Markov Decision Process to Achieve Near-Optimal Admission Control Mechanism for 5G Cloud Radio Networks

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Abstract

Fifth-generation radio access networks have been proposed as a cloud architecture to provide a common connected resource pool management. In this regard, efficiently and effectively managing radio resources and allocating perspectives on the rapidly changing traffic load is a challenge. Admission control mechanism is a key factor influencing the system performance with limited resource pools and call-blocking probability constraints. In this paper, a precise mathematical programming model of centralized management is formulated for the resource scheduling problem. Operators can manage resources according to the algorithms designed by Markov decision process (MDP) and Lagrangian relaxation (LR) method for various traffic types. They can create different business levels for resource priorities. The system revenue enhanced under call-blocking constraints and quality of service constraints. The management mechanism is flexible and scalable for pursuing the required objectives.

Keywords: 5G, Admission control, MDP, QoS, Lagrangian relaxation

1 Introduction

The fifth-generation (5G) mobile communication system is scheduled to be launched in 2020. Several research projects have focused on wireless services that can provide high capacity (10 to 1000 × the data volume per area of 4G), high data rate (10 to 100 × that of 4G), massive device connectivity (10 to 100 × that of long-term evolution (LTE)), high energy efficiency (10 to 100 × extended battery life) [1], and low end-to-end delay (5 × reduced with 4G LTE) [2]. In 5G, a traditional base station (BS) is divided into two parts—the remote radio heads and the baseband units (BBUs)—which are installed in the fronthaul and backhaul of the cellular architecture, respectively. In the backhaul with a cloud radio access network (C-RAN) [3-4], efficiently managing radio resources and allocating perspectives on the rapidly changing traffic load are challenges [1].

The cellular architecture is illustrated in Figure 1. The scalability and flexibility issues of core network radio resource management are current major 5G research topics. This work aims to address the issues to observe a near-optimal solution. BBUs are collected in a centralized pool that dynamically allocates signal processing requirement to be handled by a cluster of servers. Such centralized BBU management at the backhaul permits the implementation of efficient radio resource management algorithms, which possess several advantages over traditional cellular architectures, such as increased resource utilization efficiency, low energy consumption, and light interference [5-6]. Accordingly, this study addresses resource allocation and admission control to achieve this goal.

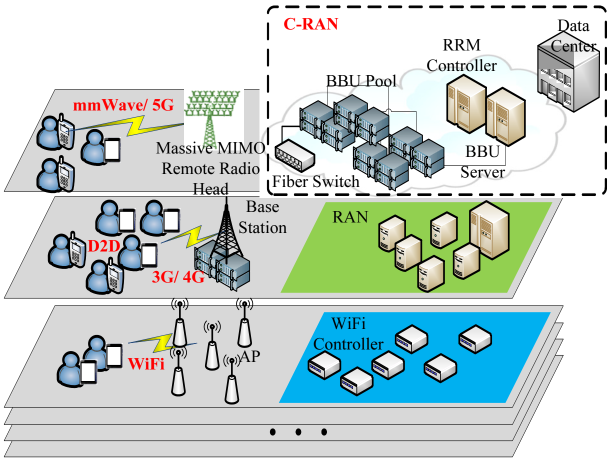

Figure 1. System architecture for HetNets

The factors influencing C-RAN operations include (1) the rapidly increasing data traffic, (2) the limited budget of the resource pool, and (3) call-blocking probability. As a network operator, one of the challenges is call admission control (CAC). This study

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optimizes individual scenarios, from an operator's perspective, by using the CAC mechanism with dynamic traffic load to maximize the system revenue. While addressing the dynamic traffic load, the decisions of CAC are linked with each other. Our goal is to determine the best CAC policy from the perspectives of budget, capacity, and call-blocking constraints. From the viewpoint of telecommunication service provider, the proposed algorithms rely on optimal decisions under the resource demands arriving time, satisfying the quality of service (QoS) metrics (e.g., call-blocking probability). Based on the varying traffic, the estimation of traffic load must also be considered.

A call admission controller of the system is designed accordingly. This system is responsible for making decisions on admitting or rejecting the task processing requests into 5G C-RAN. The Markov decision process (MDP)-based and Lagrangian relaxation (LR)-based approaches are effective methods to deal with the dynamic traffic trace and long-term-averaged performance estimation and evaluation to determine the optimal decision policy. The MDP-based and LR-based solution approaches are embedded into the controller, and the near-optimal decision policy is jointly determined for the resource admission control mechanism to improve the resource pool utilization.

The major contributions of this study are as follows:

- A precise mathematical programming model of centralized management is formulated for the task scheduling problem. The system revenue is enhanced under call-blocking constraints for evaluating a call admission problem.
- The problem with call-blocking constraints is modeled using the MDP-based and LR–based approach to obtain a near-optimal policy for long-term evaluation. This study aims to solve the trade-off between the revenue and call-blocking requirements in scheduling problems.
- The proposed task scheduling strategies blocking feasible check (BFC) and Lagrangian Relaxation & MDP learning procedure (LRMLP) methods task arrival and departure patterns are evaluated at different decision intervals. The LRMLP is used in combination with a near-optimal elastic admission control mechanism to solve the complex optimization problem. The experimental results reveal that the LRMLP is the optimal process in the cases of diverse decision intervals.
- The computational experiment results indicated that the proposed scheduling methods are used as a reference for network operations. We addressed the CAC problem under rapidly increasing data traffics emulated as 5G services (eMBB and mMTC), a limited resource pool, and a high call-blocking probability to obtain near-optimal policies.

The remainder of this paper is organized as follows. In Section 2, we present the literature review related to the current ideas and mechanisms for the emerging 5G technologies. Section 3 gives the problem description of CAC and the mathematical formulation. The proposed solution contains LRMLP, BFC, first come first served (FCFS), and LR, which is developed to find a near-optimal decision in Section 4. Various computational experiments and the corresponding results are discussed and validated in Section 5. Finally, the conclusion and future work are described in Section 6.

2 Related Work

From the viewpoint of system architecture, a major concern of wireless communication networks is to separate the traditional BS into a digital access processing unit and a simplified radio head. The digital access processing unit adopts the virtualization technology of cloud computing centralized management in a resource pool. The challenges and research problems are discovered by considering the resource pool management (including BBUs and servers in C-RAN).

