Thesis for the Degree of Master of Science

Green and Cost-efficient Fog Planning for Optimal IoT Task Scheduling

School of Computer Science and Engineering

The Graduate School

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Abstract

The incoming 5G technology is expected to proliferate tremendous internet-of-thing (IoT) services with real-time and mobility requirements, which are quite different from the legacy cloud services. Due to the centralized management relying on distant datacenters, cloud computing is short of satisfying the stringent IoT requirements, such as ultra-low latency, mobility, etc. Instead, distributed edge computing, such as fog computing has been coined as a promising approach and has received enormous attention in recent years. In this dissertation, to optimally provision the huge volume of IoT services with significant diversity, we propose to efficiently organize the leisure network devices in the network edge to form fog networks (fogs), which are then integrated with the cloud to provide storage and computing resources.

Specifically, we propose four Integer Linear Programming (ILP) models to solve the fog planning and fog topologies issue under the integrated Cloud-Fog (iCloudFog) framework. In the first ILP model, the objective is to minimize the CAPEX cost caused by planning fogs and the Utilization Cost caused by utilizing the planned fogs. In the second ILP model, the objective is to minimize the power consumption while maximizing the number of successfully provisioned IoT tasks on the planned fogs. Please note that the above two ILP models are based on fully-connected mesh topology. The third and fourth ILP models

are proposed for ring and star topologies, respectively, to study their impact on the performance of CAPEX and Utilization Cost.

The proposed ILP models are numerically evaluated by considering different IoT task requirements, such as real-time and mobility. The numerical results show that efficiently planned fogs can help to reduce the planning overhead while satisfying diverse IoT task requirements. Furthermore, star topology fogs is an optimal choice to improve network performance.

I. Introduction

The 5th generation mobile communication technology (5G) is at the forefront of supporting the emerging AI-enabled IoT applications and has evoked technology competitions among different organizations and countries. With the mature of 5G technologies, every "thing" in the world will be connected to the Internet. It is predicted that more than 50 billions of terminals and devices, such as smartphones, tablets, wearable devices, etc., will be connected to the Internet in 2020, which will generate as much as two Exabytes daily IoT data with features of volume, velocity, and variety [1]. Traditional cloud computing becomes short of handling such a huge amount of IoT data that requests ultra-low latency (i.e., real-time) and services with mobility, due to its centralized management relying on the distant enterprise datacenters belonging to some leading IT companies, such as Cisco, Google, Amazon, Facebook, etc.

In order to solve the needs of IoT tasks in 5G era, especially in mobility and real-time, this dissertation proposes a dynamic Fog Planning to achieve the best energy consumption and expenditure cost. At the same time, on the basis of the Fog planning, the performance of Fog networks with different topological structures is discussed and compared.

1.1 Background

The current datacenters in cloud are fixed and distant from the IoT end devices and thus are short of providing real-time services as well as addressing the issues induced by IoT task mobility. To make up for the above shortcomings of cloud computing and provide real-time IoT services in the vicinity of where IoT data are generated, fog computing was coined in 2012 by Cisco, aiming at making use of the leisure devices that are distributed in the network edge mostly with one-hop distance from the IoT end devices. These leisure devices can provide rich computing and storage resources after being appropriately organized as fogs [2].

Nonetheless, to efficiently provision IoT services by resorting to fog computing, a lot of significant issues should be addressed first. Amongst them, the most important one might be fog planning, in which fogs should be wisely constructed before they become available to provide effective services. The major reason lies in that the edge network devices may be wired or wireless, which differs significantly from each other in many aspects, such as computing/storage resources, capability of supporting the real-time and mobile IoT tasks, communication bandwidth, etc. How to effectively select the most appropriate candidate fog nodes (i.e., network edge devices) to form appropriate fog networks (fogs) so as to provision the diverse IoT services needs to be explored at the first stage. Secondly, considering the influence of different topologies in the formation of Fogs is also a direction worthy of consideration and Optimization for researchers. To the best of our knowledge, most of the existing research are conducted under the assumption of pre-designed fogs. Very few works have addressed the fog planning issue [3],[4] and none of them have taken into consideration various IoT data requirements.

1.2 Objectives

Referring to the current research results and existing literature, we aim at addressing the fog planning issue by taking into account the IoT task requirements of real-time and mobility in this dissertation. Specifically, we address the fog planning issue based on a scalable and flexible integrated Cloud-Fog (iCloudFog) framework proposed in [2]. iCloudFog framework consists of three layers, namely cloud layer, fog layer and IoT layer from top to bottom. The major novelty of this dissertation lies in that we consider to plan three different fog types, say the wireless fog (WLF) which consists of only wireless edge fog nodes, the wired fog (WDF) which consists of only wired edge fog nodes, and the hybrid fog (HBF) which consists of both wired and wireless fog nodes. In particular, we assume there are a lot of wired and wireless candidate fog nodes in the fog layer, and we anchor at optimally selecting some of these fog nodes to form appropriate fogs with the objective of optimizing the overall iCloudFog performance and meanwhile optimally provisioning as many IoT tasks as possible by satisfying their QoS requirements in terms of real-time and mobility. Regarding this, we proposed two integer linear programming models (ILP) models with objectives of minimizing the Utilization Cost and CAPEX overhead in fog planning, and minimizing the power consumption while maximizing the number of IoT tasks successfully served, respectively.

