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Non-Orthogonal Radio Resource Management for RF Energy Harvested 5G Networks

MEHAK BASHARAT[1], MUHAMMAD NAEEM[1,2], WALEED EJAZ[3], (Senior Member, IEEE), ASAD MASOOD KHATTAK[4], ALAGAN ANPALAGAN[1], OMAR ALFANDI[4], AND HYUNG SEOK KIM[5], (Member, IEEE)

[1]Department of Electrical and Computer Engineering, Ryerson University, Toronto, ON M5B 2K3, Canada
[2]COMSATS Institute of Information Technology, Wah Campus, Wah Cantonment 47040, Pakistan
[3]Department of Applied Science & Engineering, Thompson Rivers University, Kamloops, BC V2C 0C8, Canada
[4]College of Technological Innovation, Zayed University, Abu Dhabi 144534, United Arab Emirates
[5]Department of Information and Communication Engineering, Sejong University, Seoul 100083, South Korea

Corresponding author: Hyung Seok Kim (hyungkim@sejong.ac.kr)

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ABSTRACT Fifth generation (5G) networks are expected to support a large number of devices, provide spectral efficiency and energy efficiency. Non-orthogonal multiple access (NOMA) has been recently investigated to accommodate a large number of devices as well as spectral efficiency. On the other hand, energy efficiency in 5G networks can be addressed using energy harvesting. In this paper, we investigate NOMA in 5G networks with RF energy harvesting to maximize the number of admitted users as well as system throughput. We model a mathematical framework to optimize user grouping, power allocation, and time allocation for information transfer and energy harvesting while satisfying the minimum data rate and transmit power requirements of users. The proposed framework for optimization is a mixed integer non-linear programming problem. The mesh adaptive direct search (MADS) algorithm is adopted to find solution of the proposed framework. The MADS algorithm provides an epsilon optimal solution. The exhaustive search algorithm is used as a bench mark. Finally, the effectiveness of the proposed framework is supported by simulation results.

INDEX TERMS 5G networks, energy harvesting, non-orthogonal multiple access (NOMA), power allocation, time allocation, user grouping.

I. INTRODUCTION

Fifth generation (5G) networks are anticipated to support exponential increase in mobile traffic, significant reduction in latency, diverse range of applications, and massively connected devices [1]. In addition, 5G networks are expected to be energy-efficient and cost effective. Industrial assessment insist that in 5G networks, the data rate should be 10-20 times more than the peak data rate in 4G [2]. With extensive research in this direction, 5G networks are envisioned to meet the targets for next generation wireless networks by 2020 and beyond [3]. However, there are certain challenges associated with the successful deployment of 5G systems. For example, more spectrum is required in order to increase capacity or efficient utilization of spectrum must be ensured by using unlicensed bands (e.g., LTE-Unlicensed, use of TV white space through cognitive radio technologies) [4]. Furthermore, spectrum should be reused by deploying small cells or by accommodating multiple users on the same frequency channel. Fig. 1 shows key technologies for 5G networks for spectrum management (e.g., non-orthogonal multiple access (NOMA) [5]–[7], full duplex [8], spectrum sharing [9]–[11], and new waveform [12]), infrastructure (e.g., cloud-radio access network [13] and software-defined networks [14]). In addition, joint spectrum and energy efficient design, multi-radio access network, and flexible and efficient physical layer can certainly enhance the performance of 5G networks [15], [16].

Channel access techniques play a pivotal role in providing effective communication to mobile users in

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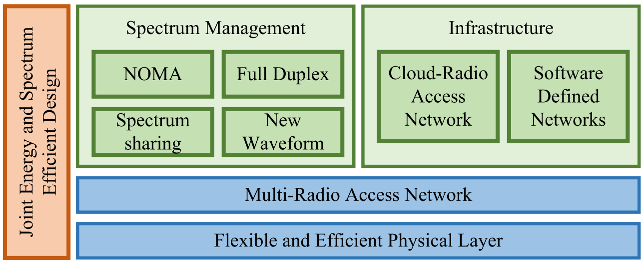

FIGURE 1. Key technologies for 5G networks.

wireless networks. For example, orthogonal frequency division multiple access (OFDMA) proved to be beneficial in 4G wireless networks. However, number of resource blocks put a constraint on the maximum number of users supported [7]. Recently, NOMA is investigated to fulfill spectrum demands of 5G networks [5]. In contrast to OFDMA, NOMA allows multiple users on the same resource block in the same cell while exploiting channel gain differences of multiple users. At receiver, successive interference cancellation (SIC) is used for decoding message signals [6]. Although NOMA provides high spectral efficiency and better connectivity at the cost of increased receiver complexity [7].

On the other hand, energy harvesting is considered as a promising solution to address the energy issues in 5G networks. The idea of energy harvesting is to gather energy from sources present in the surrounding including RF signals, solar, and wind [17]. In RF energy harvesting, users can harvest from ambient RF sources such as base station signals. Thus, allocation of time for information transfer along with energy harvesting has attracted attention of many researchers [18]. For example, Nasir *et al.* [19] have implemented a energy harvesting relay which is based on time switching and power splitting relaying. Diamantoulakis *et al.* [20] investigated time allocation methods with NOMA in uplink communication system to improve the throughput of all users. Another approach executed by Liu *et al.* [21] to prepare energy harvesting relays from NOMA users located near the base stations in order to help the users that are at a distance.

There are certain challenges associated with the NOMA in 5G including dynamic user grouping, power allocation and time allocation for energy harvesting [7]. Since in NOMA, multiple users can use the same resources simultaneously. Hence, to reduce co-channel interference the users can be divided into groups and NOMA is applied to each group. The user grouping along with power allocation when done efficiently can reduce the effect of interference and increase spectral efficiency [22]. However, 5G also constitute energy efficiency challenges because of the increase in number of wireless devices. Therefore, it is important to investigate dynamic user grouping, power allocation and time allocation jointly for NOMA with RF energy harvesting. Until now, researchers investigated either user grouping or time allocation for information transfer and energy harvesting, in NOMA systems.

A. CONTRIBUTIONS

This paper focuses on developing user grouping and power as well as time allocation for NOMA systems with RF energy harvesting. Following are the main contributions of this paper:

- We mathematically model a framework for NOMA with energy harvesting capability. The mathematical model includes grouping of users in their respective resource blocks, an optimized power, and time allocation to achieve maximum system throughput.
- The proposed mathematical model ensures the minimum throughput of each admitted user and optimal user power in each resource block.
- The proposed mathematical framework belongs to a type of optimization problem, called mixed integer non-linear programming (MINLP) and this type of problems are generally NP-hard. To get optimal solution, we need to enumerate all possible assignments of users in their respective resource blocks which is computationally very expensive. Moreover, computational complexity increases exponentially with the number of users and resource blocks. Thus, we adopted mesh adaptive direct search (MADS) algorithm which provides epsilon optimal solution.
- Finally, we evaluate the performance of joint user grouping, power allocation and time allocation for NOMA with RF energy harvesting using MADS algorithm. Simulation results using MADS algorithm are compared with the optimal solution obtained by exhaustive search algorithm (ESA).