From the viewpoint of network operator, a cloud computing service supports share-based services in a pay-as-you-go manner. It provides a flexible and lower capital expenditure architecture to operators; however, resource management is a major concern with complex on-demand traffic. If the resource allocation mechanism is not appropriately designed, the paradigms of the networks potentially increase the operating expenditure and yield dissatisfactory QoS metrics, such as call-blocking probability. The objective of this study is to maximize revenue while minimizing operational cost. The achievement of near-optimal power consumption efficiency and effectiveness is subjected to the system capacity and QoS constraints [7]. Table 1 compares our research with related studies in terms of (1) resource scheduling, (2) user information, and (3) traffic load. The current study focuses on resource scheduling in cases of different scenarios as well as an optimization-based approach is used to near-optimally solve the scheduling problem to maximize the system revenue.

In our system framework, a centralized architecture, such as 5G C-RAN, is considered for the resource allocation to develop call admission policies within limited resource pool. We addressed the call admission control problem under rapidly increasing data traffics emulated as 5G services (e.g., enhanced mobile broadband (eMBB) and massive machine-type communications (mMTC)), a limited resource pool, and a high call-blocking probability to obtain near-optimal policies through the combination approach with MDP and LR approaches. A call admission and scheduling mechanism with incomplete information

Table 1. Resource Scheduling Comparisons with Existing Work

Classification	Feature	Strategy	Related Studies	The type of our work
Resource scheduling	Static versus dynamic priority	Preemptive versus nonpreemptive	[8-10, 16, 20-21]	Dynamic and nonpreemptive
Comparison with related studies				
• The existing FCFS handles the resource scheduling with static priority and nonpreemptive that differ from our approach. Even though MDP can optimally solve the scheduling problem, this work considers both call admission and scheduling mechanisms. • According to the characteristic of 5G C-RAN, the FCFS emulates real-time resource scheduling method with static priority. Although MDP approach considers dynamic priority, this method cannot optimally solve the call-blocking problem. This is also the main reason to propose LRMLP method to near-optimally address the problem.				
Task information	Symmetric versus asymmetric	EDF versus FCFS	[11-13, 16]	Asymmetric and FCFS
Comparison with related studies				
An asymmetric and FCFS scheduling mechanism is concerned in our model. The task information, such as the finish time of processing task and the release time of new coming task, are unknown for scheduling events. The FCFS do not require any information. The MDP approach relies on the partial data, such as arrival time and finish time. However, the proposed algorithms dynamically accept or reject a task with incomplete information through a mathematical model.				
Traffic load	Uniform versus bursty	Historical data versus distribution	[17-19, 22-23]	Poisson arrival process
Comparison with related studies				
• Most of the existing work and our word adopt various traffic load to reflect the real environment. However, our work simulates varying distribution parameters, such as arrival and service rates, to compare various scenarios. • For statistical analysis, the Poisson arrival process is simulated as a task arrival pattern as well as the inter arrival time is exponential distributed for the varying traffic load. This differs from the existing work [18-19] to simulate with historical data.				

and the resource scheduling strategy is nonpreemptive. The Poisson arrival process is simulated as a task arrival pattern with varying traffic load. The proposed algorithms dynamically accept or reject a task with incomplete information through a mathematical model. An asymmetric and FCFS scheduling mechanism is concerned in batch control process. The task information, such as the finish time or the release time of new task are all unknown for scheduling events. The average arrival and departure rates of each type of tasks are given in computational experiments for a long term evaluation.

2.1 Resource Allocation and Scheduling

Resource allocation and scheduling algorithms are found in many research areas, such as transportation management, operations research, and computer science in real-time operating systems [8]. Scheduling methods, including pre-emptive and non-pre-emptive methods, have been developed in CPU resource processing control mechanisms. Static scheduling methods operate on a fixed set of procedures [9]. Moreover, both fixed and dynamic priority scheduling methods have the priority tagged with the process that the scheduler assigns as first priority depending on instantiations [10].

Earliest deadline first (EDF), which is a dynamic scheduling algorithm with complete task information, was proposed in [11] and adopted in [12]. It is used in real-time operating systems to allocate computing resources in CPUs in a priority queue. The queue is implemented for searching the tasks with the shortest deadline within the finished or released tasks in an operating system. Cho et al. combined priority and EDF scheduling to schedule both real-time and normal tasks [12]. Song et al. considered the characteristics of a task graph and virtual machines (VMs) of a cloud computing environment. The proposed task insertion method assigns the inserted task according to the deadline [13]. This study assigns various tasks according to the MDP model to maximize profit.

In the case of pre-emptive uniprocessors, EDF is an optimal scheduling algorithm that collects the tasks and completes them before deadline [11]. In the case of multiprocessor systems, a proportionally fair scheduling algorithm is a compromise-based scheduling algorithm. The main idea is to maximize resource utilization between the competing interests while maintaining a load balance. This can be done by assigning a weight priority for each flow that is inversely proportional to its anticipated resource consumption [14-15]. Ding et al. proposed the Linux scheduling policy with a priority queue, instead of FCFS queue, for kernel-based VM to improve system performance [16]. This study considers a call admission problem with call-blocking probability. A decentralized architecture of the resource management system for a datacenter is considered to develop policies and reallocate decisions to reduce data transfer overhead and network device load [20]. A fixed priority scheduling is based on a pre-emption threshold to be adopted for multicore processor scheduling [21].

Task acceptance or rejection is determined by the MDP model, where high priority tasks might not be always accepted. The priority of this study is dynamically determined by the system status. Our approach has considered an asymmetric and FCFS scheduling mechanism with incomplete environment information, such as the time of task finished and the time of new task released. The resource scheduling strategy is non-pre-emptive and FCFS emulated of real-time dynamic traffics in computational experiments.

2.2 Problems of Traffic Load Variant

From a network operator perspective, one of the challenges to provide on-demand services is caused by time-varying and periodically changing demands. Facing on the on-demand access, a cloud provider should consider an adjustable resource scheduling mechanism to satisfy the QoS and minimize the operating costs even though the traffic load is varying among peak hours and off-peak hours [17]. An accurate forecast of resource requirement is difficult because they are stochastic. Historical data are measured for an estimation of usage data to determine the load distribution and evaluate the performance of the proposed algorithm.

