Multi-Objective Optimization of Green Small Cell Allocation for IoT Applications in Smart City

HAO RAN CHI, (Member, IEEE), AND AYMAN RADWAN, (Senior Member, IEEE)
Instituto de Telecomunicações, 3810-193 Aveiro, Portugal
Corresponding author: Ayman Radwan (aradwan@av.it.pt)
This work was supported in part by the FCT/MCTES through the National Funds and When Applicable Co-Funded EU Funds under Project UIDB/50008/2020-UIDP/50008/2020.

ABSTRACT Small cells (SCs) have proven their marvelous capability, especially dealing with high density of user equipment (UE) in the configuration of Internet of Things (IoT). It is widely accepted that the SCs concept is one of the prospective solutions for 5G networks, specifically targeting IoT, to attain the high demand in the future smart city. SC deployment has attracted the attention of multiple research efforts, due to its importance and potential towards enhancing future networking for IoT. However, there is still a lack of works providing SC allocation with comprehensive optimization modeling, which provides essential infrastructural platform to SC functionalities and services (e.g. offloading). The analysis of the number and positions of SCs, towards the simultaneous optimization of both energy efficiency and data rates, is a highly required research direction. SC allocation facilitates the sustainability and reliability, to support exponentially increasing number of users, as well as yielding feasibility of achieving high traffic demand and low latency performance, in addition to longer sustainability based on enhanced energy efficiency. In this paper, a smart small cell allocation scheme is proposed for IoT in smart city. Integer programming multi-objective optimization problem is formulated, and a new algorithm, based on the fusion of Branch-and-Bound (BnB) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II), is developed. Energy efficiency optimization and data rate maximization are formulated, as mutual objectives to fulfill the key demands of IoT in smart city, based on the estimation of users’ behaviors. Simulations are conducted, whose results show that the proposed Smart-SC allocation outperforms the different considered benchmarks, resulting in higher offered data rates, while achieving better energy efficiency.

INDEX TERMS Small cell allocation, energy efficiency, multi-objective optimization, smart city.

I. INTRODUCTION
Density of user equipment (UE) in modern cities has been dramatically proliferating, owing to the vast adoption of the concept of Internet-of-Things (IoT) [1]. Meanwhile, the nature of the requirements of service in smart city has been significantly switched to be smarter, lower delay and more reliable. On an opposite trend, many devices, in the IoT area, require lower data rates, and are more concerned about their energy consumption, due to the adoption of huge number of sensors in the Smart City ecosystem. To provide sufficient data for IoT development in smart city, massive sensors will be installed, which contribute to 396 Exabyte (EB) per month in 2020 (more than 3 times compared with 2017) [2].

In fact, ultra-reliable and low-latency communication (URLLC) with energy efficiency is one of the main three pillars of 5th generation communication (5G), which still requires lots of research efforts [3]. Therefore, how to manage huge quantity of devices with satisfactory service performance, while maintaining optimal energy efficiency, has drawn great attention in the area of networking.

Densification has been recognized as one of the main technological enablers of 5G, and future networking [4]. The deployment of small cell (SC) stands out as a main pillar in the concept of densification, offering a potential solution for the ultra-dense traffic IoT applications in the smart city. The conventional macro-cell network faces the challenge of tremendous communication pressure with data aggregation from considerable high number of IoT devices. Besides, it is hard to ensure satisfactory Quality of Service (QoS)/Quality...
of Experience (QoE) for all UEs, especially those at the edge of the coverage of the macro-cell. SCs, with offloading and resource management, can provide data distribution to release the pressure of macro-cells and enhance the QoS/QoE of UEs, especially those far away from the macro-cell base station (BS) [4]. Compared to macro-cells, SCs are small radio heads providing services, either on licensed or unlicensed spectrum [5]. By its nature, SCs improve the spectrum efficiency, because the same spectrum can be adopted in multiple SCs. Though the coverage of SCs is normally small, multiple SC base stations (SBSs) can co-exist in close range to cover a larger area.

However, with the increased number of SBSs, networks will face other challenges, such as higher energy consumption and interference [6]. Energy efficiency is defined as a main requirement in 5G development, for cost efficiency and sustainable development. Additionally, energy efficiency is a main requirement for IoT applications, who usually depend on devices with small battery. Moreover, the transmission power of BSs should also be optimally determined, to provide sufficient coverage and ensure the received power of users, simultaneously yielding acceptable QoS [7].

To tackle the energy efficiency management, the number and locations of SBSs should be optimized, to better serve the distributed UEs [8]. Some research efforts have addressed the service management of SC networks, with energy management or other objectives, such as offloading, etc.; however, all these efforts build their optimization, usually targeting only one key performance indicator (KPI). Therefore, SC allocation still continues to be a challenge for the future IoT network with complicated network topology, ultra-dense UEs and heterogeneous nature of SCs. It is clear that there is still a significant lack in research efforts on SC allocation, especially simultaneously targeting energy efficiency and data rate maximization. Therefore, we propose a new smart SC allocation, with multiple objectives, namely optimizing energy efficiency, while maximizing data rates.

A. PAPER CONTRIBUTIONS
Following such line of thought, in this paper, a new SC allocation scheme is proposed for Smart-SC infrastructure. An integer programming, non-linear, multi-objective optimization formulation (IPNLMOO) for SC allocation is proposed with QoS constraints. The SC allocation is formulated into integer programming with the consideration of optimizing the number and locations of SCs. The UE behavior and SBSs operation estimations are modeled with the jointly optimization objectives, energy efficiency and data rate maximization, to tackle the high-density and low-cost IoT networking development. Because of the non-linear formulation, evolutionary optimization algorithm is adopted to deal with the solution searching for the multi-objective optimization formulation. Normally to be formulated as multi-objective optimization, the objectives should conflict, or at least depend on each other; hence, as a result, require trade-off solutions. For instance, when the transmission power of BSs increases, data rates will in turn increase, whereas it also causes negative effect on energy efficiency, because of the increased power consumption [7], and sometime increased interference, affecting network capacity. Therefore, compared with single objective optimization, or conventional method to transform multi-objectives into single objective by weighting factors, multi-objective optimization with non-dominated concept is proven to be the most suitable solution for trade-off searching [9]. Non-dominated genetic algorithm II (NSGA-II) is well acknowledged to outperform other algorithms to handle multi-objective optimization problems with high diversity and accuracy for global optimum searching [10]. Therefore, the formulation is solved by a new proposed algorithm, through the fusion of Branch and Bound (BnB) algorithm and NSGA-II. A smart city application, localization of trolleys in airports, is considered as a case study. The proposed Smart-SC allocation provides high quality of received signal for the localization algorithm with optimal energy efficiency. In addition, the proposed Smart-SC ensures optimal data rate for the SC network simultaneously. Simulation results show that both the energy efficiency and data rate performance of the proposed Smart-SC outperform the benchmarked schemes. Therefore, the proposed Smart-SC achieves optimal SC allocation, towards the future high-density, low-cost and high-QoS required IoT deployment in smart city.

The contributions of the paper can be summarized as follows:
1. Derived a network modeling for SC allocation as an integer-programming, non-linear multi-objective optimization problem (IPNLMOO) targeting energy efficiency and data rate maximization, with comprehensive QoS constraints.
2. Proposed a new algorithm through the fusion of BnB and NSGA-II, to specifically tackle the formulated IPNLMOO problem.
3. Designed a case study for localization of trolleys in the airport, which falls in the typical category of IoT applications in smart city. The results show that the proposed Smart-SC outperforms all the benchmarked schemes with energy efficiency improvement of average 12.7% and average data rate improvement of ~8.25%.