The organization of remaining paper is as follows. Section II briefly reviews related works. System model and problem formulation is presented in Section III. Then, we present ESA and MADS algorithms in Section IV. Simulation results are presented in Section V. Finally, conclusion is drawn in Section VI.

II. RELATED WORKS

Here, we briefly review the related working in the area of user grouping and power as well as time allocation for energy harvesting in NOMA systems.

A. USER GROUPING AND POWER ALLOCATION IN NOMA

Ali *et al.* [6], authors maximized cell throughput while satisfying uplink and downlink transmission power. Authors proposed a two step methodology that comprises of user grouping followed by optimized power allocation for each group. Ali *et al.* [22] proposed a dynamic user grouping and power allocation for NOMA with SIC in downlink MIMO cellular systems. The objective is to maximize overall cell capacity subject to the constraints on transmit power, data rate requirement, and received power. For both [6], [22], simulation results are presented to highlight the advantages of NOMA in terms of spectrum efficiency. A joint subcarrier and power allocation scheme with an objective to maximize energy efficiency is proposed for heterogeneous network with one macro base station and multiple small base stations [23]. Authors applied an optimal approach based on monotonic optimization. The objective of this work (maximizing energy efficiency) is different compared to our work (maximizing number of admitted users and system throughput). Zhang *et al.* [24] proposed a user grouping scheme based on their location to minimize interference in visible light communication based 5G network. Further, authors optimized power allocation for each cell to maximize sum rate subject to the constraint on quality of service (QoS). A multi-user grouping with low-complexity and a power allocation scheme is presented in [25] to enhance the performance of group users. It is concluded that for the proposed scheme there exists a trade-off between computational complexity and user fairness. Wang *et al.* [26] proposed a cooperative game theoretic approach for user grouping in order to enhance sum rate. This scheme divides the users into several groups and then assigns the time slots to each group resulting in notable improvement in sum rate. Al-Abbasi and So *et al.* [27] formulated a problem for sum rate maximization over frequency selective fading channel by pairing users corresponding to their channel powers. In addition, a divide-and-allocate approach is proposed for power allocation where users are divided in two groups to apply closed form power allocation solution and this process continues until power is allocated to all users. In [28], a user grouping scheme is proposed for downlink NOMA while considering the channel correlation between users and the channel gain. Further, precoding matrix is optimized to maximize the sum-rate. Yakou and Higuchi [29] proposed a user grouping scheme and decoding order setting in SIC for downlink NOMA. The objective is to schedule multiple users per resource block optimally. The proposed scheme offers low complexity for the SIC process as the number of decoding signals are equal to the number of users in each group. However, achievable throughput is also decreased, because the proposed scheme considers instantaneous fading conditions during user grouping process.

B. ENERGY HARVESTING AND WIRELESS POWER TRANSFER IN NOMA

A survey of cognitive networks with NOMA is presented in [30], where energy harvesting is highlighted as an important technique to maximize energy-transfer efficiency. Yang *et al.* [31] have considered a cooperative NOMA network in which energy harvesting relay is utilized as a medium of communication between users. Fixed power allocation NOMA and cognitive radio based NOMA are studied for their impact on simultaneous information and power transfer. It is concluded that two NOMA power allocation policies have trade-off among reliability, user fairness, and system complexity. Authors in [32] have proposed two cooperative spectrum sharing algorithms while utilizing the concept of both time-switching and power-splitting based energy harvesting. A set of secondary transmitters which are energy constrained are dependent on energy harvesting. The secondary transmitter acts as a relay to forward primary user symbol and also get access to channel according to the concept of NOMA simultaneously with a primary user. Authors studied optimal energy harvesting ratio that maximizes the sum data rate of both protocols. Sun *et al.* [33] considered an energy harvesting-based cooperative NOMA. It is considered that the link between source node and weaker node is not able to satisfy the QoS requirements. Therefore, the stronger node acts as an energy harvesting relay for the weaker node as it has prior knowledge about it based on the NOMA approach. The objective is to maximize rate subject to the constraints on QoS and power. A NOMA scheme for the uplink of wireless powered communication networks is proposed in [34]. Authors jointly optimize transmit power of base station and duration of energy harvesting/data transfer to maximize the rate region. The proposed approach achieved higher data rates compared to fixed power NOMA in addition to keeping the high level of fairness. Diamantoulakis *et al.* [35] have investigated wireless power transfer with NOMA in order to optimize data rate and increase fairness. Liu *et al.* [21], [36], authors have investigated a NOMA with wireless power transfer. A protocol is designed in a way that the NOMA users in the vicinity of source act as a energy harvesting relays to charge users at distance. NOMA users which are close to the source act as energy harvesting relays to provide power to users at distance. Authors proposed three user selection schemes while considering users distance from the base station and compared their results in terms of outage probability and throughput. Zhou *et al.* [37] proposed a secure cognitive beamforming with an objective to minimize power for cooperative multiple-input single-output (MISO)-NOMA using wireless power transfer. A non-linear energy harvesting model is used for analysis. Same model is used by Zhou *et al.* [38] to propose resource allocation with an objective to minimize total transmit power for secure MISO-NOMA based on artificial noise-aided cooperative jamming scheme. The non-linear energy harvesting model is more practical. However, we consider linear energy harvesting model which is vastly investigated in literature as the focus of our work is resource allocation (joint user grouping, power allocation, and time allocation). An enhancement in physical layer security for power minimization in MISO-NOMA using wireless power transfer is presented in [39]. To be precise, none of the above schemes considered user grouping in addition to energy harvesting.

Table 1 presents a summary of existing user grouping schemes. However, it is evident that existing schemes do not consider joint user grouping and power as well as time allocation for NOMA to improve the performance of 5G networks. Unlike these works, we propose a mathematical framework to optimize user grouping, power allocation, and time allocation for NOMA with RF energy harvesting.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. NETWORK MODEL

NOMA is one of the technologies considered for channel access in 5G and beyond networks. The 5G architecture consists of multiple networks with different number of

TABLE 1. Related work on NOMA with wireless power transfer.

