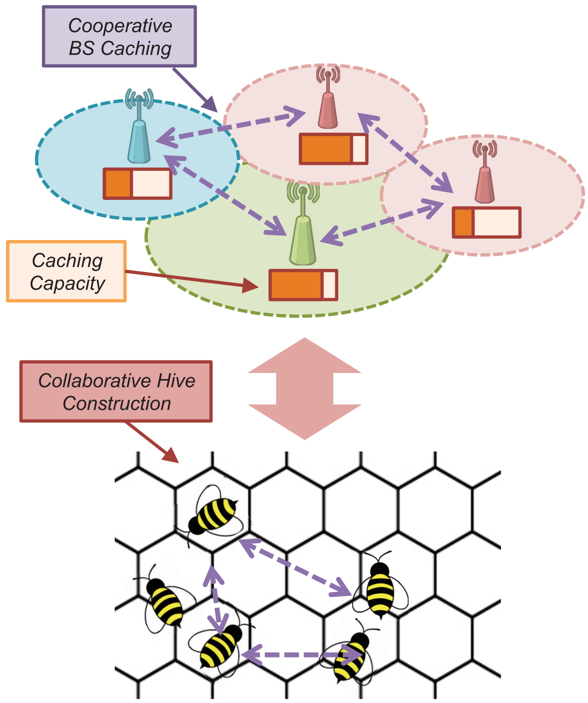

FIGURE 8. **Potential relationship between bee hive and BS caching.**

D. AI TECHNIQUES FOR MANAGING MACHINE-TO-MACHINE (M2M) COMMUNICATIONS AND INTERNET OF THINGS (IoT) IN HetNets

HetNets not only facilitate the mobile communication services of mobile users, but also integrate with the technology of **M2M Communications** [88] and **IoT** [89], which realize the information exchange among devices with intelligence, e.g., wireless sensors in body area networks, embedded smart devices in buildings, outdoor environments, and even traditionally difficult-to-reach locations. However, for supporting such an extremely large number of embedded devices, conventional networking approaches seem unsuitable for scenarios of high heterogeneity, scalability and complexity [90]. It is expected to induce natural AI-based techniques to control and optimize the collaboration of sensors and to provide stable operations and service management functionalities in fully distributed manner.

Bio-ecosystems naturally run over huge amount of entities, and thus bio-inspired techniques can deal with HetNets with

M2M and IoT inherently. For instance, a new bio-inspired approach, BIONETS [91], is proposed to enhance the system performance in terms of scalability, robustness and efficiency based on bio-inspired management. So the challenge is to treat the whole HetNets as a living ecosystem, where the functions, modules and services play the role of organisms, evolving and combining themselves to successfully adapt to the dynamic environment (e.g., user demands, network conditions etc.) [56]. Future research and development on HetNets technologies must address new requirements from M2M and IoT services, by adopting effective management and optimization techniques inspired from bio-ecosystems, e.g., GA and ACO of swarm intelligence [92].

VI. CONCLUSION

The emerging HetNets will be characterised by a higher degree of capillarity, density and higher bit rates. By integrating AI-based SON features, HetNets may have high potential to significantly boost the mobile service performance. Most of the contributions are from adaptive spectrum reutilisation, high automatic-ability on system development, and the evolutive optimization of systems, as well as the effectiveness of the system fault-tolerance.

Through this survey and analysis, AI-based techniques are discussed and proved to be able to acclimatize and be competent for the smart improvement of HetNets by the self-"X" features. Furthermore, throughout the taxonomy, we have identified their major advantages as well as their technical challenges and research problems. Particularly, interesting opening research issues include AI-based auto-optimization on virtualized resource integrated with SDN, M2M and IoT.

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XIAOFEI WANG (S'06–M'13) received the B.S. degree from the Department of Computer Science and Technology, Huazhong University of Science and Technology, in 2005, and the M.S. and Ph.D. degrees from the School of Computer Science and Engineering, Seoul National University, in 2008 and 2013, respectively. He is currently a Post-Doctoral Research Fellow with the Department of Electrical and Computer Engineering, The University of British Columbia. His current research interests are social-aware multimedia service in cloud computing, cooperative backhaul caching, and traffic offloading in mobile content-centric networks. He was a recipient of the Korean Government Scholarship for Excellent Foreign Students in the IT field from NIPA from 2008 to 2011. He received the Global Outstanding Chinese Ph.D. Student Award in 2012.

XIUHUA LI (S'12) received the B.S. and M.S. degrees from the Honors School and the School of Electronics and Information Engineering, Harbin Institute of Technology, in 2011 and 2013, respectively. He is currently pursuing the Ph.D. degree with the Department of Electrical and Computer Engineering, The University of British Columbia. His current research interests are resource allocation, optimization, distributed antenna systems, cooperative backhaul caching, and traffic offloading in mobile content-centric networks.

VICTOR C. M. LEUNG (S'75–M'89–SM'97–F'03) received the B.A.Sc. (Hons.) and Ph.D. degrees in electrical engineering from The University of British Columbia (UBC), in 1977 and 1981, respectively. He attended the Graduate School, UBC, on a Natural Sciences and Engineering Research Council Post-Graduate Scholarship. He received the APEBC Gold Medal as the Head of the Graduating Class in the Faculty of Applied Science.

He was a Senior Member of the Technical Staff and Satellite System Specialist with MPR Teltech Ltd., Canada, from 1981 to 1987. In 1988, he was a Lecturer with the Department of Electronics, Chinese University of Hong Kong. He returned to UBC as a Faculty Member in 1989, where he is currently a Professor and the TELUS Mobility Research Chair in Advanced Telecommunications Engineering with the Department of Electrical and Computer Engineering. He has co-authored over 800 technical papers in international journals and conference proceedings, 31 book chapters, and co-edited ten book titles. His research interests are in the areas of wireless networks and mobile systems. Several of his papers had been selected for best paper awards.

Dr. Leung is a fellow of the Royal Society of Canada, the Engineering Institute of Canada, and the Canadian Academy of Engineering. He was a recipient of the IEEE Vancouver Section Centennial Award and the 2012 UBC Killam Research Prize. He is a Registered Professional Engineer in the province of British Columbia, Canada. He was a Distinguished Lecturer of the IEEE Communications Society. He is a member of the Editorial Boards of the IEEE Journal on Selected Areas in Communications—Series on Green Communications and Networking, the IEEE Wireless Communications Letters, *Computer Communications*, and several other journals. He has served on the Editorial Boards of the IEEE Journal on Selected Areas in Communications—Wireless Communications series, the IEEE Transactions on Wireless Communications, the IEEE Transactions on Vehicular Technology, the IEEE Transactions on Computers, and the *Journal of Communications and Networks*. He has guest-edited many journal special issues, and contributed to the organizing committees and technical program committees of numerous conferences and workshops.