The remainder of the paper is organized as follows. Section II provides a summary of related works. Section III introduces the network modeling with energy efficiency and data rate formulation. Section IV provides the optimization modeling and algorithm for the problem. Section V discusses the simulation results. Finally, Section VI and VII are the future development and conclusion, respectively.

II. RELATED WORKS
SC allocation is widely accepted to enhance the performance of networks, providing solutions such as load balancing, etc. For instance, the number of SCs and their locations significantly affect the QoS/QoE assessment of IoT/5G networks [8]. Analysis of the coverage and load balancing of SCs was applied, which well demonstrated that the allocation (e.g. distance between SCs) had significant effect on the QoS
performance, such as signal-to-interference-plus-noise-ratio (SINR) [11]. Besides, resource allocation in SCs was the focus of the work in [12], [13], with user association to SCs, to optimally allocate the resources to UEs. However, fixed number of SCs was always assumed in these previous efforts. Moreover, some other efforts considered offloading and resource allocation schemes [14]–[16], which were developed based on a fixed allocation of SCs, but did not consider energy efficiency optimization. It is also necessary to note, here, that SC allocation needs to be optimized, with regards to determining the number and locations of SCs, which is still lacking in the literature. Therefore, SC allocation still needs more efforts, towards an optimal development to pave the way to the follow-up network services. The problem can be formulated as an integer non-linear programming by its nature, which needs advanced corresponding computation algorithms to solve it.

Energy efficiency management has been commonly recognized as one of the challenges for the development of future IoT, especially in 5G networking setup. Following the path towards that line of research, energy efficiency management of SCs have been the focus of multiple published works. To give an optimal SC allocation, energy efficiency formulation should be appropriately deployed, with UE behavior estimation and comprehensive QoS/QoE consideration. An energy efficiency management modeling for downlink was proposed in [17], for SC network. Interference among SCs was specifically considered in the formulation, and spectrum optimization was discussed. However, the work did not consider QoS performance, and thus data rate of SCs would be reduced, because of the interference mitigation scheme. Energy harvesting and energy efficiency management were also previously considered for the infrastructure of cooperation of SCs and macro-cells [18]. SINR was formulated, while considering spectrum efficiency. Similar to [17], data rate optimization was also not the focus [18]. Besides, since it is specifically for the dynamic energy harvesting strategy, the formulation of the UE behaviors may not be applicable for the SC allocation in the network initialization. Another power control algorithm was proposed in [19], which was similar to [18], without SC allocation strategy.

Therefore, there is clearly a lack of adequate optimization of SC allocation, in terms of both number of SCs and their locations, specifically simultaneously considering data rate maximization and energy efficiency. Consequently, in this paper, a new SC allocation modelling, with the simultaneous optimization of energy efficiency management and data rate maximization, is proposed. SC allocation and potential power management strategy of SCs are proposed, based on the new developed integrated BnB and NSGA-II based optimization algorithm. We verify our proposed algorithm through simulations, whose results show that the proposed SC allocation can achieve optimal energy efficiency, with satisfactory data rate to support IoT applications in smart city. The results also show that our proposed algorithm achieves higher data rates compared to benchmark algorithms.

III. PROBLEM MODELLING

This section details the proposed problem formulation and is organized into 3 sub-sections, namely: proposed smart-SC infrastructure, SC allocation specified link budget model for energy efficiency, and data rate model.

A. PROPOSED SMART-SC INFRASTRUCTURE

Fig. 1 shows the proposed Smart Small Cell (Smart-SC) infrastructure for ultra-dense traffic network in modern cities, suitable for IoT applications.

![Smart-SC infrastructure](image)

We assume that there are $M$ SC BSs (SBS), to provide service in the coverage of a Macro-cell BS (MBS), which serve $N$ UEs in the area. UEs can be connected to either SBSs or MBSs, depending on their request and link quality.

B. SC ALLOCATION SPECIFIED LINK BUDGET MODEL FOR ENERGY EFFICIENCY

To propose an optimal SC allocation, energy efficiency considering link budget should be optimally modeled and formulated. Because the SC allocation formulation is addressed in the networking initialization, the independent variables (i.e. variables that can be controlled, which affect the objectives of the system) are directly related to the allocation of SCs, while the UE allocation and association are considered as uncontrollable variables, and modeled based on the estimation of UE behavior.

Link budget has to reflect the communication quality at the user equipment. In a Smart-SC model, to improve spectrum efficiency, while ensuring sufficient user handling, the uplink and downlink adopt spectrum with close frequency bands. This paper focuses on downlink communications, while uplink will be the focus of our future work. Since the UEs can be assigned to SBSs or MBSs, based on the source assignment strategy [13], which further affects the energy efficiency of SBSs/MBSs, the formulation is derived into two cases: UEs served by i) SBSs and ii) MBSs, separately. Therefore, the link budget for UEs communicating with SBSs ($P_{r, su}$) is formulated as [20]:

$$P_{r, su} (m, n) = P_{t, m} + G_{t, m} + G_{r, n} - L_{d, m} - L_{r, n} - L_{p, n} (m, n),$$

$$m \in [1, M], \quad n \in [1, N]$$

(1)
where $P_{r, su}$ is the received power by user $n$, when it is served by SBS $m$, $P_{r,m}$ is the output power from SBS $m$, $G_{r,n}$ and $G_{r,n}$ are transmitter gain from BS $m$ and receiver gain from user $n$, respectively. $L_{d,m}$ and $L_{r,n}$ are transmitter loss of SBS $m$ and receiver loss of user $n$, including insertion loss and back-off loss etc., and $L_{p,n}$ is the path loss.

Similarly, link budget of UEs connected to MBS ($P_{r,mu}$) is derived as:

$$P_{r,mu} (n) = P_{t,MBS} + G_{t,MBS} + G_{r,n} - L_{d,m} - L_{r,n} - L_{p,n} (n), \ n \in \{1, N\}$$ (2)

where $P_{t,MBS}$, $G_{t,MBS}$ and $L_d$ are the output power, transmitter gain and transmitter loss of the MBS, respectively.

For the wireless propagation formulation of the SC allocation in Smart-SC, path loss model is considered. Therefore, based on [21], path loss model ($L_{p,n}$) from BS $m$ to UE $n$ is formulated as

$$\text{UE - SBS} : L_{p,n} (m, n) = 10 \log_{10} \left( \frac{P_{t,m}}{P_{r, su} (m, n)} \right) \text{ (dBm)}$$

$$= P_0 + 10 \alpha \log_{10} (d_{mn} + w_0), \ m \in \{1, M\}, \ n \in \{1, N\}$$ (3)

$$\text{UE - MBS} : L_{p,n} (n) = 10 \log_{10} \left( \frac{P_{t,MBS}}{P_{r,mu} (n)} \right) \text{ (dBm)}$$

$$= P_0 + 10 \alpha \log_{10} (d_{mu} + w_0), \ n \in \{1, N\}$$ (4)

where $w_0$ refers to the random Gaussian variable. $P_0$ accounts for the reference signal power in unit distance. $d_{mn}$ and $d_{mu}$ are the distance between the user $n$ and (SBS $m$) & (the MBS) respectively, which are associated with random Gaussian variable $\alpha$. It is necessary to emphasize that the path loss derived in (3) and (4) are specifically for SC allocation in networking initialization process, which indicates that the number and location of SBSs will be determined by the proposed Smart-SC, whereas the location and behavior of UEs is considered as uncontrollable variables and should be estimated. Based on the nature of the mobility and scalability of UEs in IoT networks, the distribution of UEs is estimated as Poisson distribution [22]. Therefore, $d_{mn}$ will specifically deterministic to the allocation of SBSs, which is derived as the Euclidean distance between UEs and SBSs:

$$d_{mn} = \sqrt{(x^{UE}_n - x^{SBS}_m)^2 + (y^{UE}_n - y^{SBS}_m)^2}$$ (5)

where $x^{UE}_n$ and $y^{UE}_n$ are the estimated UE location on x-y axis, which on a macroscale obeys Poisson distribution [22]. $\varphi^{SBS}_m = \{x^{SBS}_m, y^{SBS}_m\}$ are the corresponding SBS location that is serving UE $n$, which are independent variables and should be determined by the Smart-SC algorithm.