Ref.	Year	Objective	U [a]	E [b]	P [c]	Solution	Remarks
[6]	2016	Uplink and downlink sum rate maximization	✓		✓	Closed form optimal solutions are derived	Throughput is maximized while satisfying constraint on power transmit.
[22]	2017	Downlink sum rate maximization	✓		✓	Low-complexity user clustering algorithm	A dynamic user grouping and power allocation for NOMA with successive interference cancellation is proposed.
[23]	2018	Efficient resource allocation		✓	✓	Monotonic optimization	A joint subscribber and power allocation scheme is proposed.
[24]	2017	Sum rate maximization	✓		✓	MATLAB standard solver	A user grouping scheme is proposed based on their location to minimize interference.
[25]	2016	Spectral efficiency	✓		✓	Multi-user grouping scheme	The proposed scheme reduces the computational complexity compared to full search method.
[26]	2016	Sum rate maximization	✓			Preference relation and sequence game algorithms	A cooperative game theoretic approach is adopted for user grouping in order to enhance sum rate.
[27]	2016	Sum rate maximization	✓		✓	Proposed divide and allocate approach	A sub-optimal power allocation scheme is proposed user grouping in NOMA.
[28]	2015	Sum-rate maximization	✓			Proposed majorization minimization approach for a non-convex objective	A user grouping scheme is proposed for downlink NOMA while considering the channel correlation between users and the channel gain.
[29]	2015	Optimal user scheduling	✓			Proposed decoding order in SIC method	A user grouping scheme in NOMA is presented.
[31]	2017	Outage probability		✓	✓	Closed form expressions are derived	A cooperative NOMA network is considered in which energy harvesting relay is utilized as a medium of communication between users.
[32]	2017	Sum data rate		✓	✓	Proposed protocols using time-sharing and power splitting based energy harvesting	Authors have proposed two cooperative spectrum sharing algorithms for secondry user selection and NOMA.
[33]	2016	Sum rate		✓		Proposed iterative approach	An energy harvesting-based cooperative NOMA system is presented.
[34]	2016	Data rate		✓	✓	Root of transcendental equation	A NOMA based scheme is proposed for wireless power transfer enabled networks.
[35]	2016	Sum rates optimization		✓		Linear programming methods or convex optimization	Data rate is optimized and fairness is increased in a wireless power transfer enabled network with NOMA.
[21]	2016	outage probability		✓		Closed-form expressions are derived	Authors studied NOMA with wireless power transfer.
[37]	2018	Minimize power		✓		Proposed algorithms using semidefinite relaxation or a cost function	A secure cognitive beam-forming is proposed for NOMA using wireless power transfer.
[38]	2018	Minimize total transmit power		✓		Suboptimal scheme is proposed	A resource allocation scheme for secure NOMA is presented.
[39]	2018	Power minimization		✓		Proposed algorithms using semidefinite relaxation and successive convex approximation	An enhancement in physical layer security of MISO-NOMA using wireless power transfer is presented.
Our work	2018	Maximization of admitted users and throughput	✓	✓	✓	MADS algorithm	We investigate joint user grouping and power as well as time allocation for NOMA with RF energy harvesting.

[a](U)ser grouping.
[b](E)nergy harvesting.
[c](P)ower allocation.

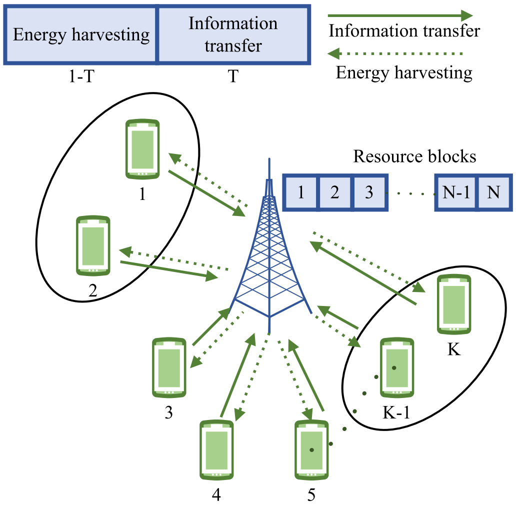

FIGURE 2. An illustration of network that consists of K users and N resource blocks for NOMA with RF energy harvesting.

available resource blocks. However, for the sake of simplicity and analysis, we assume a network that consists of K users and N resource blocks in one cell as shown in Fig. 2. It is assumed the number of users is greater than the number of resource blocks, i.e., $K > N$. We assume that each frame with length one is divided into two time slots [35]. In the first time slot, the base station transmit power beacon to the users such that the users can harvest energy for uplink transmission. This is mainly because we consider that each user is equipped with a single antenna. Thus, each user can only transmit or harvest at a particular time [17], [40]. The amount of time for energy harvesting is set to $1-T$ and time for information transfer is set to T such that $0 \leq T \leq 1$. It is challenging to associate resource block to the users and determine the time sharing between energy harvesting and information transfer such that their required rate is satisfied. Therefore, we use NOMA to accommodate K users in N resource blocks while satisfying user rate requirements. Let g_k, and η be the channel power gain of the *k-th* user to the base station and energy harvesting efficiency, respectively. It is important to note that η is considered constant for all users for the sake of illustration. The structure of the proposed mathematical model will not change by using different values of η for each user. The channel power gain is $g_k = |h_k|^2$, where h_k is the amplitude channel gain. We consider amplitude of channel gain h_k as Rayleigh distribution in our system model.

We assume that the total energy harvested in $1-T$ duration for the *k-th* user is the energy that is used for transmission in time T. Let P_{BS} be the amount of base station transmission power at the first time slot then the harvested energy by the *k-th* user will be $E_k = \eta g_k P_{BS}(1-T)$. Then, the uplink transmit power of the *k-th* user is

$$P_k = \frac{E_k}{T} = \Delta g_k \eta P_{BS}, \tag{1}$$

where $\Delta = \frac{1-T}{T}$ and E_k is the energy harvested by the *k-th* user.

The base station will use SIC for decoding. Rate of each user depends on its decoding order. We assume that users are sorted according to their channels such that $g_1 > g_2 \ldots\ldots > g_k$. Let there be only one resource block and K users then the rate for first user will be

$$R_1 = T \log_2\left(1 + \frac{P_1 g_1}{N_0 + \sum_{i=2}^{K} P_i g_i}\right), \tag{2}$$

where N_0 is the noise spectral density. It can be written as (See Appendix **??** for details):

$$R_1 = T \log_2\left(1 + \frac{\Delta\rho g_1^2}{1 + \Delta\rho \sum_{i=2}^{K} g_i^2}\right), \tag{3}$$

The rate for *k-th* user can be written as,

$$R_k = T \log_2\left(1 + \frac{\Delta\rho g_k^2}{1 + \Delta\rho \sum_{i=k+1}^{K} g_i^2}\right), \tag{4}$$

where $\rho = \frac{\eta P_{BS}}{N_0}$. It is evident from (2) and (4) that the user 1 will face interference from all other $K-1$ users. The *k-th* user will perform SIC to cancel interference from *K-k* users and so on. For example, if we have three users than user 1 will perform SIC to cancel interference from users 2 and 3. While user 2 will perform SIC to cancel interference from user 3. On the other hand, user 3 will not cancel interference from users 1 and 2, although user 3 will be interfered by them [6]. Thus, the rate of user K can be written as

$$R_K = T \log_2\left(1 + \Delta\rho g_K^2\right). \tag{5}$$

A detailed list of symbols and their description is provided in Table 2.