As a subsequent work, we explore the impact of different fog topologies on the iCloudFog performance, by means of proposing ILP for star and ring topologies (different from the fully-connected mesh mentioned above), respectively. In developing the ILP models, we take into consideration of diverse QoS requirements of IoT tasks, so as to optimize the overall performance.

1.3 Organization

The rest of the thesis is outlined below:

In section II, related works are introduced, where we review the research on the Internet of things and the existing network computing paradigm, as well as the current research results and challenges of fog computing.

In section III, iCloudFog framework and problem statement are described, where we declare the three-layer network architecture iCloudFog and state the problems to be solved. Specifically, Fog planning and Fogs topology. Here first introduces the shared parameters, variables, preconditions and other settings about the ILP model. Secondly, we have detailed constraints on the specific models of Fog planning and Fogs different topologies.

In section IV, experimental results and analysis are given, where we explain the numerical setting of our mathematical model, follow by analyzes the important experimental results, and get the best green and economic IoT task scheduling.

In section V, conclusions are mentioned, where we summarize our work and evaluate the results of the model. At the same time, the future research work is also prospected.

II. Related Works

This section first introduces the current status and issues of IoT, as well as the various network computing paradigms that have been proposed so far. After that, we introduce the current research hotspots of fog computing. Finally, we elaborate on the bottlenecks and challenges encountered in the development of fog computing.

2.1 Challenges of the Internet of Things

As an upgraded version of information technology, the IoT has become a new growth point of economic development in various countries and regions around the world. After years of development, the IoT industry plays an important role in industrial upgrading, energy conservation and emission reduction, employment promotion, etc., especially in the fields of intelligent transportation, smart grid and logistics, the IoT technology is widely used [5].

Although the IoT as a whole shows a rapid development trend, it is still in the simple application stage. Not only the application and promotion of technology are not standardized, but many major technologies are still in the stage of R & D. This leads to the IoT can not be efficient and feasible into the industrial development, especially in the network constructed by millions of mobile devices, security, real-time, mobility, bandwidth, reliability and other issues are particularly prominent.

2.2 Computing Paradigms

The development of IoT has greatly promoted various forms of computing paradigm. At the same time, computing paradigm also promotes the development and popularization of IoT.

- *Cloud Computing*

We are all familiar with cloud computing, which is a computing mode that uses the network to realize the use of shared computing facilities, storage devices, applications and other resources anytime, anywhere, on-demand and conveniently. Cloud computing is the most developed and still the most mainstream computing paradigm, but in the current 5G and Internet of things background, delay, congestion, low reliability, security attacks and other issues are increasingly prominent in cloud computing.

- *Edge Computing*

Edge computing can be understood as an operation program that uses the edge zone close to the data source. Edge computing further advances the concept of "local processing power", which is closer to the data source. Not in the central server after finishing the implementation of processing, but in the network of equipment implementation of processing. Compared with the cloud computing, there are few fault points due to the single nature. Each device acts independently to determine what data is stored locally and what data is sent to the cloud [6].

- *Mist Computing*

Mist computing can be understood as poor cloud computing or edge computing, because although the two concepts are advanced, they are not without disadvantages. First, privacy and security. In todays

Internet world, its common to be attacked by hackers, so customers privacy data is easy to leak. Second, network delay or interruption. Cloud computing is accessed remotely through the Internet. Although the speed of the network has been improved rapidly now, compared with the local area network, the speed is still delayed. Although edge computing is slightly better in terms of delay, if the network is interrupted, no matter cloud computing or edge computing, the service cannot be accessed. Third, bandwidth will consume the budget. Sometimes, the manufacturer will charge more than the budget according to the traffic, the application software performance is not stable enough, the data may not be worth putting on the cloud, the scale is too large and difficult to expand, and the lack of human capital is the root cause of mist computing [7].

In addition, the concepts of *sea computing*, *shared computing*, *mobile edge computing* and so on have been proposed. But in terms of current research and development, cloud computing has developed to a certain extent, with limited promotion space and increasingly obvious limitations. In addition to cloud computing, fog computing is the most widely studied and the most abundant computing paradigm in theory and practice. Therefore, this dissertation makes an in-depth exploration and practice of fog computing.

- *Fog Computing*

It was originally started by Prof. Stolfo of Columbia University in New York. The intention at the time was to use "fog" to stop hacking. Later, Cisco made a theoretical development. To put it simply, Fog Computing expands the concept of cloud computing (Cloud

Computing). Compared to the cloud, it is closer to the place where the data is generated.Almost all are stored in the cloud.