For UE association, UEs are supposed to be assigned to SBSs with the best link budget:

$$n \rightarrow m : \arg P_{r, su} (m, n)$$ (6)

The signal-quality based UE association strategy is well developed and proven to be effective and simple-to-operate for the UE-BS association in SC networks [23].

The channel power gain of the link from the SBS $m$/MBS to the associated UE $n$ is, respectively, given by

$$\text{UE - SBS} : \Delta P_{r, su} (m, n) = P_{r, su} - P_{r, su} (m, n) - G_{r,m} - G_{r,n}$$ (7)

$$\text{UE - MBS} : \Delta P_{r, mu} (n) = P_{r, mu} - P_{r, mu} (n) - G_{r,MBS} - G_{r,n}$$ (8)

Channel power gain intuitively reflects the difference between the transmission power from both SBSs and MBSs to the associated UEs. Moreover, channel power gain also provides valuable reference to the evaluation of the channel quality, which will be considered in the Bit Error Rate (BER) modeling in Section III.C.

C. SC ALLOCATION SPECIFIED DATA RATE MODEL

The average BER of user, $\hat{B}_N$ is derived for the SC allocation, which is determined as (9), as shown at the bottom of the next page, where $P_{f,i}$ is the fading loss, and $Q(.)$ follows the Gaussian distribution. $\gamma$ is the multiplying coefficient with range of (0,1] [10]. $n_{su}$ and $n_{mu}$ are the number of UEs connected with SBSs and the MBS, respectively. As defined in (5) and (6), $n_{su}$ and $n_{mu}$ are deterministic by the number and location of BSs (independent variables), whereas UE locations are considered as Poisson distribution [22].

In this paper, data rate in Smart-SC is considered with the packet successful transmission rate [24]. We denote $p_{\text{succ}, N}$ to be the average probability of successfully transmitted packet of a UE with the packet length as $l$ bits. $p_{\text{succ}, N}$ is expressed as:

$$p_{\text{succ}, N} = (1 - B_N)^{l}$$ (10)

The average data rate ($\overline{\text{SN}}$) is defined as:

$$\overline{\text{SN}} = \frac{L_{\text{ucc}, N}}{T_{d_{\text{ucc}, N}} + T_{d_{\text{ucc}, N}} + T_{\text{ho}_{\text{ho}, N}}}$$ (11)

where $T_{d_{\text{ucc}, N}}$ is the average channel busy time, due to successful transmission; $T_{d_{\text{ucc}, N}}$ and $T_{\text{ho}_{\text{ho}, N}}$ are the average channel busy time due to transmission failure (e.g. caused by interference) and probability of transmission failure, respectively; and $T_{\text{ho}_{\text{ho}, N}}$ are the handover period and probability that a random user has to implement handover. These uncontrollable variables can be determined, based on the specifications of the wireless communication protocol.

IV. OPTIMIZATION FORMULATION FOR IPNLMOO

In the proposed Smart-SC, since some of the independent variables belong to integer (e.g. number of SCs), the formulation is categorized as integer programming. Therefore, in order to achieve optimal SC allocation, energy efficiency and data rate models are formulated into an integer-programming non-linear multi-objective optimization problem (IPNLMOO). The allocation of SCs and potential power strategy of all BSs are the independent variables, while UE behavior, networking transmission parameters (e.g. $T_{d_{\text{ucc}, N}}$, $T_{d_{\text{ucc}, N}}$, $T_{\text{ho}_{\text{ho}, N}}$, etc.) are considered as uncontrollable...
variables. Therefore, the key challenges in the optimization modeling for solving the SC allocation problem include: 1) how to deal with the integer programming caused by the determination of the number of SCs, and 2) how to jointly optimize multiple non-linear objectives, simultaneously. It should be elaborated that the multiple objectives for joint optimization have to be interdependent with each other; otherwise, the objectives should be optimized separately.

It is well proven that the Branch and Bound (BnB) is one of the most effective algorithm categories for integer programming [25]. In this paper, the integer-based problem is relaxed by the BnB algorithm. After integer relaxation, data rate and energy efficiency optimization fulfill the characteristics of multi-objective optimization with dependent objectives. As such, a method that matches all the objective requirements is sought. Compared to single objective optimization, multi-objective optimization has advantages in diversity for solution searching and higher possibility of searching for the optimal solution set for the problem. To solve the multi-objective optimization, evolutionary algorithms are proven to outperform other algorithms on non-linear optimization solution searching [10]. Genetic Algorithm (GA) has been revived because of the rising demand of multi-objective optimization formulation in smart city development. With its elite retention strategy, diversity enhancement and fast convergence management with non-dominated sorting, NSGA-II is an improved evolutionary algorithm, which is analyzed to outperform most of the other multi-objective optimization algorithms [26].

In summary, the proposed Smart-SC is formulated as an integer-programming, multi-objective optimization problem. A new algorithm with fusion of BnB algorithm and NSGA-II is developed for integer relaxation and multi-objective optimization problem solving.

A. NSGA-II BASED MULTI-OBJECTIVE OPTIMIZATION

Before introducing the proposed BnB based integer relaxation, multi-objective optimization formulation with defining objective functions in SC allocation is discussed, to better illustrate the problem modeling.

In this paper, Non-dominated Sorting Genetic Algorithm II (NSGA-II) is adopted for the multi-objective optimization solving. NSGA-II already gains excellent convergence and diversity performance compared with other variant, and still yields the most concise programing and fast non-dominated sorting for two-objective optimization problem [27], [28], which matches our optimization case, in this paper.

Similar to conventional GA, NSGA-II also envisages population initialization, crossover and mutation parameter settings, and selection strategy. The population operation and non-dominated sorting generate the offspring for the new population in the next generation. Niche count calculation provides the degree of crowdedness of population in the solution space, to prevent premature convergence, and most importantly to increase diversity to find the real Pareto Front. To give a full view of the NSGA-II in SC allocation, TABLE 1 illustrates the pseudo-code for the NSGA-II based SC allocation in the proposed Smart-SC. The different steps of the NSGA-II are further detailed in the remaining of the section.

1) NETWORK REPRESENTATION: DEVELOPMENT OF OBJECTIVE FUNCTIONS AND CONSTRAINTS

In this process, the application is customized into the objective function modeling. Some independent variables are determined. In general, for multi-objective optimization, the objective function is expressed as

\[
\max F(x) = (f_1(x), \ldots, f_o(x))^T
\]  

where \( f_o(x) \) is one objective function \( (o \in O) \), and \( O \) is the total number of the objective functions in the formulation, and \( \Omega \) is the variable range of the variable set \( x \).