TABLE 2. Symbols and their description used in the model.

Symbol	Description
K	Number of users
N	Number of resource blocks
T	Sharing time of the resource block
P_{BS}	Power of the Base station
P_k	Uplink transmit power of the *k-th* user
R_k	Data rate of *k-th* user
R_{min}	Minimum data rate of each user
g_k	Channel gain for *k-th* user
η	Energy harvesting efficiency
x_r^k	Usage of *k-th* user for *r-th* resource block
y_k	User selection
Ψ_i	Set of finite points where the objective function is to be evaluated
P_{BS}^{MAX}	Maximum base station power

B. PROBLEM FORMULATION

In this paper, the goal is to maximize both the number of admitted users and system throughput. It is important to note that total throughput can be maximized without considering the minimum data rate requirement of individual users. Thus, there must be a constraint on minimum data rate requirement of individual users. An individual user can use *r-th* resource block for data transmission. We define a binary indicator function x_r^k that defines usage of *k-th* user for *r-th* resource block. $x_r^k = 1$ in case, when *k-th* user is using *r-th* resource block and 0 otherwise. This can be represented as:

$$x_r^k = \begin{cases} 1, & \text{if } k\text{-}th \text{ user is using } r\text{-}th \text{ resource block} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

The individual user can either selected for data transmission or not. A binary indicator function y_k defines user selection where $y_k = 1$ when *k-th* user is selected and 0 otherwise. This can be written as:

$$y_k = \begin{cases} 1, & \text{if } k\text{-}th \text{ user is selected} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

The objective is to maximize both admitted users and the data rate by optimizing the X, Y, T_r, and $P_{BS,r}$, where X is the assignment matrix which consists of x_r^k $\forall$ k and r, Y is the user selection vector that consists of y_k $\forall$ k, T_r is the time sharing in each resource block, and $P_{BS,r}$ is the power in each resource block. The data rate of each user must meet a minimum data rate requirement, i.e., R_k^{min} in order to meet QoS requirements. However, practically it may not be possible to meet rate requirement due to transmit power constraint. In this paper, we maximize system throughput and number of admitted users by dynamic user grouping, power allocation, and time allocation while satisfying constraints on user throughput and power in each resource block. The data rate maximization problem for NOMA with RF energy harvesting can be stated as follows:

Given:

- Total number of users (K)
- Total number of resource blocks (N)
- Minimum QoS requirement of *k-th* user (R_k^{min})
- Maximum base station power P_{BS}^{MAX}

Objective:

- Maximize both number of admitted users and system throughput

Determine:

- Assignment matrix X
- User selection vector Y
- Time sharing for all *r-th* resource blocks T_r
- Power in *r-th* resource block $P_{BS,r}$

The utility function for the proposed framework for NOMA with RF energy harvesting can be formulated as in (8), as shown at the bottom of this page. The data rate maximization problem can be formulated as:

$$\begin{aligned}
&\max_{X,Y,T_r,P_{BS,r}} : U, \\
&\text{Subject to } C1: \underbrace{\sum_{r=1}^{N} x_r^k \leq 1, \forall k}_{\text{User resource block assignment}} \\
&C2: \underbrace{\sum_{r=1}^{N} T \log_2\left(1+\frac{x_r^k \Delta_r \rho_r g_k^2}{1+\Delta_r \rho_r \sum_{i=k+1}^{K} x_r^i g_i^2}\right) \geq y_k R_{min}, \forall k}_{\text{Rate constraint of selected user}} \\
&C3: \underbrace{\sum_{r=1}^{N} P_{BS,r} \leq P_{BS}^{MAX},}_{\text{Power budget constraint}} \\
&C4: \underbrace{x_r^k \leq y_k, \forall k, r,}_{\text{User assignment/ selection couple constraint}} \\
&C5: y_k \in \{0,1\}, \quad x_r^k \in \{0,1\}, \; T \in [0,1], \\
&\qquad P_{BS,r} \geq 0, \quad \forall k, r
\end{aligned} \tag{9}$$

where C1 ensures one user cannot use more than one resource block, C2 guarantees minimum data rate requirement of selected user for all resource blocks, where $\Delta_r = \frac{1-T_r}{T_r}$, C3 ensures power of base station should be less than maximum power for all resource blocks, C4 assures that x_r^k should be zero if the *k-th* user is not selected.

The problem in (9) is a mixed integer non-linear programming problem (MINLP) since both utility function and constraints have logarithmic terms. Moreover, due to discrete variables this problem is non-convex. Thus, the problem in (9) is MINLP, such problems are generally NP-hard. In order to get optimal solution, we need to compute all possible combinations of users assignment in their respective resource blocks. However, the complexity in this case increases with the increase in number of users and/or resource blocks. Therefore, in this paper we adopted mesh adaptive direct search (MADS) algorithm which is computationally efficient and provides epsilon optimal solution.

IV. SOLUTION APPROACHES

We use two approaches to solve the problem given in (9): 1) optimal solution using exhaustive search algorithm (ESA) and 2) MADS algorithm. We now describe the detailed operations of both approaches.

$$U = \left[\overbrace{\sum_{r=1}^{N}\sum_{k=1}^{K} \underbrace{y_k}_{\text{Admission control}} \underbrace{T_r}_{\text{Time sharing}} \underbrace{\log_2\left(1+\frac{x_r^k \Delta_r \rho_r g_k^2}{1+\Delta_r \rho_r \sum_{i=k+1}^{K} x_r^i g_i^2}\right)}_{\text{Rate}}}^{\text{Rate of network}} \right] \tag{8}$$

Algorithm 1 Dynamic User Grouping, Time Allocation, and Power Allocation Using Exhaustive Search Algorithm

Initialization:
$K \leftarrow$ Number of users
$N \leftarrow$ Number of resource blocks
$R_{min} \leftarrow$ Minimum rate requirement
$D \leftarrow K + K \times N$ // Number of discrete variables
BestSolution $\leftarrow 0$
for i=1 to 2^D **do**
  Z$\left[x_1^1, \cdots, x_B^K, y_1, \cdots, y_K\right] \leftarrow$ getbinary(i)
  $X \leftarrow$ getx(Z) // Association matrix
  $Y \leftarrow$ gety(Z) // User selection
  Isfeasible=IsXandYFeasible(X,Y)
  if Isfeasible==1 **then**
    Solution $\leftarrow$ Apply NLP to the optimization problem in (9) with known x and y
    if Solution $\geq$ BestSolution **then**
      BestSolution=Solution
  end if
end for
Output: BestSolution

Algorithm 2 IsXandYFeasible(x,y)

Isfeasible=0
if $\sum_{k=1}^{K} y_k == 0$ **then**
  return Isfeasible
end if
for k=1 to K **do**
  if $y_k == 0$ && $\sum_{r=1}^{N} x_r^k > 0$ **then**
    return Isfeasible
  else if $y_k == 1$ && $\sum_{r=1}^{N} x_r^k == 0$ **then**
    return Isfeasible
  end if
end for
Isfeasible=1
return Isfeasible

A. OPTIMAL SOLUTION

In this section, we will provide details of optimal solution obtained using ESA to solve (9). The steps of the ESA are shown in Algorithm 1. This method enumerates all possible combinations of X and Y. Hence, we achieve the optimal solution, however, at the cost of computational complexity.