A centralized methodology has been previously proposed to precisely predict the probability distribution of requirements for multiple intervals [18-19]. The aforementioned computer science and datacenter concepts are also applicable to the wireless communication field. C-RAN enables the baseband resources with centralized management that a pooling system was proposed on a general-purpose processor for LTE and WiMAX [22]. Prathibha et al. proposed a non-dominated sorting particle swarm optimization method to schedule workflow applications and optimize energy consumption on a cloud environment [23]. This study focuses on the scheduling method with an optimization-based approach to near-optimally solve the scheduling problem. In this study, a centralized architecture of the resource management system for a datacenter is considered to develop call admission policies to maximize system revenue. Poisson arrival process is simulated as task arrival pattern. Task acceptance or rejection is determined by the proposed algorithms and the performance metrics are evaluated in some computational experiments.

2.3 Research Method

A cloud admission problem was modeled as MDP and solved using dynamic programming (DP) in [24]. The MDP framework is broadly used for solving problems analytically and numerically. However, it is not applicable to high-dimensional problems. A phenomenon is often determined to be a reference to make decisions from a low-dimensional to a high-dimensional problem [25]. In [26], the theoretic control techniques for solving admission control and resource allocation problems in a virtual environment were transformed as a cloud framework to model a linear programming problem to obtain an optimal solution. DP and MDP were proposed to obtain admission policies in [27]. In [28], a mobile cloud computing hotspot with a cloudlet was analyzed using MDP for dynamic resource sharing among mobile users.

3 Mathematical Formulation

In 5G C-RAN, BBUs are emulated as tasks (a subset of a job) to form VMs, which are deployed on physical machines. A limited number of VMs can be served simultaneously due to capacity constraints [29-30]. Thus, operators need an admission mechanism that relies on a feasible resource assignment to address the maximum system revenue with the limited resource problem. Admission control policies are defined according to various requirements, such as system utilization, task call-blocking probabilities, and user expectations in 5G C-RAN. Figure 2 shows an illustration of call admission control concept that the request arrival in the beginning of the admission control process. The inter arrival and departure time follows exponential distribution, where the transition rate is changed depending on the action taken.

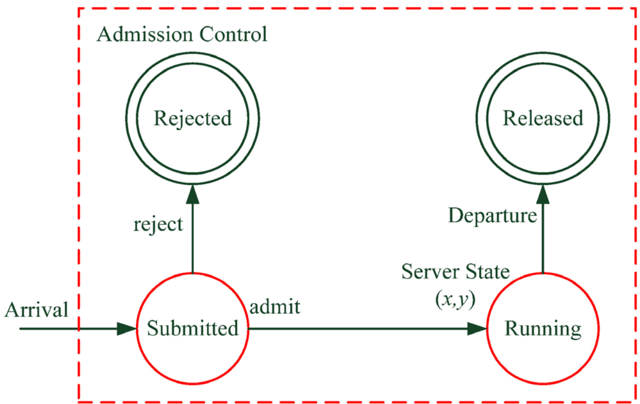

Figure 2. An example of CAC concept

This study uses MDP as a basic and analytical model to propose a dynamic admission control algorithm for the optimal task admission policy. Figure 3 shows a state transition rate diagram for reliability behavior. Poisson process is adopted for using the independent rates of task arrival and departure. The varying types of traffic are emulated as three types of 5G service, namely eMBB, mMTC, and uRLLC (Ultra-reliable and Low-latency Communications). We classify the tasks into two types of them—Types I (mMTC) and II (eMBB)—which represent emulated BBU computing requirements. The tasks are packed into a limited resource pool by the admission control policies. The types of tasks are characterized by the mean arrival rate λ_i and mean service rate μ_i. An appropriate admission control mechanism is proposed to observe the maximum system revenue subject to constraints.

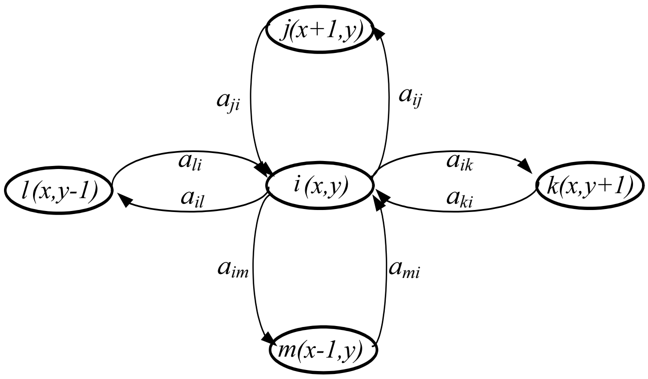

Figure 3. State transition rate diagram

However, some tasks are dropped when the traffic load higher than the limited resources. The aggregate BBU requirement load is occasionally higher than what a C-RAN can handle. If the traffic load cannot fit into the machine, the reject decision is made, as shown in Figure 4, where the state transition loops into itself.

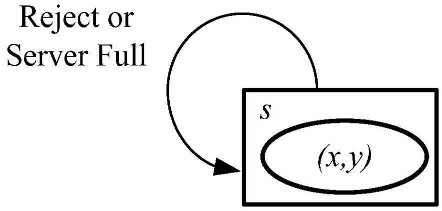

Figure 4. Station transition loop

Various revenue margins, resource requirements of tasks, and the system call-blocking rates are jointly considered. This work considers the problem to determine admission or rejection, the system revenue, and respect the requirements. It results in a trade-off between revenue and call-blocking requirements. We aim to observe the near-optimal decision policy to get the maximum system revenue under the call-blocking probability constraints.

Following assumptions are made for a system modeling:

- The system includes one pool with capacity C.
- Two types of tasks (Type I and Type II) are considered.
- The arrival and service rates of the tasks follow exponential distribution.
- Each state is denoted by (x,y), where x represents the number of tasks in service for Type I and y represents those for Type II.
- State transition is changed one at a time.

The set of actions decision k is defined in Table 2. Elements of an MDP problem are formulated by a pool with capacity C and the types of tasks are given and the state space, reward, transition rates, and actions are derived. Furthermore, call-blocking probability constraints are converted into a mathematical programming problem. How to design the optimal admission control policy is a goal to satisfy these constraints. The description of a verbal problem are listed in Table 3. The notations adopted in this paper are summarized in Table 4 and Table 5. To analyze the long-term behavior of the network, we evaluate the limiting distribution of this controlled continuous-time MDP. The objective function (Primal) is determined by the maximum expected reward. A set of decision variables is used to control the actions of each state to change the arrival rate to derive the stationary distribution vector of system states for a long-term evaluation.