In this paper, the objective functions for SC allocation are derived as: \( f_1 \) dedicated to maximize the energy efficiency \( (\eta_N) \); and \( f_2 \) is specific to maximize the average data rate \( (\bar{\sigma}_N) \), to provide infrastructural platform for ultra-dense IoT traffic in Smart-SC:

\[
\max f_1(x) = \eta_N
\]  

\[
\max f_2(x) = \bar{\sigma}_N
\]  

where \( \eta_N \) and \( \bar{\sigma}_N \) are the energy efficiency and the average data rate respectively, and \( f_i(x) \) and \( f_j(x) \) are the \( i \)-th and \( j \)-th objective functions respectively.

\[
B_{N} = \sum_{i=1}^{N} Q \left( 2y \left[ 10 \log_{10} \frac{P_{r,i} \Delta P_{r,i}}{P_{m,i}} + G_{S,i} (i) - P_{f,j} \right] \right) + \sum_{j=1}^{\mu} Q \left( 2y \left[ 10 \log_{10} \frac{P_{r,\mu} \Delta P_{r,\mu}}{P_{m,\mu}} + G_{\mu,\mu} (j) - P_{f,j} \right] \right)
\]

\[
\text{st. } N = n_{su} + n_{mu}, \ G_{S,i} (i) = G_{r,i}, \ G_{\mu,\mu} (j) = G_{r,\mu,\mu} + G_{r,j}
\]

TABLE 1. Proposed NSGA-II based algorithm for Smart-SC.

| Algorithm | The Energy Efficiency and Data Rate Optimization for Smart-SC |
|-----------|------------------------------------------------------------|
| 1: Input: \( x \in \{P_{r,m}\}_M, P_{r,MBS}, \{\varphi_{m}\}_M \) |
| 2: Output: \( f_1, f_2 = \{\eta_N, \bar{\sigma}_N\} \) |
| 3: Iteration \( g = 1 \) |
| 4: Initialization (population) |
| 5: Objective evaluation for individuals \( (f_1, f_2) \) |
| 6: Rank the individuals based on Line 7 |
| 7: Niche count calculation |
| 8: while Iteration \( \leq \) max Iteration do |
| 9: Selection: two parents from iteration |
| 10: Offspring generation: selection method, crossover, mutation |
| 11: Objective evaluation for the offspring \( (f_1, f_2) \) |
| 12: Rank the individuals based on Line 11 |
| 13: Niche count calculation |
| 14: Generation: new population from the offspring |
| 15: \( g = g + 1 \) |
| 16: end while |
| 17: Pareto Front |
where
\[
\eta_N = \frac{\sigma_N \cdot N}{\sum_{m=1}^{M} (P_{t,m} + P_{s,m}) + P_{t,MBS} + P_{s,MBS}}
\]  \hspace{1cm} (15)
and \( P_{s,m} \) and \( P_{t,MBS} \) are the transmission power for SBSs and MBS, respectively. \( x \) is defined in this paper as:
\[
x \in \{ \{ P_{t,m} \}_M, P_{t,MBS}, \{ \varphi_m^{SBS} \}_M \}
\]  \hspace{1cm} (16)

It is necessary to mention that \( M \) is defined as an integer, which cannot be directly solved by NSGA-II. Therefore, BnB algorithm is developed to relax integer programming, and thus the relaxed problem formulation can be tackled by NSGA-II, which will be discussed in Section IV.B.

The constraints of the optimization problem are:
\[
\begin{align*}
C_1: \ 0 & \leq P_{t,m} \leq P_{max}^{t,m}, \ \forall m \\
C_2 : \ P_{r,su}(m, n) & \geq P_{r}^{min} , \\
C_3 : \ \sigma_N \geq \sigma_N^{min} \\
C_4 : \ B_N \geq B_N^{min}
\end{align*}
\]  \hspace{1cm} (17)

\( C_1 \) limits the transmission powers of SBSs to be non-negative and do not exceed the maximum allowed (the allowed maximum can be determined by each mobile operator, or based on regulations). \( C_2 \) ensures the received power by users to be sufficient for communication. \( C_3 \) and \( C_4 \) gives the threshold for the average data rate and BER requirements to achieve the acceptable QoS performance, respectively.

2) INITIALIZATION

Algorithm parameters should be determined in the networking initialization process. In this paper, NSGA-II is adopted and customized for the optimization, because of the simplicity of its programming and outstanding performance. Population size, number of functions and constraints, and the number of parameters should be determined regarding to the modeling of the application. The crowding distance and other specific parameters for algorithms (such as crossover/mutation rates) are also determined in this process.

Population is initialized based on the variables. Suppose \( x^{0}_{cv} \) is the \( v^{th} \) dimensional variable (\( V \) variables in total) for the \( c^{th} \) individual \( (c = 1, 2, ..., C, \) where \( C \) is the population size) of iteration \( g \), where \( g = 0 \) for the initialization of the algorithm. \( x^{0}_{cv} \) is generated as:
\[
x^{0}_{cv} = \text{rand} (0, 1) \cdot (U_{cv} - L_{cv}) + L_{cv}
\]  \hspace{1cm} (18)

where \( L_{cv} \) and \( U_{cv} \) are the upper and lower bounds of the \( v^{th} \) dimensional variable in the solution space. In this paper, \( x \in \{ \{ P_{t,m} \}_M, P_{t,MBS}, \{ \varphi_m^{SBS} \}_M \} \) for \( x^{g}_{cv} \). Depending on the precision and bounds of variables, there are \( a_v \) bits for \( x^{g}_{cv} \). Suppose the individual \( c \) is programmed with \( A \) bits as \( \{ b_{c1}, b_{c2}, ..., b_{cA} \} \) (\( b_{cA} \) is the \( A^{th} \) bit for individual \( c \)) to represent all the variables, where
\[
A = \sum_{v=1}^{V} a_v
\]  \hspace{1cm} (19)

Crossover and mutation are implemented on the programmed individuals, with crossover (cros) and mutation (mutat) operators respectively [10]:
\[
\begin{align*}
& \begin{cases} c^{g+1}_{1} & c^{g+1}_{2} \\
n & n \end{cases} = \text{cros} \left( c^{g}_{1}, c^{g}_{2} \right) \\
& c^{g+1}_{3} = \text{mutat} \left( c^{g}_{3} \right)
\end{align*}
\]  \hspace{1cm} (20)

where \( c^{g+1}_{1}, c^{g+1}_{2} \) and \( c^{g+1}_{3} \) are the corresponding offspring of the selected individuals from the population in the former iteration \( g \), \( c^{g}_{1}, c^{g}_{2} \) and \( c^{g}_{3} \), respectively. \text{cros} and \text{mutat} are computational commands for NSGA-II, which can be directly cited from open sources [29].

3) MULTI-OBJECTIVE SEARCHING PROCESS

The main aim of this process is to generate new populations from the former population and individuals, generated by genetic operators for solution searching in the solution space. Three necessary sub-steps are needed in the proposed Smart-SC: Non-dominated sorting, Niche count calculation, and selection method.

According to the objective values, the populations are ranked and sorted. In Smart-SC, the ranking of the individuals can refer to the non-dominated concept. Assume two individuals \((u, w)\) for the maximization problem, it is defined that \( u \) is dominated by \( w \), if and only if
\[
\begin{align*}
u & \rightarrow w : \forall o \in O, \ f^u_o \leq f^w_o, \exists o \in O, f^u_o < f^w_o
\end{align*}
\]  \hspace{1cm} (22)

where \( O \) represents the total number of objectives. In this example, \( w \) gains higher ranking and thus, higher probability to be selected as next population than \( u \). Non-dominated scenario is defined as the exception of \( u \rightarrow w \) and \( w \rightarrow u \). Non-dominated individuals share the same ranking, when implementing the selection strategy for new populations.