The algorithm takes number of users (K), number of resource blocks (N), minimum data rate requirement (R_{min}) as an input. We initialized parameter D as number of discrete variables which is equal to $K + K \times N$ and initial best solution as 0, i.e., we are looking for the best solution. During the execution phase, which runs for 2^D iterations all values of X and Y are evaluated to find best solution for (9). In each iteration, a binary vector is initiated and corresponding values are saved in Z. In the next steps, the functions *getx* and *gety* extract the association matrix X and user selection vector Y from the Z and stores corresponding values in X and Y, respectively. Then, we check the feasibility of X and Y to avoid evaluation of objective function using infeasible solution. The pseudo code to check feasibility of X and Y is given in Algorithm 2. X and Y will produce infeasible solutions if 1) no user is selected, or 2) *k-th* user is not selected and its corresponding assignment variables are non-zero, or 3) *k-th* user is selected and none of its corresponding variable are non-zero. For better understanding, let $K = 3$ and $N = 2$ which results in $D = 9$ discrete variables, i.e., $\{x_1^1\ x_1^2\ x_1^3\ x_2^1\ x_2^2\ x_2^3\ y_1\ y_2\ y_3\}$. Then the vectors $X = \{x_1^1\ x_1^2\ x_1^3\ x_2^1\ x_2^2\ x_2^3\}$ and $Y = \{y_1\ y_2\ y_3\}$. Now X and Y will be infeasible solutions if 1) Y=[0 0 0] or 2) X=[1 1 0 0 0 0] and Y=[1 0 0] (user 2 is not selected but its corresponding assignment variable $x_1^2 = 1$, or 3) X=[0 1 0 0 0 0] and Y=[1 0 0] (user 1 is selected but none of its corresponding variable is non-zero).

If the X and Y are feasible then we apply non-linear programing (NLP) (we used solver of optimization toolbox of MATLAB) to the optimization problem in (9) with feasible x_r^k and y_k. Then we will update BestSolution if the solution obtained is better than the one in previous iteration. Finally, at the end of 2^D iterations, the output of the algorithm is BestSolution which represents the optimal solution of problem in (9).

B. MESH ADAPTIVE DIRECT SEARCH ALGORITHM

We adopted mesh adaptive direct search (MADS) algorithm to obtain the sub-optimal solution of problem given in (9) [41], [42]. The MADS algorithm is usually a solution for non-linear optimization problems. The MADS is an extended version of generalized pattern search (GPS) based on polling mechanism. Polling is the local scrutiny of objective function in the space of optimization variables. The MADS is a derivative free procedure and iterative in nature, where *i-th* iteration consists of two steps, i.e., *searching* and *polling*. During the *search step*, if it gets a better solution, then it elongates search space and perform *searching step* again. When the *searching* step fails to find a better solution, then polling step invokes and narrows down the search around the current solution. This will lead to the convergence of the algorithm.

Given an iteration i, the MADS algorithm generates a current mesh and finite number of trial points. In *i-th* iteration, the current mesh can be defined as:

$$M_i = \bigcup_{a \in \Psi_i} \{a + \nabla_{i,m} D_{i,m}\}, \tag{10}$$

where a is any arbitrary starting trial point in the feasible region and Ψ_i is the set of finite points where the objective function is to be evaluated, $\nabla_{i,m} \in \mathbb{R}_+$ is the mesh size parameter, and $D_{i,m}$ is the finite set of mesh directions.

In this paper, we consider fixed number of trial points in current mesh which are located on the current mesh with four directions (left, right, up, and down) scaled by $\nabla_{i,m}$. Now, in the first step called *searching*, the objective function values are computed at four mesh points. These values are then compared with the current value which is so far the best solution of objective function in (9) to find yet better solution. If a better solution is found at any trial point then the trial point, is called an *improved mesh point* and iteration is considered as *successful iteration*. When an improved mesh point is found then it may stop or continue searching for better mesh points. It is worth to mention that the constraints of (9) are evaluated to determine feasibility of the solution, and objective function first values are then computed only in the case when constraints are feasible. The next iteration $i+1$ will start with updated incumbent solution and mesh parameter $\nabla_{i+1,m} \geq \nabla_{i,m}$.

In the case when no improved mesh point is found, then the *polling* step is invoked. Here, set of poll points is defined as P_i with poll size parameter $\nabla_{i,p}$ where $\nabla_{i,m} \leq \nabla_{i,p}$. The objective function is then evaluated at each poll point to find better solution, however, $\nabla_{i+1,p}$ is reduced in case better solution is found and choose the improved point as incumbent solution for next iteration. This will help to further explore better solution in the vicinity of incumbent solution. The key difference between the MADS and GPS is the size parameter. In the case of MADS, $\nabla_i^m \leq \nabla_i^p$; whereas in the case of GPS there is only a single parameter $\nabla_i = \nabla_i^m = \nabla_i^p$. The MADS algorithm to solve optimization problem in (9) is given in Algorithm 3.

Algorithm 3 Mesh Adaptive Direct Search Algorithm

Initialization:
Set $i \leftarrow 0$, $\nabla_i^m \leq \nabla_i^p$
Terminate $\leftarrow$ FALSE, ImprovedFound $\leftarrow$ FALSE
while Terminate==FALSE **do**
  // Current mesh
  $M_i = \bigcup_{a\in\Psi_i} \{a + \nabla_i^m D_z\}$
  //Step 1: Search step
  Compute values of objective function in (9) in all directions of mesh
  if Improved mesh point found **then**
    ImprovedFound $\leftarrow$ TRUE
  else if Improved mesh point not found **then**
    // Step 2: Poll Step
    $P_i = \bigcup_{z\in\beta_i} \{x + \Delta_i^p D_i^p\}$
    Compute values of objective function in (9) in all directions of mesh
    if Improved poll point found **then**
      ImprovedFound $\leftarrow$ TRUE
    end if
  end if
  if ImprovedFound == TRUE **then**
    $\Delta_{i+1,m} \leftarrow \Delta_{i,m}/\Theta^m$
  else
    $\Delta_{i+1,p} \leftarrow \Delta_{i,p}\Theta^p$
  end if
  ImprovedFound $\leftarrow$ *FALSE*
  $i \leftarrow i+1$
  if Termination Criterion Satisfied **then**
    Terminate $\leftarrow$ *TRUE*
  end if
end while