Fog computing is not a powerful server, but is made up of weaker and more dispersed functional computers. It emphasizes the number of servers, no matter how weak a single computing node is. Fog computing is a new generation of distributed computing, which conforms to the "decentralization" feature of the Internet of things. More generally, Fog computing can be understood as localized cloud computing.

In the past years, some progresses have been made on fog computing, with most of them being conducted based on the assumption that fogs have already been there. To list a few, *G. Li*, et al. proposed edge learning as a service for knowledge-centric applications by applying fog computing into the healthcare infrastructures, monitoring the patients physical health and calling in an emergency [8]. *J. Wu*, et al. proposed a fog-computing-enabled cognitive network function virtualization (NFV) approach for an information-centric future Internet [9]. *Z. Zhou*, et al. believed that fog computing can effectively provide data processing methods to mobile crowd sensing [10].

There are also some literature discussing the applications of fog computing in various fields. *Z. Ning*, et al. combined fog computing with deep reinforcement learning to build an intelligent offloading system that can effectively improve the quality of experience (QoE) of the Internet of Vehicles (IoV) [11-13]. *X. Hou*, et al. proposed the vehicular fog computing (VFC) by using vehicles as communications and computing infrastructures to solve the problems of traffic congestion and insufficient resources of vehicular networks. The performance of VFC under four traffic scenarios has been simulated and analyzed [14]. *F.Y. Okay*, et al. mainly considered the current global warming and climate issues, and proposed to apply fog computing to smart grids in order to enable real-time monitoring, data privacy protection, service fault tolerance, and location awareness, which was demonstrated to be able to improve the global energy efficiency [15]. *A.M. Rahmani* and B. *Negash*, et al. investigated whether fog computing is feasible in healthcare by conducting real-time data analyses, monitoring power consumption and evaluating the performance of wearable devices with the assistance of fogs [16],[17].

Some other literature focused on addressing the challengesof fog computing in aspects of QoS guarantee [18]–[20], service latency [19], [21], blockchain [22], [23], energyefficiency [20], [24]–[26], machine learning [10], [27], costmanagement [28], data privacy and information security[25], [29], [30]. Most of the literature were based on theassumption of well-prepared fog networks (fogs). Very few of them addressed the fog planning and design issues, not tomention the solutions to a series of consequential issues [3],[4]. *F. Haider* and *A. Yousefpour's* have addressed similarissues by considering to interconnect fog nodes to form fogsthat can be used to share resources and serve IoT tasks [3],[4]. Nonetheless, they have neither considered the differentcharacteristics of wireless and wired candidate fog nodes northe real-time and mobility requirements of IoT tasks.

III. iCloudFog Framework and Problem Statement

In this section, the thesis introduces iCloudFog, an architecture suitable for three-layer networks, and constructs three ILP mathematical models to explore the performance differences between Fog planning and Fogs different topologies.

3.1 iCloudFog Framework

The iCloudFog framework is shown in Figure 3.1. It consists of three layers, i.e., IoT end layer, fog layer and cloud layer from bottom to top. The bottom IoT layer consists of various types IoT devices, such as sensors, smartphones, wearable devices, tablets, etc. These tremendous IoT devices generate a large volume of heavyweight or lightweight IoT tasks that would require services from fogs and/or cloud. Note that we assume there is no direct connection from the IoT end layer to the cloud. Any IoT task must bypass some wired fog node in the fog layer to access the resources in the cloud, if needed.

The middle fog layer is mainly composed of wireless and wired fog nodes, which can provide network resources such as transmission bandwidth and computing/storage resources. In this layer, we dynamically organize the candidate fog nodes to form different fog types, i.e., wireless fogs (WLF), wired fogs (WDF), and hybrid fogs (HBF) as shown in Figure 3.2 [2], with the objective of optimally satisfying diverse QoS requirements of the uploaded IoT tasks while minimizing the required cloud and/or fog resources. One naive approach is to upload the IoT tasks to the fogs for processing based on their geographic locations.

For the top cloud layer, we assume it has sufficient resources in terms of both transmission bandwidth and computing/storage units, which tends to serve the legacy heavyweight cloud services that may require a large number of transmission bandwidth and computing/ storage resources with no real-time or mobility requirements.