Table 2. Decision set of actions

Decision (k)	Action
1	Grant All
2	Grant Type I
3	Grant Type II
4	Reject all tasks

Table 3. Scope and problem definition

Model: The BBU allocation strategy one at a time	
Given parameters	Type I tasks arrival rate Type II tasks arrival rate Call blocking probability for Type I tasks Call blocking probability for Type II tasks The reward rate for each state
Constraints	Server capacity Call blocking probability
Objective	To maximize the system revenue
To determine	Call admission policy to determine which types of tasks are accepted in each time.
Solution Approach	MDP and LR with call blocking constraints for the BBU allocation

Table 4. Given parameters

Notation	Description
S	The index set of states for a system which is $\{1,2,3,\ldots,s\}$
N	The index set of types for tasks which is $\{1,2,3,\ldots,n\}$
λ_n	Mean arrival rate of tasks for Type n (Exponential distribution) (number of tasks / hour)

Table 4. Given parameters (continue)

μ_n	Mean service rate of tasks for Type n (Exponential distribution) (number of tasks / hour)
q_i	The reward rate which is the revenue per unit time (amount of profit / hour) of state $i \in S$
P^{B_n}	The requirement of call blocking probability of tasks for Type n
B_n	The set of states that tasks of Type n are blocked
β_i	The set of Lagrangian multipliers for state $i \in S$
α_n	Lagrangian multipliers of Type $n \in N$

Table 5. Decision variables

Notation	Description
π_i	The steady-state probability of state i for $i \in S$.
a_{ij}	The transition rate from state i to state j for $i,j \in S$.

Objective function:

$$Z = \max \sum_{i \in S} \pi_i q_i \qquad \text{(Primal)}$$

Subject to:

The summation of steady-state probability for all states equals one. Hence, constraint (1) requires that the sum of the steady-state probabilities to equal 1.

$$\sum_{i \in S} \pi_i = 1 \tag{1}$$

The constraint is illustrated as a balance equation to be adopted by birth-death processes of the $M/M/1$ queueing system. The balance of flows equation describes transition in and out of the state, as shown in (2).

$$\sum_{i \neq j, j \in S} a_{ij}\pi_i = \sum_{i \neq j, j \in S} a_{ji}\pi_j \quad \forall i \in S \tag{2}$$

Each steady-state probability is greater and equal to zero.

$$\pi_i \geq 0 \quad \forall i \in S \tag{3}$$

The call-blocking probability does not exceed the bound for each type of task.

$$\sum_{j \in B_n} \pi_j \leq p^{B_n} \quad \forall j \in S, n \in N \tag{4}$$

4 Solution Approach

4.1 Model Analysis

The solution processes are followed to the processes of Markov decision process, Lagrangian relaxation methods, and FCFS iteratively changed actions or decisions. Two task scheduling methods, namely the BFC, LRMLP methods, are used on the task arrival and departure pattern to determine the level of superiority of the proposed MDP-based and LR-based obtaining primal feasible solutions, respectively. FCFS is an initial solution process to be a baseline for the performance comparison with BFC and LRMLP.

First is the feasibility analysis of the constraint region which comprises two parts: (a) global balance equation (2) with probabilities (1), (3), and (b) constraints of call blocking probabilities (4). If (4) can be directly ignored from the primal problem, which means that the remaining constraints and the global balance equation can be related as a standard MDP optimization problem. It is expressed as a Bellman equation and solved by using the value iteration and policy improvement algorithm, as illustrated in Figure 5 [31]. The algorithm is started from value iteration process to determine the value of q_i according to the given policy. Value iteration computes the optimal value of each state by iteratively improving the estimate of q_i. While value-iteration algorithm keeps improving the q_i values at each iteration, the iteration with the same policy will continually process. Once the value-function converges for next policy improvement input, it will run the policy improvement module to re-define the new policy. Value iteration and policy improvement processes are repeatedly exchanged to improve the value-function estimate until the optimal policy is converged.

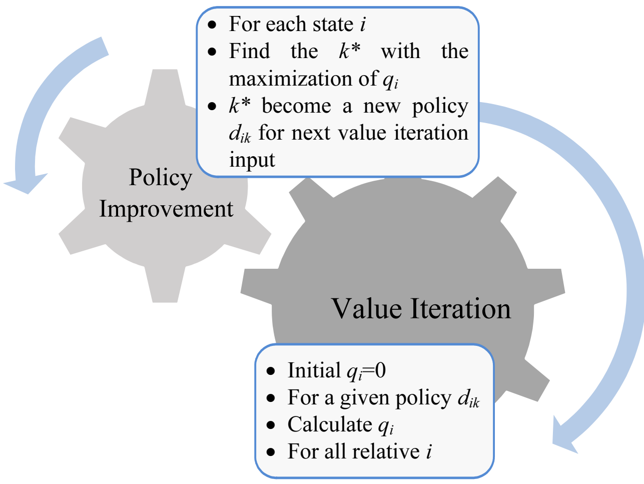

Figure 5. Value iteration and policy improvement algorithm for MDP

4.2 MDP-based Solution Approach

BFC is proposed to a MDP-based solution approach for statistical evaluation. The solution flowchart of BFC is shown in Figure 6. In BFC, the process is followed in the constraints (1)-(3) to iteratively calculate the probability of each state in each sub-problem with MDP method. The sum of arrival rate for a task type is checked feasible for constraint (4) and correspondingly changed one state at a time to approach a feasible solution and to evaluate the objective revenue. The solutions are derived within the number of iterations to reach a feasible solution.