V. PERFORMANCE ANALYSIS

We evaluate the performance of adopted ESA and MADS algorithm using MATLAB. The ESA provides optimal solution and thus is used as a benchmark to compare results of MADS algorithm. We consider the following four scenarios based on number of users (K), number of resource blocks (N) and minimum data rate requirement (R_{min}) for the dynamic user grouping, power allocation, and time allocation for NOMA with RF energy harvesting: 1) $K=6, N=2$, and $R_{min}=125$kbps, 2) $K=6$, $N=2$, and $R_{min}=1000$kbps, 3) $K=5$, $N=3$, and $R_{min}=125$kbps, and $K=5$, $N=3$, and $R_{min}=2000$kbps. The users are uniformly distributed within a distance of 1km radius. The channel propagation is considered to be Rayleigh fading over log-normal shadowing. We consider a scenario of urban area in this paper for which pathloss exponent is 3 and antenna gain factor 1 for simulations.

Detailed simulation parameters are given in Table 3.

TABLE 3. Simulation parameters.

Parameter	Value
Number of users (K)	5-6
Number of resource blocks (N)	2-3
Minimum data rate requirement (R_{min})	125kbps 2000kbps
Path loss exponent	3
Antenna gain	1
P_{BS}^{MAX}	$1e^{-4}W$

Fig. 3 illustrates comparison for MADS algorithm and ESA for scenario 1. Fig. 3 (a) shows resource block index versus user index when the minimum data rate requirement is 125Kbps for each user. It is evident that ESA allocates only user 1 to resource block 1 and rest of all users to resource block 2. On the other hand, MADS algorithm allocate resource block 1 for user 1, 3, and 4 and resource block 2 for user 2 and 6. However, user 5 is not assigned to any of the resource block since all of the constraints are not satisfied. Fig. 3 (b) shows the user power in dBm for each resource block. It is obvious that the user power is a little more in the case of resource block 2, however, there is not significant difference when MADS algorithm is compared with ESA. Fig. 3 (c) shows user rate for each user index. It is clear that each user has equal or higher data rate in the case of MADS when compared with ESA. This is because we are not only maximizing rate rather we are doing joint maximization of users and sum rate. It is important to note that MADS assigned only 5 users out of total 6 users, whereas ESA successfully assigned all 6 users. Therefore, rate of users in the case of MADS is equal or higher compared to ESA. Fig. 3 (d) compares MADS and ESA in terms of time

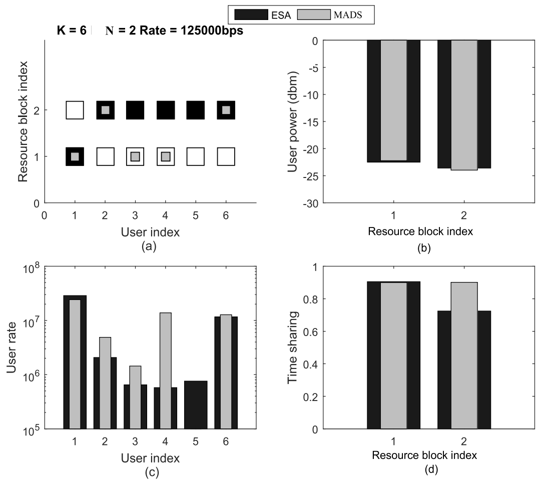

FIGURE 3. Performance comparison of MADS algorithm versus ESA for K=6, N=2, and R_{min}=125Kbps: (a) Resource block index versus user index, (b) user power for each resource block, (c) user rate for each user, and (d) time sharing for each resource block.

sharing for each resource block. It is noticeable that the time shared between transmission and energy harvesting is same for both MADS and ESA in the case of resource block 1. On the contrary, in the case of resource block 2, more time is allocated for transmission when MADS algorithm is applied in comparison with ESA. This means, in ESA, each user has more time for energy harvesting compared with MADS algorithm.

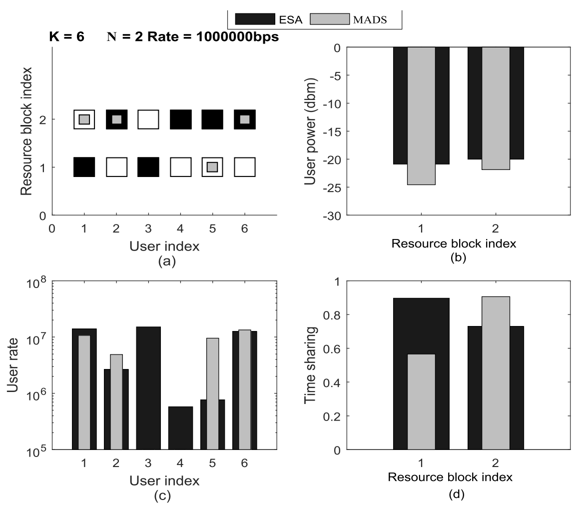

FIGURE 4. Performance comparison of MADS algorithm versus ESA for K=6, N=2, and R_{min}=1000Kbps: (a) Resource block index versus user index, (b) user power for each resource block, (c) user rate for each user, and (d) time sharing for each resource block.

Fig. 4 shows a comparison for scenario 2. Resource block index versus user index is shown in Fig. 4 (a) where $K = 6, N = 2$, and $R_{min} = 1000$Kbps. In this case ESA allocates user 2, 4, 5 and 6 to resource block 1 and user 1 and 3 to resource block 2. On the contrary, MADS algorithm allocate resource block 1 only to user 5 and resource block 2 to user 1, 2, and 6. User 3 and 4 are not assigned any resource block for this case since all constraints are not satisfied. Fig. 4(b) shows the user power in dBm for each resource block. It is clear for both resource blocks that ESA assigned more power to meet the data rate requirement when compared to the power assigned by MADS. Fig. 4 (c) clearly illustrates that each user has equal or higher user rate in the case of MADS when compared with ESA. However like in scenario 1, ESA was successful in assigning all 6 users to the resource blocks whereas MADS only assigned 4 out of 6 users. Fig. 4 (d) provides a comparison for time sharing for both approaches. For resource block 1, MADS gets more time for energy harvesting whereas for resource block 2, MADS allocates more time for transmission as compared to ESA.