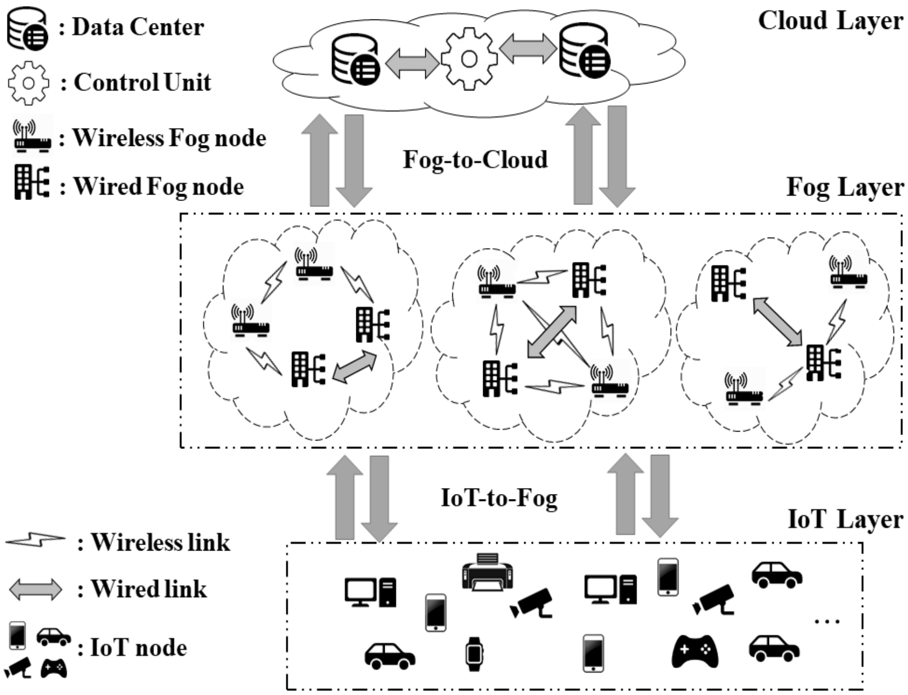


Fig 3.1 iCloudFog framework.

The above is iCloudFog under a fully-connected mesh, which is used to study Fog planning more intuitively. Besides, we consider the fog planning cost (i.e., CAPEX) due to constructing different types of fogs and the fog utilization cost (i.e., Utilization Cost) induced by serving IoT tasks on planned fogs. The CAPEX cost of constructing a homogeneous fog, i.e., WLF or WDF, is the same and less than that of a heterogeneous one, i.e., HBF; the Utilization Cost overhead of WDF is the least, followed by HBF, WLF, and cloud in an increasing order. For WLF, WDF, and HBF, we consider topologies of ring, star and fully-connected mesh. These three different topologies are shown in Figure 3.3.

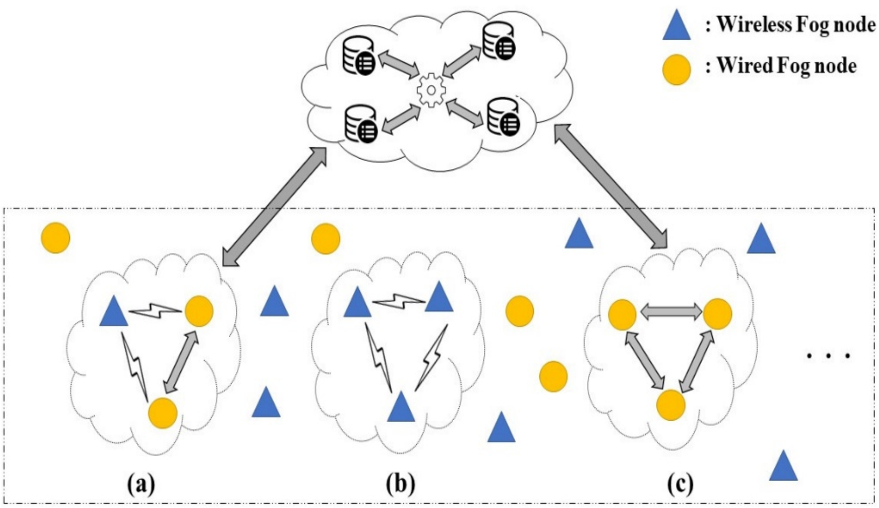


Fig 3.2 Fog types: (a) Wireless fogs (WLF); (b) Hybrid Wired-Wireless fogs (HBF); (c) Wired fogs (WDF) [2].

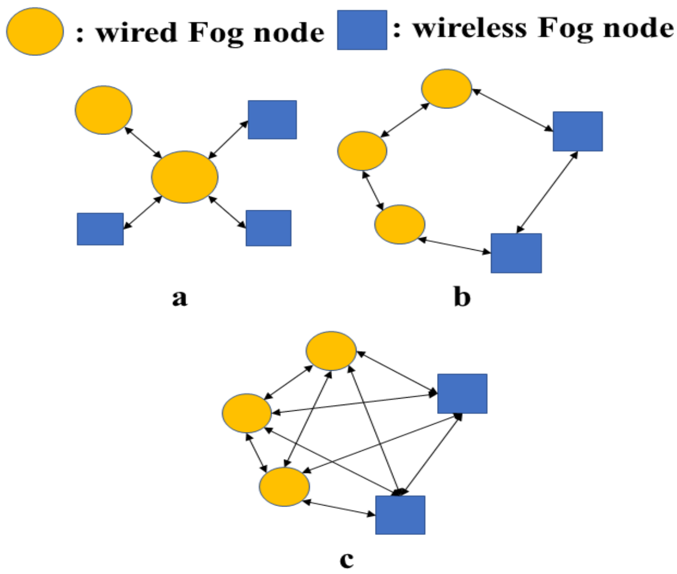


Fig 3.3 a: star topology; b: ring topology; c: fully-connected mesh.