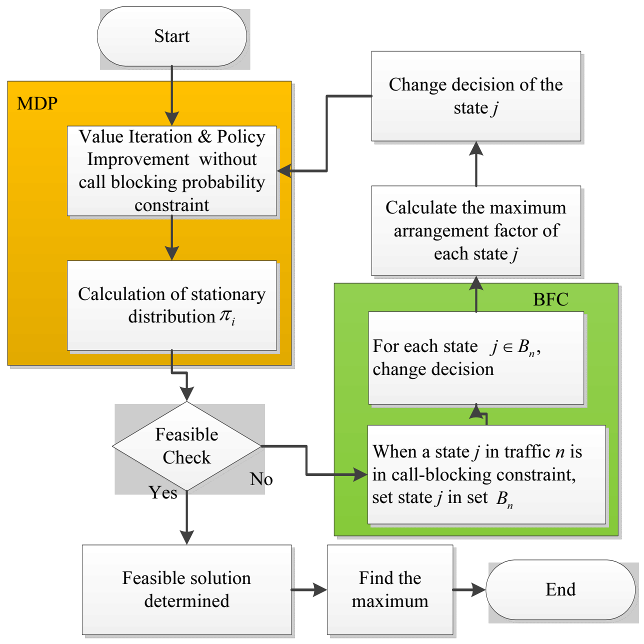

Figure 6. Flowchart of BFC

4.3 Lagrangian Relaxation-based Solution Approach

4.3.1 LR Method

The Lagrangian relaxation (LR) method was proposed to solve large-scale mathematical programming problems [32]. It has become a solution procedure, as shown in Figure 7 for overcoming mathematical programming problems, including optimization problems, such as integer programming problems or nonlinear programming problems in many practical situations. The key idea is to relax complicated constraints into the objective function and to extend feasible solution regions to simplify the primal problem. The primal problem is transformed into an LR problem associated with Lagrangian multipliers.

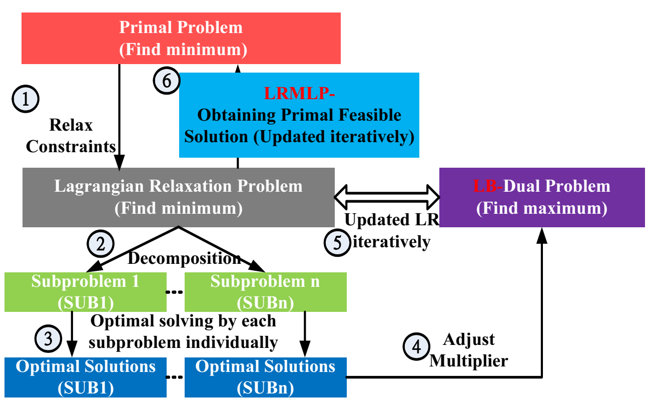

Figure 7. Concept of Lagrangian relaxation method

According to analysis of primal problem, Constraint (4) is relaxed into the objective function to reformulate to Z_{LR}. The reformulated problem (LR) is also viewed as a new standard MDP problem in each subproblem by decision variable decomposition. Other non-relaxed constraints are the same listed in (Primal) problem. Therefore, q_i is updated by $\sum_{i \neq j, j \in S} a_{ij}(r_{ij} - \beta_i)$ into the objective function of LR problem whereas the Lagrangian multipliers iteratively updated by solving Lagrangian dual problems (Dual). The primal objective function $r_{ii} + \sum_{i \neq j, j \in S} a_{ij} r_{ij}$ of q_i is relaxed with call-blocking probability constraints. The loop reward, r_{ii}, is always zero, so equation $q_i = r_{ii} + \sum_{i \neq j, j \in S} a_{ij} r_{ij}$ is modified as $\sum_{i \neq j, j \in S} a_{ij}(r_{ij} - \beta_i)$. The solutions determined by the LR problem are the other lower bounds of primal feasible solutions through solving LR and dual problem.

Objective functions:

$$Z_{LR} = \max \sum_{i \in S} \pi_i \Big[\sum_{i \neq j, j \in S} a_{ij}(r_{ij} - \beta_i) \Big] \quad \text{(LR)}$$

Subject to:
Constraints (1), (2), (3), and (5).

$$\beta_i = \sum_{n \in N} \alpha_n, \begin{cases} \alpha_n, & i \in B_n \\ 0, & i \notin B_n \end{cases} \tag{5}$$

The LR problem can be divided into several independent subproblems through decomposition methods associated with their own decision variables and constraints. Some heuristic approaches or other well-known algorithms are designed or adopted to solve each subproblem to determine the optimal solution, which is referred to as a suboptimal solution. The set of suboptimal solutions combined with the multipliers is a bound of primal solution. If the set of suboptimal solutions is satisfied with the relaxed constraints, the solutions are referred to as feasible solutions. The key to solve the primal problem is determined by the optimal feasible solutions. Therefore, the objective values of the primal problem are iteratively updated after feasible verifications are obtained. The solution processes are similarly followed to the processes of MDP-based solution approach iteratively changed actions or decisions after the observation of objective values or rewards.

4.3.2 Lagrangian Dual Problem

If a minimization problem is considered, solutions to the LR and dual problems are lower bounds (LB) for the primal problem. The lower bounds are iteratively improved by adjusting the set of multipliers. The formulation of dual problem is listed as follows. By applying the LR method and subgradient method to solve the subproblems, we observe a theoretically LB from the primal feasible solution and identify some information about the primal feasible solution that is iterated when solving the dual problem. The feasible region of a mathematical programming problem defined by the solutions must be satisfied by all constraints. The gap between the LB and feasible solutions is calculated within whole processes and iteratively repeated until the termination conditions are satisfied. To accelerate the convergence of the minimization gap, the subgradient optimization method is sufficiently efficient to adjust the multipliers in each iteration [32].

Objective functions:

$$Z_D = \min \sum_{i \in S} \pi_i \left[\sum_{i \neq j, j \in S} a_{ij}(r_{ij} - \beta_i) \right] \quad \text{(Dual)}$$

Subject to $\alpha_n \geq 0$

4.3.3 LRMLP

In this paper, a LRMLP heuristic is proposed for obtaining primal feasible solutions. The solution flowchart of LRMLP is shown in Figure 8. The left-hand side process is the same as Figure 6, which is followed by constraints (1)–(3) to iteratively calculate the probability of each state in each sub-problem with MDP method. The right-hand side process is the sum of arrival rate of one task type for feasible checking. Correspondingly changed the decision variables are based on a new criterion evaluated by the values of multiplier $\beta_i = \sum_{n \in N} \alpha_n$ in dual problem. For each iteration, the value of β_i is used to evaluate the importance index of the state i that the actions are changed properly. The sum of α_n can be also used as an index to interpret the importance of type n related to state i.