Niche count calculation of individual \( c \) is a unique calculation in NSGA-II, to prevent solution tracking in local optimum or premature convergence, which is calculated as [10]:
\[
n_c = \sum_{c \in C, c \neq j} \text{sf} \left( d_{c j} \right)
\]  \hspace{1cm} (23)

where
\[
\text{sf} \left( d_{c j} \right) = \begin{cases} 1 - \frac{d_{c j}}{\sigma}, & \text{if } d_{c j} < \sigma \\
0, & \text{otherwise}
\end{cases}
\]  \hspace{1cm} (24)

and \( \sigma \) is the predetermined desired distance between two individuals \((d_{c j})\) according to the application, and
\[
d_{c j} = \sqrt{\sum_{o \in O} \left( \frac{f^c_o - f^j_o}{f^{max}_o - f^{min}_o} \right)^2}
\]  \hspace{1cm} (25)

where \( f^c_o \) is the \( o^{th} \) objective value of individual \( c \), \( f^{max}_o \) and \( f^{min}_o \) are the maximum and minimum values of the \( o^{th} \) objective among the population. Higher value of \( n_c \) reveals that \( c \) positions densely with other individuals, and therefore it will be assigned with a lower ranking, to ensure that the
searching result can cover the solution space representatively, instead of converging into a local optimum.

Selection of the new population follows the principle that individuals, with higher ranking, have higher probability of being selected. It is necessary to notice that the selection operates, based on probabilistic way, instead of deterministic way, to further increase the diversity of the algorithm.

The iteration will be terminated, when the maximum population is reached, or the output converges. The final solution set is referred to, as Pareto-Front (PF). Every solution in PF can be an optimal choice. The selection of the final solution for the specific application can be determined according to the requirement. In this paper, a generic selection method, reference point selection [26], is adopted to extract the final solution from PF. The reference point, \( \bar{r} \), is determined by the maximum point of each objective, which is:

\[
\bar{r} = \{ \max(f_1), \max(f_2) \}
\]  

(26)

We emphasize that max \( f_1 \) and max \( f_2 \) are the maximum value of \( f_1 \) and \( f_2 \), respectively, which are separately calculated. In other words, max \( f_1 \) and max \( f_2 \) represent the maximum possible (or ideal) values in the solution space for \( f_1 \) and \( f_2 \), respectively. The final solution \( (Q^*) \) will be determined as the nearest solution in PF to the reference point \( \bar{r} \):

\[
Q^* = \arg \min_{c \in PF} \sqrt{\sum_{o \in O} (f_o(x_c)) - \max(f_o))^2}
\]  

(27)

where \( x_c \) is the corresponding independent variable for the individual \( c \) in PF.

Fig. 2 shows the flowchart of the NSGA-II based optimization algorithm for multi-objective optimization problem in SC allocation. With a properly designed maximum iteration, the optimality (i.e. convergence and diversity performance) of NSGA-II is well proven, in previous researches [10], [28].

**FIGURE 2.** Flowchart for NSGA-II based optimization algorithm for Smart-SC.

---

**B. INTEGER PROGRAMMING RELAXATION BASED ON BnB**

Though BnB is not specifically limited to integer programming, it is well recognized as an effective way for integer related problem solving, based on the principle that the total set of solutions can be partitioned into smaller subsets [29]. These subsets are evaluated systematically, until the final solution is found.

Normally, BnB algorithm generates a tree-based structure, which contains nodes (stages) and branches as the framework. When initializing, the upper and lower bounds of the solution space, \( B_u \) and \( B_l \), should be defined. In our model, because the two objectives are both derived as maximization problems in (13) and (14), \( B_u \) can be obtained by relaxing the integer variables into real numbers. In this case, the number of SCs, \( m \), will be relaxed.

The initial stage in BnB \( (S_0) \) relaxes the integer \( m \in M, m \in \mathbb{Z} \) into \( \bar{m} \in \bar{M}, \bar{m} \in \mathbb{R} \). The corresponding \( \bar{m} \) refers to the relaxed value of the variable \( m \) to get \( B_u = \{B_{u_f}, \ldots, B_{u_l}, \ldots, B_{u_o}\} \), where \( B_{u_o} \) is the optimal solution for the \( o \)-th objective function. NSGA-II is exploited to obtain the optimal solution, by applying reference point selection to the PF (illustrated in Section IV.A) and corresponding \( \bar{m}_0 \) for \( S_0 \). \( B_{l_0} \) can be simply set as \( (-\infty, \ldots, -\infty) \).

The branch will then be obtained with \( S_{1,1} : m \leq [\bar{m}_0] \) and \( S_{1,2} : m \geq [\bar{m}_0] \), as added constraints in (15), where \( S_{1,1} \) and \( S_{1,2} \) refer to the stage 1 and 2 in BnB iteration 1, respectively. NSGA-II is then implemented for all the stages, separately. \( S_{1,1} \) and \( S_{1,2} \) are then considered again in NSGA-II (illustrated in Section IV.A) separately with the added constraints. To generalize it, the corresponding objective values obtained by \( S_{1,j} = \{J_{1,l_1}, \ldots, J_{1,l_o}, \ldots, J_{1,i_1}, \ldots, J_{1,i_o}\} \) (stage \( j \) in BnB iteration \( i \)), and the corresponding value of \( \bar{m} \) is \( \bar{m}_{i,j} \). For Smart-SC maximization problem, the lower bound will be updated through iterations as:

\[
B_{l_{i,j}} = \{B_{l_{i,l_1}}, \ldots, B_{l_{i,l_o}}, \ldots, B_{l_{i,i_1}}, \ldots, B_{l_{i,i_o}}\},
\]  

(28)

\[
B_{l_{i+1,f_o}} = \begin{cases} B_{l_{i,f_o}}, &\text{if } B_{l_{i,f_o}} \geq J_{i,f_o} \\ J_{i,f_o}, &\text{if } B_{l_{i,f_o}} \leq J_{i,f_o} \end{cases} \quad o \in O \quad (29)
\]

where \( B_{l_{i,j}} \) is the updated lower bound for BnB iteration \( i \). \( B_{l_{i+1,f_o}} \) is updated as \( J_{i,f_o} \), when the value \( J_{i,f_o} \) is no less than \( B_{l_{i,f_o}} \). The process repeats, until reaching the termination criteria, when 1) all the possible values of \( m \) has been visited; 2) maximum iteration is reached; or 3) the normalized difference between the lower bound and the upper bound is smaller than a predefined tolerance coefficient \( \epsilon \) [30]:

\[
\sum_{o \in [1,2]} \left| \frac{B_{u_{f_o}} - B_{l_{i,f_o}}}{B_{u_{f_o}}} \right| \leq \epsilon
\]  

(30)

**V. SIMULATION RESULTS AND ANALYSIS**

To evaluate the proposed scheme, an IoT-network based indoor-outdoor seamless localization for the airport is developed, to track the location of trolleys, which is highly demanded by the global airport to improve the usage efficiency of the trolleys with human power saving. Additionally, this can also prevent loss of trolleys. Generally, the localization of the trolleys is determined by the received signal strength (RSS), received by the BSs. The proposed Smart-SC infrastructure thus should ensure an optimal SC allocation with high RSS accuracy, optimal energy efficiency and data
 TABLE 2. Simulation parameters of NSGA-II.

| Parameters                        | Value |
|-----------------------------------|-------|
| No. of trolleys                   | 1000  |
| Area to be covered (m²)           | ~140,000 |
| SC radius (m)                     | 200   |
| Path loss exponent α              | 4     |
| Path loss constant \( \sigma_0 \) | 0.01  |
| SC transmission power range (dBm) | 0-20  |
| Packet length \( l \) (bits)      | 128   |
| Maximum BER requirement \( B_{\text{min}} \) | 0.05% |

 TABLE 3. Parameters of NSGA-II.

| Parameters                        | Value |
|-----------------------------------|-------|
| Population size                   | 100   |
| No. of runs                       | 5     |
| Maximum number of iterations      | 350   |
| Crossover type                    | Uniform |
| Crossover rate                    | 0.8   |
| Mutation rate                     | 0.2   |

The performance of SC allocation is the focus here, and it is evaluated, to provide optimal infrastructure for the follow-up networking operations and applications. Therefore, localization algorithm and handover strategy are not emphasized in this paper.