3.2 Problem Statement

Based on the above iCloudFog framework and assumptions, we mainly consider two types of IoT tasks differing in whether the real-time and mobility requirements should be satisfied. In addition, we have described the problem solving models of Fog planning and Fogs topology in detail.

For an IoT task with mobility requirement, we assume that it can only be offloaded to a planned fog via a wireless fog node and thus it can be provisioned by either a WLF or a HBF; for an IoT task with real-time requirement, it can be offloaded to a planned fog which consists of at least one wireless fog node. Therefore, a real-time IoT task can also be served by a WLF or a HBF. The difference with that of IoT mobile tasks lies in that a real-time IoT task can be offloaded to a WLF or a HBF via either a wireless or a wired fog node in a planned fog. Nonetheless, IoT tasks with either real-time or mobility requirement cannot be uploaded to the cloud for processing. In other words, only IoT tasks with neither real-time nor mobility requirement can be uploaded to the cloud via some wired fog node deployed in the middle fog layer.

In the middle layer of Figure 3.1, we assume that there are a lot of distributed wired and wireless candidate fog nodes. Amongst them, we aim to optimally select the most appropriate wireless or wired fog nodes to form either WLFs, WDFs, or HBFs with the objective of minimizing the fog planning overhead while maximizing the number of successfully served IoT tasks with significant diversities.

In terms of the fog planning overhead, we mainly consider the CAPEX deployment cost, i.e. fog planning cost caused by connecting different types of fog nodes and the fog utilization cost, i.e., Utilization Cost, caused by serving IoT tasks after fogs are constructed. Note that the cost of constructing a WLF, a WDF, and a HBF are different. We assume that the CAPEX cost of constructing a WLF is the least, followed by a WDF and a HBF in an increasing order. The overhead of using different fogs and cloud is also different. We assume that the Utilization Cost of using a WDF is the least, follows by a HBF, a WLF, and cloud in an increasing order.

With the above assumptions, we first address the issue of fog planning and IoT task provisioning via proposing two integer linear programming (ILP) models, aiming at optimally planning several fogs of different types, ie., WLFs, WDFs, and HBFs, to provision the IoT tasks w/o real-time and mobility requirements, by collaborating with cloud. Note that for simplicity, we consider fully-connected topology for all the planned fogs despite their sizes.

The first ILP model is proposed to minimize the planning overhead in terms of the CAPEX and Utilization Cost and is named as ILP-TotalCost. The second ILP model is proposed to minimize the power consumption while maximizing the number of successfully provisioned IoT tasks upon the planned fogs and is named as ILP-Energy.

3.3 Proposed ILP Model for Fog Planning

3.3.1 Minimizing CAPEX and Utilization Cost (ILP- TotalCost)

The CAPEX cost in fog planning mainly comes from constructing different fog types using different links, such as wireless and wired links. The Utilization Cost considered in this dissertation is due to using different types of fogs to serve IoT tasks with different QoS requirements as introduced previously.

Assume the total number of candidate fog nodes in the fog layer is $\boldsymbol{j}$ and the number of fog nodes that can participate in constructing any fog is identically set to $\boldsymbol{N}$. Note that not all candidate fog nodes will be selected in the planning process. Regarding this, we use $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ as the lower and upper bound ratios of the candidate nodes that should participate in the overall fog planning process. The definitions of the objectives, sets, parameters, decision variables, and constraints of the first ILP model are given in the following.

1) Sets and Parameters

IT	Set of IoT tasks
FN	Set of fog nodes, which could be wireless (WL) and wired (WD)
CF	Set of Cloud, WL nodes, WD nodes
$\boldsymbol{IC_i}$	Total number of computing resources required by IoT task $\boldsymbol{i}$, $\boldsymbol{i} \in IT$
$\boldsymbol{IS_i}$	Total number of storage resources required by IoT task $\boldsymbol{i}$, $\boldsymbol{i} \in IT$
$\boldsymbol{IM_i}$	Binary parameter. One indicates IoT task $\boldsymbol{i}$ requires mobility; zero, vice versa, $\boldsymbol{i} \in IT$
$\boldsymbol{IR_i}$	Binary parameter. One indicates IoT task $\boldsymbol{i}$ requires real-time; zero, vice versa, $\boldsymbol{i} \in IT$
$\boldsymbol{FC_j}$	Total number of available computing resources in fog node $\boldsymbol{j}$, $\boldsymbol{j} \in FN$
$\boldsymbol{FS_j}$	Total number of available storage resources in fog node $\boldsymbol{j}$, $\boldsymbol{j} \in FN$
$\boldsymbol{FT_j}$	Binary parameter. One indicates fog node $\boldsymbol{j}$ is wireless one; zero indicates fog node $\boldsymbol{j}$ is wired one, $\boldsymbol{j} \in FN$
$\boldsymbol{DC_{h,k}}$	CAPEX cost of deploying links between fog nodes $\boldsymbol{h}$ and $\boldsymbol{k}$, $\boldsymbol{h}, \boldsymbol{k} \in CF$
$\boldsymbol{UC_{j,l}}$	Utilization Cost of using fog node or Cloud node $\boldsymbol{l}$ to serve any IoT tasks $\boldsymbol{i}$, $\boldsymbol{i} \in IT, \boldsymbol{l} \in CF$
$\boldsymbol{N}$	The number of fog nodes that can participate in constructing a fog
$\boldsymbol{\alpha}$	Lower bound ratio of fog nodes that will be selected to