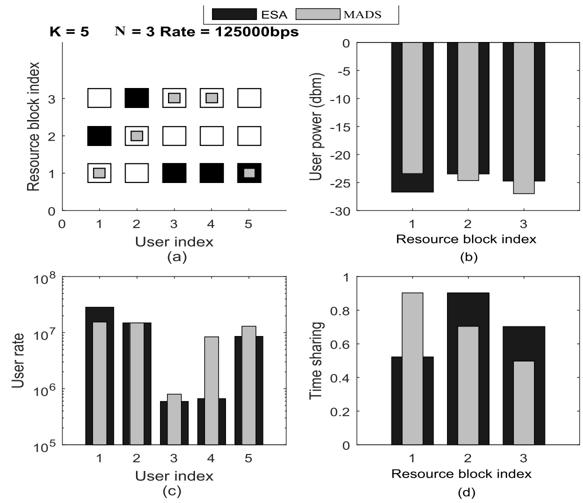

FIGURE 5. Performance comparison of MADS algorithm versus ESA for K=5, N=3, and R_{min}=125Kbps: (a) Resource block index versus user index, (b) user power for each resource block, (c) user rate for each user, and (d) time sharing for each resource block.

Fig. 5 is an illustration for scenario 3. $K = 5, N = 3$, and $R_{min} = 125$Kbps are choosen for the resource block index versus user index in Fig. 5 (a). In this case, ESA allocates user 3, 4 and 5 to resource block 1, user 1 to resource block 2 and user 2 to resource block 3. On the contrary, MADS algorithm allocates user 1 and 5 to resource block 1, user 2 to resource block 2, and user 3 and 4 to resource block 3. Unlike resource blocks 2 and 3, resource block 1 requires more power with MADS as compared to ESA shown in Fig. 5(b). Fig. 5(c) depicts that MADS users rate is better or very similar to when ESA is used. Fig. 5 (d) illustrate time sharing for each resource block. For resource block 1, unlike resource block 2 and 3, MADS needs more time for transmission as compared to ESA.

Fig. 6 shows a comparison for scenario 4. Where $K = 5$, $N = 3$, and $R_{min} = 2000$Kbps. resource block index versus user index is shown in Fig. 5 (a). In this case, ESA allocates user 2, 4 and 5 to resource block 1, user 3 to resource block 2 and user 1 to resource block 3. Whereas, MADS algorithm allocate user 1 and 3 to resource block 1, user 2 to resource block 2, and user 5 to resource block 3. User 4 is not allocated any resource by MADS since all the constraints are not satisfied. Unlike resource blocks 1 and 2, resource

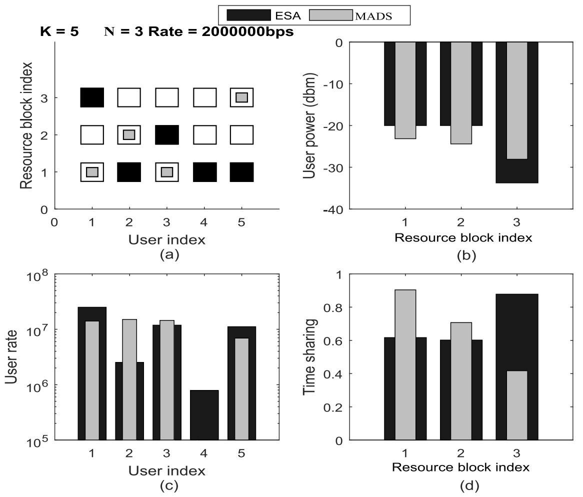

FIGURE 6. **Performance comparison of MADS algorithm versus ESA for K=5, N=3, and R_{min}=2000Kbps: (a) Resource block index versus user index, (b) user power for each resource block, (c) user rate for each user, and (d) time sharing for each resource block.**

TABLE 4. **Complexity comparison of ESA versus MADS algorithm.**

Parameters	ESA	MADS ($\epsilon = 0.001$)
$K = 4$ and $N = 2$	4,096	12,000
$K = 6$ and $N = 2$	262,144	18,000
$K = 8$ and $N = 2$	16,777,216	24,000
$K = 4$ and $N = 3$	100,000	16,000
$K = 6$ and $N = 3$	16,800,000	24,000
$K = 8$ and $N = 3$	4.2950e+09	32,000

block 3 requires more power with MADS as compared to ESA as shown in Fig. 5 (b). It is evident from Fig. 5 (c), that with MADS users rate is better or very similar to when ESA is performed. Fig. 5 (d) shows time sharing between energy harvesting and information transfer. For resource block 3, unlike resource block 1 and 2, MADS needs less time for transmission as compared to ESA. Which also means that resource block 3 will get more time to harvest energy in MADS as compared to ESA.

A. COMPLEXITY

The complexity (directly proportional to computation time) of ESA is increased exponentially with the number of resource blocks and users and can be written as $O(2^{K+K\times N})$. In contrast, the MADS algorithm converges to ϵ-optimal solution in finite number of steps [43], [44]. Further, the convergence of MADS algorithm is independent of starting point and converges to global optimal solution with ϵ error tolerance. $\epsilon = 0.001$ is used as error tolerance in the simulations. The complexity of MADS algorithm is $O(\frac{(K+K\times N)^2}{\epsilon})$. Therefore, we can achieve a sub-optimal solution using the MADS algorithm for the problem in (9) with less complexity when compared to the ESA. Table 4 shows a complexity comparison of ESA versus MADS algorithm for different number of users (K) and resource blocks (N). It is worth to note that complexity of MADS is high for small values of K and N, however, MADS clearly outperforms ESA for all other cases.

VI. CONCLUSIONS

In this paper, we presented mathematical framework for NOMA with RF energy harvesting. This framework includes dynamic user grouping in their respective resource blocks power allocation and, time allocation for transmission and energy harvesting. The objective of this framework is to maximize both admitted users and throughput in the network while satisfying minimum data rate requirement of each admitted user and optimal user power in each resource block. The proposed mathematical framework is mixed integer non-linear programming (MINLP). We performed ESA which provides optimal solution and used it as a benchmark for MADS algorithm which provides sub-optimal solution. Four scenarios based on the number of users, number of resource blocks, and minimum data rate are considered for simulation results. Dynamic user grouping in their respective resource blocks is shown for each scenario. User power for each resource block, user rate for each user, and time sharing for each resource block are also compared for MADS algorithm and ESA. It is shown that the performance of MADS algorithm is near to or equal to the ESA in most of the cases, i.e., near to optimal solution with less complexity.

Future work can involve the extension of proposed framework for the heterogeneous 5G and beyond networks while considering multiple cells and cloud radio access network. Moreover, the proposed framework can be improved by allowing one user to use more than one resource block.

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MEHAK BASHARAT received the B.S. degree in telecom engineering from the National University of Computer and Emerging Sciences, Islamabad, Pakistan, and the M.A.Sc. degree in electrical and computer engineering from Ryerson University, Toronto, Canada, where she is currently pursuing the Ph.D. degree. Her current research interests include 5G networks, the Internet of Things, and RF energy harvesting.