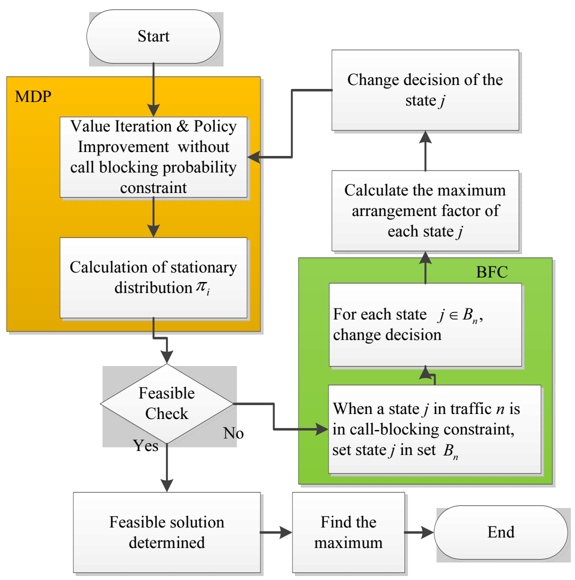

Figure 8. Flowchart of LRMLP

If there is a feasible solution to the primal problem, the solution is marked. The best solution in the distinguished algorithm is to be determined and compare the performance with existing methods. From the viewpoint of a telecommunications service provider, the proposed algorithms to determine a set of optimal decision variables based on the arrival time and QoS metrics.

5 Computational Experiments

5.1 Performance Evaluation

The experiment environment is initialized with two types of tasks—Types I (mMTC) and II (eMBB)—which represent emulated BBU request computing requirements respectively. An experiment program is self-implemented in Python on a Windows system. Several experimental cases are conducted for objective revenue evaluation. The given amounts of traffic loads of tasks and arrival time intervals are generated by exponential distribution with parameters λ_i and μ_i, respectively. Table 6 shows the attributes of the parameters used in the experiments. The experiments evaluation is used to improve the policy and observe high objective revenue from the viewpoint of system operators.

Table 6. Given parameters for experiments

Given parameter	Value
Number of task types	2
Resource pool capacity (unit)	10
Resource requests of Type I task (unit)	1
Resource requests of Type II task (unit)	5
Reward rate of Types for tasks	100~800
Number of actions	4
Mean arrival rate of tasks for Type n (λ_n)	1~50
Mean service rate of tasks for Type n (μ_n)	1~50
Requirement of call blocking probability of tasks	0.2~0.4

The state space based on the experiment setting is illustrated in Figure 9, where the transition rate a_{ij} is selected by decisions. If task traffic requirements are higher than the system capacity, the reject decision is made. Consequently, the state transition loops into itself. The total number of states for the two-type scenario is 18 for the designed experimental cases.

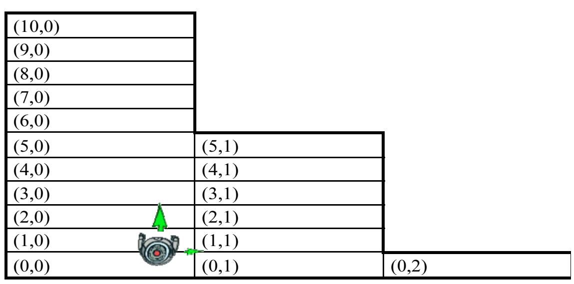

Figure 9. State space and possible transitions

5.2 Experimental Cases

5.2.1 Statistical Evaluation

Five experimental cases were evaluated in this paper. **Case A.** Control the arrival rate of task type I to evaluate the objective revenue for solving process with the call blocking constraints with LRMLP method. The arrival rate of another task type is fixed. In this experimental case, a 3D graph was evaluated to determine how the objective revenue was affected by λ_1 with fixed λ_2 from 1 and 50, as shown in Figure 10. The experiment results were as follows: The revenue increases when λ_1 is greater than 10 as well as the condition λ_2 is fixed. However, the higher arrival rate of type II tasks results in the higher revenue, implying that the higher arrival rate of type II tasks selected by actions of LRMLP to increase the objective values. The objective revenue has an increasing trend with a higher arrival rate for Type II tasks with fixed arrival rate of Type I. This means that Type II tasks have higher opportunity to be served to observe higher objective values. The objective values showed a significantly increasing trend, implying that decisions were made by choosing type II tasks with high values.

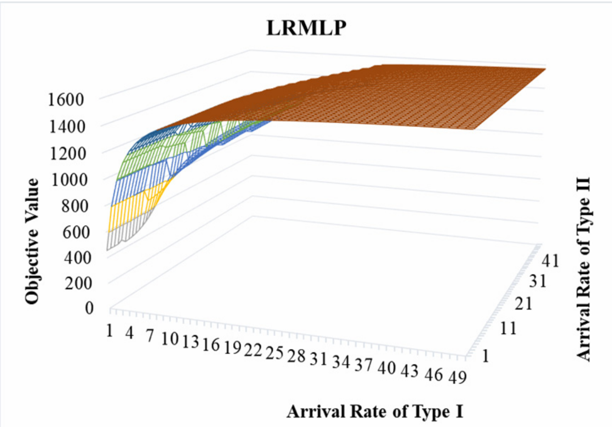

Figure 10. Evaluation of total revenue with type I and type II arrival rate

The physical meaning of the experimental results revealed that the low arrival rate of Type II tasks leads to a lack of opportunity for serving these tasks, and therefore, the system decides to serve Type I tasks. A high arrival rate of Type I tasks increases the objective revenue. The saturation of the objective revenue is reached at a stage when no more resources can be contained by Type I tasks. However, high arrival rates of Type II tasks resulted in monotonic revenue increases. The increased arrival rate of Type II tasks with limited server capacity caused insufficient space to be allocated to Type II tasks. As a result, the objective curve was flat.

Case B. In this case, the control variable is changed to the reward per Type I task. The main purpose is to exam the sensitivity of the reward and arrival rates effect on the system revenue. Figure 11 shows the evaluation results for the $\lambda_1 = 3.5$ curve at reward 100. Other settings are the same as Case A. The inset of Figure 11 indicate three points. The $\lambda_1 = 50$ curve has the deepest increasing rate with λ_1 being greater than the other curves., the intersection of the curves on the graph marks the point where the reward is equal to 60 to compare the other two cases with λ_1 equal to 3.5 and 5.4, respectively. By contrast, the increasing rate of the objective value for the $\lambda_1 = 5.4$ is greater than that for the $\lambda_1 = 3.5$ curve when the reward per Type I task is larger than 60. The objective revenue increases when the average reward per task increases. The objective revenue is in inverse proportion to the arrival rate of Type I tasks. However, the objective revenue is in directly proportional to the arrival rate. Accordingly, the policy is to set the low reward per Type I task when the arrival rate is low. Oppositely, the high reward per Type I task is set when the arrival rate is high.