TABLE 2 gives simulation parameters for the scenario, according to the typical setup of an international airport, such as Hong Kong [31].

A. INITIAL STAGE ANALYSIS OF BnB AND CONVERGENCE ANALYSIS OF SMART-SC

First of all, the parameters in the \( S_0 \) of BnB should be determined, e.g. \( B_u, B_l, \) and the tolerance coefficient \( \epsilon = 0.01 \). As mentioned in Section IV.B, \( B_l \) could simply be initialized as \([-\infty, +\infty]\) with two objectives considered. \( B_u \) is determined by implementing the NSGA-II based algorithm, derived in Section IV.A, with a relaxed integer into real number: \( m \): \( m \in Z^+ \rightarrow \tilde{m} \): \( \tilde{m} \in R^+ \) added to the constraints in (17).

TABLE 3 shows the parameter settings for NSGA-II based Smart-SC to handle the problem solving. The population size is designed as 100 to handle the non-linear formulation in (13) and (14). To have an accurate optimization process, 5 runs are implemented and the overall performance of all runs is analyzed and sorted to give an accurate solution set. Uniform crossover and random-point mutation with the rate as 0.8 and 0.2, respectively.

To determine the maximum iteration, Fig. 3 shows the convergence performance of Smart-SC, which is defined as Hyper-Volume Index (HVI) [32]. Generally, HVI for iteration \( g \) is defined as the difference between the solutions in the adjacent iterations, which is calculated as:

\[
HVI^g = \frac{1}{C} \sum_{i \in EC} \left| c_i^g - c_{i-1}^g \right| (31)
\]

where \( C \) is the population size, \( c_i^g \) and \( c_{i-1}^g \) are the \( i^\text{th} \) individual after ranking, in the iteration \( g \) and \( g-1 \), respectively. With a range of [0,1], HVI reflects the difference between two iterations in the evolutionary algorithms, with 0 representing the unchanged two iterations. It can be shown from Fig. 3 that the value of HVI tends to be ~0 with the difference between two iterations less than 1%, when the iteration reaches 302. Therefore, the set of the maximum iteration as 350 with difference less than 0.2% is enough to search for the optimal solution set.

Based on the PF obtained by NSGA-II, and reference point selection in (27), the final solution is determined for \( B_u \) as: \( S_0 : B_u = \{42.4MB/s, 1.604Mbps\} , \tilde{m}_0 = 4.72 \). Therefore, two sub-stages are designed in Stage 1, \( S_{1,1} : \tilde{m} \leq 4 \) and \( S_{1,2} : \tilde{m} \geq 5 \). Similar process repeats for \( S_{1,1} \) and \( S_{1,2} \), and other follow-up stages, if any.

Fig. 4 shows the final tree for BnB with the corresponding variables \( J_{ij} \) and \( \tilde{m} \) for SC allocation in the designed scenario. \( S_{1,1} \) terminates the branch of \( \tilde{m} \leq 4 \) by obtaining the PF with integer \( \tilde{m} = m = 4 \). Similar situation happens to \( S_{2,1} : \tilde{m} = m = 5 \), which also achieves the termination criteria, with the difference between the upper (\( B_u \)) and lower bound (\( B_l \)) less than 1%. Now, we move to detailed energy efficiency and data rate analysis.

B. ENERGY EFFICIENCY AND DATA RATE PERFORMANCE OF THE PROPOSED SMART-SC

To comprehensively analyze the energy efficiency and data rate performance of the proposed Smart-SC, Fig. 5 (a)-(c)
To intuitively compare the performance of different $m$, the distribution of the energy efficiency ($\eta_N$) and data rate ($\sigma_N$) are shown in Fig. 6 (a) and (b), respectively. It is shown that the obtained optimal solution based on reference point selection (shown by the red line) are marked in Fig. 6 (a) and (b). $\eta_N$ and $\sigma_N$, when $m = 6$, are 37.2 Mb/J and 1.583 Mbps, respectively. Compared with the optimal $\eta_N$ and $\sigma_N$ for the case when $m = 5$ as 42.2 Mb/J and 1.592 Mbps, the $\eta_N$ with $m = 6$ is 13.5% lower with similar $\sigma_N$ performance. Therefore, the overall performance of $m = 5$ dominates that of $m = 6$.

When $m = 4$, the performance of both $\eta_N$ and $\sigma_N$ are similar to $m = 5$, with less than $\sim 3.4\%$ $\eta_N$ difference and both acceptable $\sigma_N$. However, it may be harder to handle load balancing with less SCs, and thus the pressure of the SBSs tends to be higher for $m = 4$. Therefore, in this paper, $m = 5$ is adopted for the designed scenario, with the parameters detailed in TABLE 2, achieving energy efficiency of 42.2 Mb/J. Besides, the corresponding average data rate is 1.592 Mbps, which is sufficient for the considered application of the sensor network, and IoT application in general.

C. PERFORMANCE COMPARISON BETWEEN THE PROPOSED SMART-SC AND BENCHMARKS

Four types of benchmark models are selected for performance comparison with the proposed Smart-SC, which are:
1) Macro-cell structure ("MCS"): a centralized macro-cell structure without SC deployment is considered. Multi-objective optimization to maximize the energy efficiency and data rate is developed for the MCS with the MBS only to keep the comparability with the Smart-SC;

2) SC allocation with random allocation in the area ("SC-RA"): SCs are deployed, and randomly allocated. Theoretically, these SCs will be distributed evenly in the operation area;

3) SC allocation with single objective for data rate maximization ("SC-SODRM"): SCs are deployed, with the optimization goal being only data rate maximization, while energy efficiency is defined as a constraint with an acceptable level, which adopts the formulation in [33].

4) SC allocation with single objective transferred from weighted multiple objectives ("SC-SOW-\(\omega\)"): instead of solving \(\left\{ f_1(x), f_2(x) \right\} \) with non-dominated concept and reference point selection, one objective: \(F = \sum_{o=0}^{2} \omega_o f_o(x)\) is tackled, where \(\omega_o\) is the weighting factor for the \(o^{th}\) objective. "\(\omega\)" in "SC-SOW-\(\omega\)" represents the scenarios with different set of weightings, e.g. "SC-SOW-\{0.25,0.75\}" refers to the scenario with \(\omega_1 = 0.25\) for \(f_1\) in (13) and \(\omega_2 = 0.75\) for \(f_2\) in (14)). In this paper, to comprehensively reflect the performance of benchmarked "SC-SOW-\(\omega\)”, three scenarios with different setting of \(\omega\) are considered, such as "SC-SOW-\{0.25,0.75\}", “SC-SOW-\{0.5,0.5\}” and “SC-SOW-\{0.75,0.25\}”.