MUHAMMAD NAEEM received the B.S. and M.S. degrees in electrical engineering from the University of Engineering and Technology, Taxila, Pakistan, in 2000 and 2005, respectively, and the Ph.D. degree from Simon Fraser University, BC, Canada, in 2011. From 2000 to 2005, he was a Senior Design Engineer with Comcept (pvt) Ltd., where participated in the design and development of smart card-based GSM and CDMA pay phones with the Design Department. From 2012 to 2013, he was a Postdoctoral Research Associate with the WINCORE Laboratory, Ryerson University, Toronto, ON, Canada. Since 2013, he has been an Assistant Professor with the Department of Electrical Engineering, COMSATS Institute of Information Technology, Wah Campus, Pakistan, and a Research Associate with the WINCORE Laboratory, Ryerson University. He is also a Microsoft Certified Solution Developer. His research interests include the optimization of wireless communication systems, non-convex optimization, resource allocation in cognitive radio networks, and approximation algorithms for mixed integer programming in communication systems. He was a recipient of NSERC CGS scholarship.

WALEED EJAZ (S'12–M'14–SM'16) received the B.Sc. degree in computer engineering from the University of Engineering and Technology, Taxila, Pakistan, the M.Sc. degree in computer engineering from the National University of Sciences and Technology, Islamabad, Pakistan, and the Ph.D. degree in information and communication engineering from Sejong University, South Korea, in 2014. He held academic and research positions at Ryerson University, Carleton University, and Queen's University, Canada. He is currently an Assistant Professor with the Department of Applied Science & Engineering, Thompson Rivers University, Kamloops, BC, Canada. He is also the Founding Director of the Next Generation Wireless Networks Research Laboratory. He has coauthored more than 90 papers in prestigious journals and conferences, and three books. His current research interests include the Internet of Things (IoT), energy harvesting, 5G and beyond networks, and mobile edge computing. He is a member of ACM. He is an Associate Editor of the *IEEE Communications Magazine*, the IEEE Canadian Journal of Electrical and Computer Engineering, and the IEEE Access. He completed certificate courses on Teaching and Learning in Higher Education from the Chang School, Ryerson University. He is a registered Professional Engineer (P.Eng.) in the province of British Columbia, Canada. He is an ACM Distinguished Speaker.

ASAD MASOOD KHATTAK (M) received the M.S. degree in information technology from the National University of Sciences and Technology, Islamabad, Pakistan, in 2008, and the Ph.D. degree in computer engineering from Kyung Hee University, South Korea, in 2012, where he was a Postdoctoral Fellow with the Department of Computer Engineering, for seven months and then he joined as an Assistant Professor. In 2014, he joined with the College of Technological Innovation, Zayed University, Abu Dhabi, United Arab Emirates, where he is currently an Associate Professor. He is also leading three research projects and collaborating in four research projects in the fields of data curation, context-aware computing, the IoT, and secure computing. He has authored or coauthored more than 90 journal and conference articles in highly reputed venues. He and his team have secured several internal and external awards in different competitions.

ALAGAN ANPALAGAN (SM) received the B.A.Sc., M.A.Sc., and Ph.D. degrees in electrical engineering from the University of Toronto. He is currently a Professor with the Department of Electrical and Computer Engineering, Ryerson University, where he directs a research group working on radio resource management and radio access and networking areas within the WINCORE Laboratory. He coauthored three edited books, *Design and Deployment of Small Cell Networks*, (Cambridge University Press, 2014), *Routing in Opportunistic Networks*, (Springer, 2013), and *Handbook on Green Information and Communication Systems*, (Academic Press, 2012). Dr. Anpalagan is a Fellow of the Institution of Engineering and Technology. He was a recipient of the Dean's Teaching Award, in 2011, the Faculty Scholastic, Research and Creativity Award, in 2010, 2014, and 2017, the Faculty Service Award in Ryerson University, in 2011 and 2013. He also received the Exemplary Editor Award from IEEE ComSoc, in 2013 and Editor-in-Chief Top10 Choice Award in *Transactions on Emerging Telecommunications Technology*, in 2012. He currently serves as a TPC Vice-Chair, IEEE VTC Fall-2017, and served as a TPC Co-Chair, IEEE GLOBECOM'15: SAC Green Communication and Computing, the IEEE WPMC'12 Wireless Networks, the IEEE PIMRC'11 Cognitive Radio and Spectrum Management, and the IEEE CCECE'04/08. He served as a Vice Chair, ComSoc Toronto Chapter Chair, from 2004 to 2005, the IEEE Toronto Section Chair, from 2006 to 2007, and the IEEE Canada Professional Activities Committee Chair, from 2009 to 2011, the IEEE Canada Central Area Chair, from 2012 to 2014, and the IEEE SIG on Green and Sustainable Networking and Computing with Cognition and Cooperation, since 2015. He served as an Editor of *EURASIP Journal of Wireless Communications and Networking*, from 2004 to 2009, the IEEE Communications Letters, from 2010 to 2013, Springer *Wireless Personal Communications*, from 2011 to 2013, and the IEEE Communications Surveys and Tutorials, from 2012 to 2014. He is a registered Professional Engineer in the province of Ontario, Canada.

OMAR ALFANDI received the M.Sc. degree in telecommunication engineering from the University of Technology Kaiserslautern, Germany, in 2005, and the Ph.D. (Dr.rer.nat.) degree in computer engineering from the Georg-August-University of Goettingen, Germany, in 2009. From 2009 to 2011, he enjoyed a Postdoctoral Fellowship at the Telematics Research Group and he founded the Research and Education Sensor Lab, where he is currently as a Lab Advisor. He carried his Ph.D. Research as part of an Industry, Academia, and Research centers collaboration European Union (EU) project. He was a Package Leader of EU DAIDALOS II in the 6th Framework Project. In 2015, he was appointed as the Assistant Dean for Abu Dhabi Campus. He is currently an Associate Professor with the College of Technological Innovation, Zayed University. He is also the Co-Founder and the Co-Director of the Sensors and Mobile Applications Research and Education Lab, CTI. He published numerous articles on Authentication Framework for 4G Communication Systems, Future Internet, and Trust and Reputation Systems in Mobile ad hoc and Sensor Networks. His current research interests include the Internet of Things, security in next generation networks, smart technologies, security engineering, mobile, and wireless communications.

HYUNG SEOK KIM (S'02–M'06) received the B.S. degree from the School of Electrical Engineering, Seoul National University, South Korea, in 1996, and the M.S. and Ph.D. degrees from the School of Electrical Engineering and Computer Engineering, Seoul National University, in 1998 and 2004, respectively. In 2003 and 2004, he held visiting researcher positions with the University of Virginia. From 2004 to 2006, he was with the Telecommunication R&D Center, Samsung Electronics. He is currently a Faculty Member with the Department of Information and Communication Engineering, Sejong University. His research interests include networking with special emphasis on wireless communication and visual light communication.