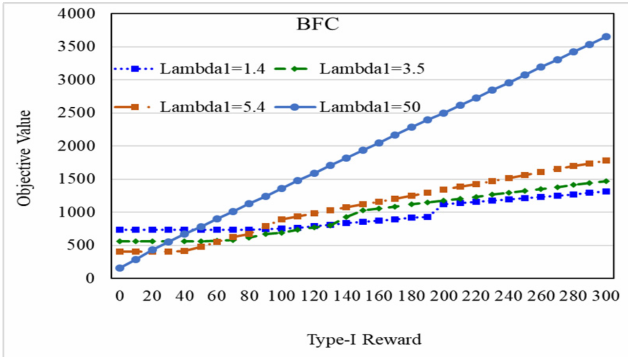

Figure 11. The Reward of Type I Effect on the Objective Revenue

5.2.2 Batch Process

Case C. Two previous cases determined the decision variables through LRMLP and BFC statistical evaluation for a long period of time. The following cases used a real-time evaluation considering call blocking constraints with task selection strategies (BFC, LB, LRMLP, and FCFS) in a decision time period. A sequence of arrival and departure patterns of tasks were set in a short-term evaluation. The task selection strategies are evaluated and compared within a decision period. The order of task arrival and departure patterns are used for a short-term evaluation. In Figure 12(a) and Figure 12(b) display the experimental results based on the system state (x,y). The results can be determined from the previous observations of the performance. The state transition changes from (x,y) to (x',y') with tasks arriving and simultaneously being implemented into systems one at a time. However, in the batch control process, the system state is transiently changed from (x',y') to (x'',y'') because some tasks departure in the decision processing interval, which is called the two decision intervals implementation. The cases are all established using the configurations for the analysis of the trade-off between the task arrival rate, decision intervals, and the task selection strategies.

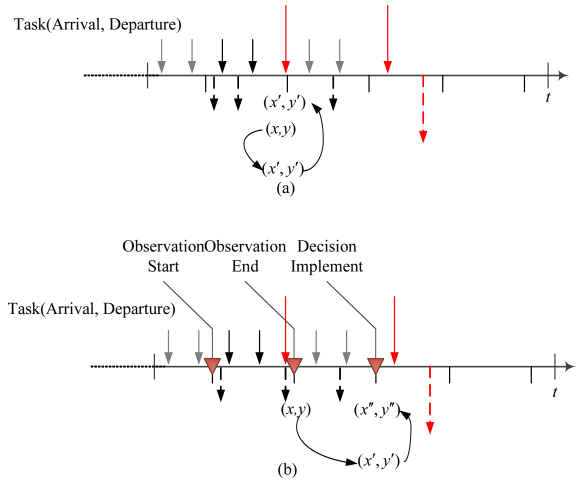

Figure 12. Decision interval and batch process

Two stages were set to determine the effects on the objective revenue and evaluation intervals for batch decisions. Overall, stage 1 evaluated the interval range *t* from 1 to 5 in which the objective revenues are increasing, as shown in Figure 13. The larger numbers of arrival tasks were buffered (aggregated) and served with higher revenue when the assignment interval increased. However, stage II set the decision intervals from 6 to 50 time slots. Overflow might have occurred to buffer such a large set of tasks owing to the limited capacity and the system utilization is decreased by the larger numbers of departure tasks in long decision intervals, and therefore, the objective revenue decreased. The curve of LRMLP was the highest primal feasible solution to take advantage of the server utilization without overflow under a given set of parameters. The curves of LRMLP and lower bound (LB) are closed in many cases which means the optimal solutions were determined. However, the decreasing trend of objective value was shown that overflow have occurred in large number of arrival tasks were buffered when the decision interval increased.

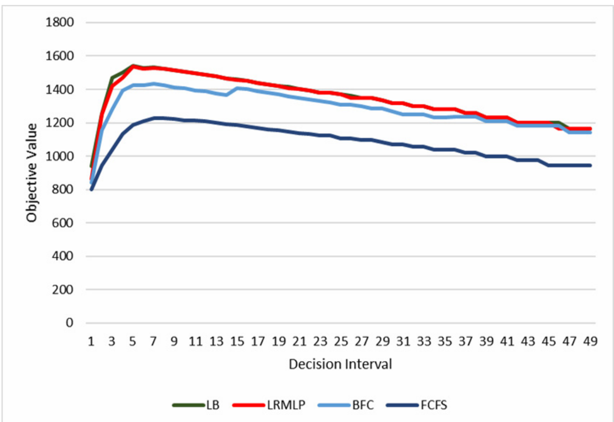

Figure 13. Evaluation of objective value when scaling decision interval

The previous case is used for a real-time evaluation with two task selection strategies in a variant decision time period. A special case is the decision interval approaching to zero, as shown in Figure 12(a) with the task arrival one at a time. The larger numbers of arrival tasks were buffered (aggregated) results in higher opportunity served with high revenue when the assignment interval is increased. Therefore, the objective revenue is decreased owing to the system utilization was decreased with the larger numbers of departure tasks in longer decision intervals. Owing to the best solutions of LRMLP in previous case, the following case is shown as ignoring the decision intervals for processing. The implementing decisions were made immediately by a table lookup method corresponding to the system states without the system state (x'', y''). The experimental results revealed the strategies offer more benefits than the cases of the decision intervals for processing in Figure 14. The solutions of LRMLP can be reused for operators to determine the maximum revenue and achieve flexibility by leveraging the previous solutions without processing time delay in variant decision intervals.