Because the usage of trolleys depends on uncontrollable environmental parameters (e.g. human density, time, etc.), the number of trolleys that need localization simultaneously could be dynamic. In other words, the number of UEs is considered uncontrollable variable. Therefore, to generalize the performance of the Smart-SC and benchmarks, the comparison is designed with various number of trolleys (i.e. UEs), ranging from 100 to 1000. Fig. 7 and 8 show the comparison of the proposed Smart-SC and the benchmark, in respect to overall data rate and energy efficiency, respectively.

In Fig. 7 and Fig. 8, the proposed Smart-SC has outstanding performance, in both data rate and energy efficiency performance. Concretely, SC-SODRM achieves similar data rates compared to the proposed Smart-SC, as shown in Fig. 7. However, SC-SODRM achieves 22.74% less energy efficiency compared to the Smart-SC. Additionally, SC-SOW-\{0.25,0.75\} achieves the worst data rate among all the benchmarks, because the weighting of data rate maximization is much smaller compared to that of energy efficiency. In contrast, SC-SOW-\{0.75,0.25\} achieves high data rates among the benchmarks, whereas its achieved energy efficiency performance falls into disadvantageous position, due to high weighting factor of data rate maximization, compared to that of energy efficiency. Among all the considered benchmarks, MCS achieves the worst energy efficiency performance compared to SC deployed, and this inferiority even worsens, when the number of trolleys (i.e. UE) increases. The reason is the lack of offloading from MBSs to SBSs. In summary, the proposed Smart-SC outperforms all the considered benchmarks, with on average data rate improvement of 8.25% and energy efficiency improvement of 12.7%, throughout the comparison with all benchmarks. The proposed Smart-SC is, hence, analyzed to achieve the best performance to simultaneously provide energy efficiency and high data-rates, for IoT enabled networking development in smart city settings.

VI. FUTURE DEVELOPMENT

Although the allocation of SCs was proposed in the current paper, to give more accurate modelling and analysis of the Smart-SC, graph theory is suitable for large-scale networks and ultra-dense traffic with the adoption of parameters besides the distance of the SBSs and users. For example, eigenvalues reflect the connectivity of the Smart-SC and the weight of the edge in graph theory represents the channel loading of the connection, etc. Therefore, the graph theory provides more comprehensive analysis of the Smart-SC. As mentioned, the scale of the network should be analyzed, to classify if the network is an ultra-dense network. It is necessary to mention that specific formulation and modeling should be developed for ultra-dense traffic.

Additionally, the proposed algorithm fuses BnB and NSGA-II for the integer-programming multi-objective optimization problem. When there are more integer variables that are considered as controllable variables (e.g. No. of UEs associated with each SBS, when real-time offloading is
considered, the complexity of the exhaustive BnB algorithm may lead to heavy computation burdens. Therefore, a new multi-objective optimization algorithm, with a different simplified integer relaxation is required for optimization of SC allocation, in real-time networking services.

VII. CONCLUSION
5G networks are widely considered as the main enabler of wide IoT adoption. Densification is at the heart of 5G paradigm, enabling the provision of services to the foreseeable huge number of UEs in the future IoT era. In order to achieve densification, small cells (SCs) have been widely adopted to provide better service quality, lower energy consumption, in addition to supporting big number of UEs; however, the optimization of SC allocation still requires further research. In this paper, we proposed a small cell allocation scheme for IoT applications within the setup of smart city environment, called Smart-SC. An optimal SC allocation, as a vital setup in the SC networking, significantly affects the energy efficiency and QoS performance of the SC network services; therefore, decides the feasibility of the SC network deployment to provide the required services to IoT applications. The proposed SC allocation scheme is formulated as an integer-programming multi-objective optimization problem, fusing BnB and NSGA-II algorithms, to simultaneously optimize energy efficiency and maximize data rate. This is the first time such combination is considered in small cell allocation.

Towards the analysis of the performance of the proposed SC allocation scheme, a typical IoT application in smart city is considered as an exemplary scenario. Simulation results demonstrate that the proposed Smart-SC outperforms the benchmarked schemes at all different numbers of UEs, achieving on average 12.7% of energy efficiency improvement and 8.25% of data rate increase. We have proposed a Smart-SC allocation algorithm, which provides an enhanced energy-efficiency and higher data-rates, simultaneously, perfectly matching the foreseen requirements of the upcoming IoT applications in the future smart city.

REFERENCES

[1] Z. Zhou, P. Liu, J. Feng, Y. Zhang, S. Mumtaz, and J. Rodriguez, “Computation resource allocation and task assignment optimization in vehicular fog computing: A contract-matching approach,” IEEE Trans. Veh. Technol., vol. 68, no. 4, pp. 3113–3125, Apr. 2019, doi: 10.1109/TVT.2019.2849851.

[2] H. Liao, Z. Zhou, X. Zhao, L. Zhang, S. Mumtaz, A. Jolfaei, S. H. Ahmed, and A. K. Bashir, “Learning-based context-aware resource allocation for Edge-Computing-Empowered industrial IoT,” IEEE Internet Things J., vol. 7, no. 5, pp. 4260–4277, May 2020, doi: 10.1109/JIOT.2019.2963371.

[3] Release 16. Accessed: Feb. 13, 2020. [Online]. Available: https://www.3gpp.org/release-16

[4] M. De Reec, G. Mantas, A. Radwan, S. Mumtaz, J. Rodriguez, and I. E. Otung, “Key management for beyond 5G mobile small cells: A survey,” IEEE Access, vol. 7, pp. 59200–59236, 2019, doi: 10.1109/ACCESS.2019.2914359.

[5] H. Zhang, Y. Dong, J. Cheng, M. J. Hossain, and V. C. M. Leung, “Fronthauling for 5G LTE-U ultra dense small cell networks,” IEEE Wireless Commun., vol. 23, no. 6, pp. 48–53, Dec. 2016, doi: 10.1109/MWC.2016.1600060WC.

[6] S. Mollahasani and E. Onur, “Density-aware, Energy- and spectrum-efficient small cell scheduling,” IEEE Access, vol. 7, pp. 65852–65869, 2019, doi: 10.1109/ACCESS.2019.2917722.

[7] H. R. Chi, C. K. Wu, K. T. Ko, K. F. Tsang, and F. H. Hung, “Efficiency and robustness management for IEEE 802.15.4 in healthcare sensor network,” in Proc. IEEE 41st Annu. Conf. IEEE Ind. Electron. Soc., Nov. 2015, pp. 003586–003585, doi: 10.1109/IECON.2015.7392653.

[8] B. Dudin, N. A. Ali, A. Radwan, and A.-E.-M. Taha, “Resource allocation with automated QoE assessment in 5G/5SG wireless systems,” IEEE Netw., vol. 33, no. 4, pp. 76–81, Jul. 2019, doi: 10.1109/MNET.2019.1800463.

[9] Q. Biao, B. Nener, and X. Wang, “A modified NSGA-II for solving control allocation optimization problem in lateral flight control system for large aircraft,” IEEE Access, vol. 7, pp. 17696–17704, 2019, doi: 10.1109/ACCESS.2019.2894061.

[10] H. R. Chi, K. F. Tsang, K. T. Chui, H. S.-H. Chung, B. W. K. Ling, and L. L. Lai, “Interference-mitigated ZigBee-based advanced metering infrastructure,” IEEE Trans. Ind. Informat., vol. 12, no. 2, pp. 672–684, Apr. 2016, doi: 10.1109/TII.2015.2527618.

[11] G. Ghatak, A. De Domenico, and M. Coupechoux, "Coverage analysis and load balancing in HetNets with millimeter wave multi-RAT small cells," IEEE Trans. Wireless Commun., vol. 17, no. 5, pp. 3154–3169, May 2018, doi: 10.1109/TWC.2018.2807426.