	form fogs
$\boldsymbol{\beta}$	Upper bound ratio of fog nodes that will be selected to form fogs
$\boldsymbol{D_{jj'}}$	The set of distances in kilometers between fog nodes $\boldsymbol{j}$ and $\boldsymbol{j'}$, $\boldsymbol{j}, \boldsymbol{j'} \in FN$

2) *Decision variable*

$\boldsymbol{x_{ij}}$	Binary variable. One indicates IoT task $\boldsymbol{i}$ is successfully served by fog node $\boldsymbol{j}$ in some fog types; zero, vice versa $\boldsymbol{i} \in IT$ & $\boldsymbol{j} \in FN$
$\boldsymbol{y_{jj'}}$	Binary variable. One indicates the link between fog node $\boldsymbol{j}$ and fog node $\boldsymbol{j'}$ is deployed; zero, vice versa; $\boldsymbol{j}, \boldsymbol{j'}$ FN & $\boldsymbol{j} \neq \boldsymbol{j'}$
$\boldsymbol{z_{ij}}$	Binary variable. One indicates IoT task $\boldsymbol{i}$ is handled in Cloud by connecting to wired fog node $\boldsymbol{j}$; zero, vice versa; $\boldsymbol{i} \in IT$ & $\boldsymbol{j} \in WD$
$\boldsymbol{u_j}$	Binary variable. One indicates fog node $\boldsymbol{j}$ is selected to form a fog types; zero, vice versa; $\boldsymbol{j} \in FN$

3) *Objective*

Minimize (Total_Cost):

$$Minimize\left(\sum_{h}\sum_{k} DC_{h,k} + \sum_{i}\sum_{l} UC_{i,l}\right),$$
$$i \in IT, h, k \in FN, l \in CF \tag{3.1}$$

The above equation expresses the first objective. It aims at minimizing the total CAPEX and Utilization Cost, where the first item, say $\sum_h \sum_k DC_{h,k}$, indicates CAPEX cost due to deploying link between fog nodes ***h*** and ***k***; while the second item, say $\sum_m \sum_n UC_{i,l}$, indicates Utilization Cost due to serving IoT task ***i*** via cloud or fog node ***l***. The specific calculation of the two items are given in equations (3.2) and (3.3).

$$\sum_h \sum_k DC_{h,k} = \sum_j^{j \in FN} \sum_{j'}^{j' \in FN} y_{jj'} * \begin{pmatrix} DC_{WL,WD} * \left(FT_j * \{(1 - FT\}_{j'}\right) + \{(1 - FT\}_j) * FT_{j'}) + \\ DC_{WL,WL} * FT_j * FT_{j'} + \\ DC_{WD,WD} * \left(1 - FT_j\right) * (1 - FT_{j'})\,) \end{pmatrix} \tag{3.2}$$

$$\sum_i \sum_l UC_{i,l} = \sum_i^{i \in IT} \sum_j^{j \in FN} (IC_i + IS_i) * \begin{pmatrix} \mathrm{x_{ij}} * \left(\mathrm{UC_{i,WD}} * \left(1 - \mathrm{FT_j}\right) + \mathrm{UC_{i,WL}} * \mathrm{FT_{j'}}\right) \\ + \\ \mathrm{z_{i,j}} * \mathrm{UC_{i,Cloud}} \end{pmatrix}, \tag{3.3}$$

4) Constraints

- Constraints on fog planning

$$0.5 * (N - 1) * \sum_j^{j \in FN} u_j = \sum_j^{j \in FN} \sum_{j'}^{j' \in FN} y_{jj'} , \tag{3.4}$$

$$u_j * (N-1) - \sum_{j'}^{j' \in FN} y_{jj'} = 0 \,, \forall j \in FN \,, \tag{3.5}$$

$$u_j + u_{j'} \geq 2 * y_{jj'} \,, \forall j, j' \in FN \,, \tag{3.6}$$

$$\alpha * \sum_{j}^{j \in FN} j \leq \sum_{j}^{j \in FN} u_j \leq \beta * \sum_{j}^{j \in FN} j \,, \tag{3.7}$$

$$y_{jj'} + y_{jj''} + y_{j'j''} = \begin{cases} 0 \\ 1 \\ 3 \end{cases} , \ \forall \ j', j'', \in \ FN \,, \tag{3.8}$$

Since we consider to plan fogs with full connection, constraint (3.4) ensures that the total number of links in all the planned fogs is conservative while satisfying the fully-connected condition.