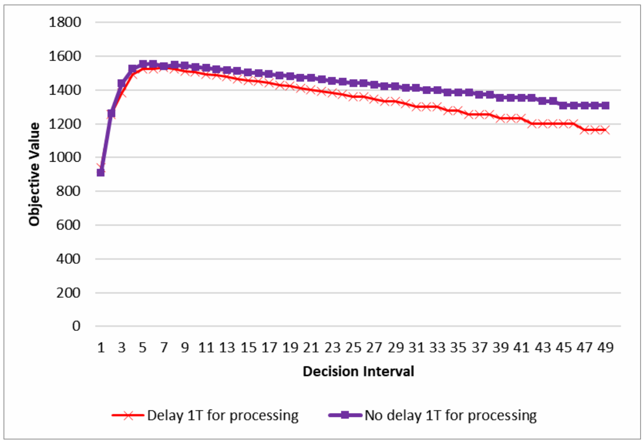

Figure 14. Evaluation of objective value when scaling decision interval with/ without processing time

Case D. The additional results of BFC were compared by controlling the arrival rate of Type I tasks, as shown in Figure 15. BFC is considered as a simple heuristic to determine a feasible solution with less processing time for real time network operations. For 5G applications, the delay is sensitive for variant decision intervals. In this case, the four types of curves had decision intervals $t = 1$, $t = 2$, $t = 4$, and $t = 7$, respectively. The main reason for the curve fluctuation was the random distribution of varying arrival rates for each period in which the number of arrival tasks varied in a short period. The effect of the controlled decision periods is clear when the average arrival rates of Type I tasks are provided. The objective revenue increased when the arrival rate also increased for $t = 1$ and $t = 2$ when the Type I task arrival rate increased from 0 to 12; however, the objective value decreased when the Type I task arrival rate increased from 14 to 50. Furthermore, for t = 4 and t = 7, the objective revenue decreased when the arrival rate increased. Therefore, the relatively long decision interval led the system to accept Type II tasks to achieve a relatively high objective value, and therefore, Type I tasks had less opportunity to be processed. The expected values of Type I tasks increased to occupy a relatively large amount of resources, and therefore, the objective revenue decreased when the arrival rate of Type I tasks increased. Furthermore, the curve with decision interval t = 4 had the highest objective values. However, the length of decision intervals was not always long enough to produce high objective values. This resulted in a trade-off between the task arrival rate and the decision intervals.

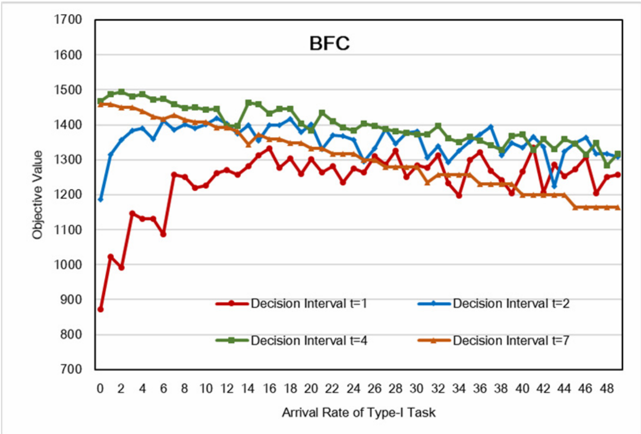

Figure 15. Evaluation of decision interval with various type I arrival rates

Case E. Figure 16 shows the curves of the objective revenue improvement ratio (denotes as IR), which is defined as percentage difference between the objective revenue. The ratio observed by LRMLP and BFC solutions is calculated using the equation $IR = \frac{V_{LRMLP} - V_{BFC}}{|V_{BFC}|} \times 100\%$, where V_{LRMLP} is the objective value obtained by the LRMLP algorithm and V_{BFC} is the objective value obtained by the BFC algorithm. The decision interval approaches zero and decisions are made with the tasks arriving individually. Figure 16 displays the improvement ratio evaluation for diverse arrival rates of Type I tasks. The vertical axis of Figure 16 represents the IR value that the zero of the vertical axis indicates the baseline of V_{BFC}. The objective revenue improvement ratio is positive, which indicates that V_{LRMLP} is greater than V_{BFC} at various decision intervals. It is possible that V_{LRMLP} was smaller than V_{BFC}. Then, the objective revenue improvement ratio was negative. According to our finding, the performance observed by LRMLP might worse than BFC method when the decision interval is long. It also shows the proposed method is limited to the reasonable decision period.

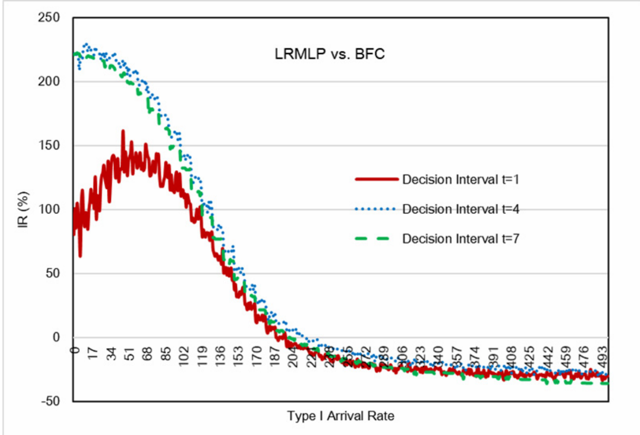

Figure 16. Improvement ratio evaluation with type I task arrival rate

In extreme case of type I task arrival rate increased (arrival rate = 400-500), a large decision interval (e.g., t = 7) was established, and the tasks were queued in starting from the beginning to the end of observation interval. The IR value resulted negative, the physical meaning was that the lower system utilization owing to the longer processing time for implementing decisions and a larger number of dropped tasks in queue. The objective values of LRMLP were lower than BFC in the extremely long decision interval cases. This computational experiment validated and resulted in a trade-off between the task arrival rate and the decision intervals.

6 Conclusion

We study the factors influencing C-RAN operations, including rapidly increasing data traffics emulated as 5G service types (eMBB and mMTC), a limited resource pool, and a high call-blocking probability to obtain near-optimal policies through the MDP-based and LR-based approaches. Some scenarios are evaluated for the performance metrics with dynamic traffic loads to maximize the system revenue. The proposed resource scheduling strategies BFC and LRMLP methods are used in combination with a near-optimal elastic admission control mechanism to solve the complex optimization problem. The experimental results revealed strategies (BFC and LRMLP) and trends that offer services. The finding supports operators to determine the maximum revenue and achieves flexibility in the cases of different decision intervals. Network operation, resource allocation, and task scheduling are embedded in a management controller, which will be considered in the next stage of the system covered in future work.

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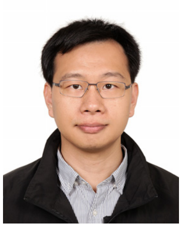

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