[12] M. T. Islam, A.-E.-M. Taha, S. Akl, and S. Choudhary, “A two-phase auction-based fair resource allocation for underlying D2D communications,” in Proc. IEEE Int. Conf. Commun. (ICC), May 2016, pp. 1–6, doi: 10.1109/ICC.2016.7511460.

[13] Y. L. Lee, T. C. Chuah, A. A. El-Saleh, and J. Loo, “User association for backhaul load balancing with quality of service provisioning for heterogeneous networks,” IEEE Commun. Lett., vol. 22, no. 11, pp. 2338–2341, Nov. 2018, doi: 10.1109/LCOMM.2018.2867181.

[14] F. Guo, H. Zhang, H. Ji, X. Li, and V. C. M. Leung, “An efficient computation offloading management scheme in the densely deployed small cell networks with mobile edge computing,” IEEE/ACM Trans. Netw., vol. 26, no. 6, pp. 2651–2664, Dec. 2018, doi: 10.1109/TNET.2018.2873002.

[15] L. Chen, S. Zhou, and J. Xu, “Computation peer offloading for energy-constrained mobile edge computing in small-cell networks,” IEEE/ACM Trans. Netw., vol. 26, no. 4, pp. 1619–1632, Aug. 2018, doi: 10.1109/TNET.2018.2841758.

[16] T. D. Tran, T. D. Hoang, and L. B. Le, “Caching for heterogeneous small-cell networks with bandwidth allocation and caching-aware BS association,” IEEE Wireless Commun. Lett., vol. 8, no. 1, pp. 49–52, Feb. 2019, doi: 10.1109/LWC.2018.2851202.

[17] S. Samarakoon, M. Bennis, W. Saad, M. Debbah, and M. Latva-aho, “Ultra dense small cell networks: Turning density into energy efficiency,” IEEE J. Sel. Areas Commun., vol. 34, no. 5, pp. 1267–1280, May 2016, doi: 10.1109/JSAC.2016.2545539.

[18] Z. Zhou, C. Zhang, J. Wang, B. Gu, S. Mumtaz, J. Rodriguez, and X. Zhao, “Energy-efficient resource allocation for energy harvesting-based cognitive Machine-to-Machine communications,” IEEE Trans. Cognit. Commun. Netw., vol. 5, no. 3, pp. 595–607, Sep. 2019, doi: 10.1109/TCCN.2019.2929205.

[19] J. Zheng, Y. Wu, N. Zhang, H. Zhou, Y. Cai, and X. Shen, “Optimal power control in ultra-dense small cell networks: A game-theoretic approach,” IEEE Trans. Wireless Commun., vol. 16, no. 7, pp. 4139–4150, Jul. 2017, doi: 10.1109/TWC.2016.2610284.

[20] W. Lee, F. H. Hung, K. F. Tsang, C. K. Wu, and H. R. Chi, “RSS-based localization algorithm for indoor patient tracking,” in Proc. IEEE 14th Int. Conf. Inf. Informat. (INDIN), Jul. 2016, pp. 1060–1064, doi: 10.1109/INDIN.2016.7819321.

[21] W. Lee, F. H. Hung, K. F. Tsang, C. K. Wu, H. R. Chi, K. T. Chui, and W. H. Lau, “High accuracy localization of long term evolution localisation algorithm for indoor patient tracking,” in Proc. IEEE 90th Veh. Technol. Conf. (VTC-Fall), Sep. 2019, pp. 1–6, doi: 10.1109/VTCFall.2019.8891455.

[22] A. Mesodiakaki, F. Adelantado, L. Alonso, and C. Verikoukis, “Energy-efficient context-aware user association for outdoor small cell heterogeneous networks,” in Proc. IEEE Int. Conf. Commun. (ICC), Jun. 2014, pp. 1614–1619, doi: 10.1109/ICC.2014.6883553.
Z. Xue, J. Wang, G. Ding, H. Zhou, and Q. Wu, “Maximization of data dissemination in UAV-supported Internet of Things,” IEEE Wireless Commun. Lett., vol. 8, no. 1, pp. 185–188, Feb. 2019, doi: 10.1109/LWC.2018.2865775.

P. Wang, B. Di, H. Zhang, K. Bian, and L. Song, “Platoon cooperation in cellular V2X networks for 5G and beyond,” IEEE Trans. Wireless Commun., vol. 18, no. 8, pp. 3919–3932, Aug. 2019, doi: 10.1109/TWC.2019.2919602.

L. Xiaoping, D. Haiying, L. Hongwei, L. Mingxue, and S. Zhiqiang, “Optimization control of front-end speed regulation (FESR) wind turbine based on improved NSGA-II,” IEEE Access, vol. 7, pp. 45583–45593, 2019, doi: 10.1109/ACCESS.2019.2908995.

M. H. Arshad, M. A. Abido, A. Salem, and A. H. Elsayed, “Weighting factors optimization of model predictive torque control of induction motor using NSGA-II with TOPSIS decision making,” IEEE Access, vol. 7, pp. 177595–177606, 2019, doi: 10.1109/ACCESS.2019.2958415.

G. Campos Ciro, F. Dugardin, F. Yalaoui, and R. Kelly, “A NSGA-II and NSGA-III comparison for solving an open shop scheduling problem with resource constraints,” IFAC-PapersOnLine, vol. 49, no. 12, pp. 1272–1277, 2016, doi: 10.1016/j.ifacol.2016.07.690.

A Branch-and-Bound Algorithm for the Time-Dependent Rural Postman Problem | Elsevier Enhanced Reader. Accessed: May 28, 2020. Online. Available: https://reader.elsevier.com/reader/sd/pii/S1007570420300125?token=5B142D21616F209A0321990BDF2BFB5D583D81B121F1A54156578E9E606EB21FE303969AA09068D828ED9ACDCCA24CF. Accessed: May 28, 2020. Online. Available: https://reader.elsevier.com/reader/sd/pii/S0305054818302004?token=00B487111B55DA40F226729139777ACB9FAECC84DC355B863B99EF4739EE2104F56B0D37D98018DBA85DB8E93CC35F76B1C.

A Branch-and-Bound Algorithm for the Time-Dependent Rural Postman Problem | Elsevier Enhanced Reader. Accessed: May 28, 2020. Online. Available: https://reader.elsevier.com/reader/sd/pii/S0305054818302004?token=00B487111B55DA40F226729139777ACB9FAECC84DC355B863B99EF4739EE2104F56B0D37D98018DBA85DB8E93CC35F76B1C.

C.-M. Lam, I. K. M. Yu, F. Medel, D. C. W. Tsang, S.-C. Hsu, and C. S. Poon, “Life-cycle cost-benefit analysis on sustainable food waste management: The case of hong kong international airport,” J. Cleaner Prod., vol. 187, pp. 751–762, Jun. 2018, doi: 10.1016/j.jclepro.2018.03.160.

K. Yang, M. Emmerich, A. Deutz, and T. Bäck, “Multi-objective Bayesian global optimization using expected hypervolume improvement gradient,” Swarm Evol. Comput., vol. 44, pp. 945–956, Feb. 2019, doi: 10.1016/j.swevo.2018.10.007.

Z. Xue, J. Wang, G. Ding, H. Zhou, and Q. Wu, “Maximization of data dissemination in UAV-supported Internet of Things,” IEEE Wireless Commun. Lett., vol. 8, no. 1, pp. 185–188, Feb. 2019, doi: 10.1109/LWC.2018.2865775.