Constraint (3.5) ensures that the total number of links in a single fog type is conservative while satisfying the fully-connected condition.

Constraint (3.6) restricts that if any two fog nodes are selected, the link between them should also be selected.

Constraint (3.7) limits the lower and upper bound ratios of the number of candidate fog nodes that should participate in constructing fogs.

Constraint (3.8) ensures the following aspects: 1) the full-connection assumption; 2) any fog node can only participate in constructing at most one fog. Specifically, since we consider fully-connected structure for each planned fog, for any randomly selected three links, they should be either not selected, where the equality value is 0, or selected to form a two-node fog, where the equality value is 1. For a fog consisting of more than three fog nodes, any three links selected in the fog should form a triangle to satisfy the fully-connected assumption. Therefore, the equality cannot be equal to 2 since it indicates that only two links are planned among three selected nodes which breaks the full-connection assumption.

- Constraints for provisioning IoT tasks

$$\sum_{j}^{j \in FN} \left(x_{i,j} + z_{i,j}\right) = 1 , \forall i \in IT , \tag{3.9}$$

$$x_{ij} + z_{ij} \leq u_j , \quad \forall j \in FN , \tag{3.10}$$

$$\sum_{j}^{j \in FN} x_{ij} * FT_j \geq IM_i , \quad \forall i \in IT , \tag{3.11}$$

$$\sum_{j}^{j \in FN} \sum_{j'}^{j' \in FN} x_{ij} * \left(FT_j + y_{jj'} * FT_{j'}\right) \geq IR_i , \forall i \in IT , \tag{3.12}$$

$$z_{ij} \leq (1 - IR_i) * (1 - IM_i) * \left(1 - FT_j\right) , \forall i \in IT, \; j \in FN \tag{3.13}$$

$$FC_j + \sum_{j'}^{j' \in FN} y_{jj'} * FC_{j'} \;\geq\; \sum_{j'}^{j' \in FN} \sum_{i}^{i \in IT} \left(x_{ij} + \& x_{ij'} * y_{jj'}\right) * IC_i , \quad j \in FN , \; j \neq j' , \tag{3.14}$$

$$FC_j + \sum_{j'}^{j' \in FN} y_{jj'} * FS_{j'} \geq \sum_{j'}^{j' \in FN} \sum_{i}^{i \in IT} \left(x_{ij} + \& x_{ij'} * y_{jj'}\right) * IS_i \,,$$
$$j \in FN \,,\; j \neq j' \,, \tag{3.15}$$

Constraint (3.9) ensures that an IoT task must be connected to a fog node, so that it can be either served by a fog or by the cloud.

Constraint (3.10) restricts that if an IoT task is served by a fog node, the node must be selected in any planned fog.

Constraint (3.11) indicates that any IoT task with mobility requirement should be directly connected to a wireless fog node in a WLF or a HBF and it cannot be uploaded to the cloud for processing.

Constraint (3.12) indicates that an IoT task with real-time requirement must be served by either a WLF or a HBF consisting of wireless fog node(s).

Constraint (3.13) indicates that if an IoT task is uploaded to cloud for processing, it must not be an IoT task with real-time or mobility requirement and the fog node directly connecting it must be a wired one.

Constraints (3.14) and (3.15) ensure that the sum of computing/ storage resource units of each fog being planned must be greater than the total number of resource units required by all IoT tasks to be served in this fog.

3.3.2 Maximizing energy-efficiency (ILP-Energy)

In this section, we aim to minimize the power consumption so as to increase the energy efficiency while maximizing the number of IoT tasks successfully served. Since most of the sets, parameters, variables, and constraints are overlapped with that of ILP- TotalCost model, we focus on introducing the additional parts.

We consider the IoT task size in unit of bits and assume that the power consumption in serving a bit by a wired and a wireless fog node are different. In the following, we introduce the sets and parameters, objective, and constraints of the ILP-Energy model.

1) Sets and Parameters

Note that all the sets and parameters used in ILP- TotalCost model are required here. The additional ones are shown as follows.

$\boldsymbol{IP_i}$	Size of a IoT task $\boldsymbol{i}$ in unit of bits, $\boldsymbol{i} \in IT$
$\boldsymbol{FE_j}$	Total available power in joules for processing IoT tasks in fog node $\boldsymbol{j}$, $\boldsymbol{j} \in FN$
$\boldsymbol{EC_l}$	The power in joules consumed to process each bit unit of an IoT task in a fog node $\boldsymbol{l}$, $\boldsymbol{l} \in CF$
$\boldsymbol{\theta}$	The weight value for multi-objective optimization

2) Objective

$$\boldsymbol{Minimize}\left(\sum_{\boldsymbol{l}}\sum_{\boldsymbol{i}}(\boldsymbol{EC_l} * \boldsymbol{IP_i})\right), \boldsymbol{l} \in \boldsymbol{CF}, \ \in \boldsymbol{IT}, \tag{3.16}$$

$$\sum_{l}\sum_{i}(EC_l * IP_i) = \sum_{i}^{i\in IT}\sum_{j}^{j\in FN} IP_i * \begin{pmatrix} x_{ij} * \left(EC_{WD} * \left(1 - FT_j\right) + EC_{WL} * FT_j\right) \\ + z_{ij} * EC_{Cloud} \end{pmatrix} \tag{3.17}$$

In objective (3.16), we aim at minimizing the total power consumed when serving an IoT task via a wireless fog node, a wired fog node, or a cloud node, respectively. The complete calculation of $EC_l * IP_i$ is shown in equation (3.17).

In addition, we also consider to unify the two objectives, i.e., (3.1) and (3.16), and propose the weighted sum objective as shown in (3.18), where $\boldsymbol{\theta}$ is the weight value that is used to adjust the significance of cost and energy efficiency in the combined objective.

$$Minimize\left(\sum_{h}\sum_{k} DC_{h,k} + \sum_{i}\sum_{l} UC_{i,l} + \theta * \left(\sum_{l}\sum_{i}(EC_l * IP_i)\right)\right), i \in IT, h, k \in FN, l \in CF\ , \tag{3.18}$$

3) Constraints

$$\sum_{i}^{i\in IT} x_{ij} * IP_i * \left(EC_{WD} * \left(1 - FT_j\right) + EC_{WL} * FT_j\right) \le F\ , \quad \forall j \in FN\ , \tag{3.19}$$

Note that all the constraints from (3.9)-(3.15) are required here. Constraint (3.19) restricts that the total power consumed in serving the IoT tasks in a fog node should not exceed the fogs total available power. Specifically, in the left side of the inequation, the first and second items constrain the power consumed by wired and wireless links, respectively.

3.4 Proposed ILP Model for Fogs Topology

Considering that the CAPEX of a fully-connected mesh Fogs is exponentially increasing with the number of nodes in the composed Fogs, it may not be the best choice when weighing the costs. In this section, we propose two integer linear programming (ILP) models to study the impact of the star and ring topology of WLF, WDF and HBF on iCloudFog performance.

1) Sets and Parameters

Note that all the sets and parameters used in ILP- TotalCost model are required here. The additional ones are shown as follows. Besides, the decision variables are also the same as ILP- TotalCost and ILP-Energy, so they are not repeated here.

$D_{jj'}$	The set of distances in kilometers between fog nodes $\boldsymbol{j}$ and $\boldsymbol{j'}$, $\boldsymbol{j},\boldsymbol{j'} \in FN$
γ	Average hops of IoT tasks traverse in a fog
$\boldsymbol{M}$	A coefficient to balance the average hops and the total Cost

2) Objective

The objective of the proposed two models are given in (3.22), which is a weighted objective of (3.20) and (3.21).

Minimize ($Total\_Cost$):

$$Minimize\ \left(\sum_h \sum_k DC_{h,k} + \sum_i \sum_l UC_{i,l}\right),$$
$$i\ \in IT, h, k\ \in\ FN, l\ \in CF \tag{3.20}$$

Minimize ($\boldsymbol{M}$ * average hops):

$$Minimize\ (M * p)\ , p \in\ \gamma \tag{3.21}$$

Minimize ($General\_Objective$):

$$Minimize\ \ (Total\_Cost + \boldsymbol{\theta} * \boldsymbol{M} * average\ hops) \tag{3.22}$$

The objective in Equation (3.20) is to minimize the total CAPEX and Utilization Cost, where the first item, say $\sum_h \sum_k DC_{h,k}$, indicates CAPEX cost due to deploying a link between fog nodes h and k; while the second item, say $\sum_m \sum_n UC_{i,l}$, indicates Utilization Cost due to serving IoT task i via cloud or fog node l. The specific calculations of the two items are given as follows in Equations(3.23) and (3.24).

Equation (3.20) aims at minimizing the number of average hops required by a fog node to offload tasks to other fog nodes in the same planned fog. When the number of fog nodes in a fog type is N, the average hop count of a star is $\boldsymbol{2(N-1)^2/N^2}$. For a ring, the average hop count is $\boldsymbol{N^2 - 1/4N}$ and $\boldsymbol{N/4}$ when $\backslash bmN$ is odd and even, respectively. For the fully-connected mesh, the average hop count to serve the offloading task between fog nodes (if necessary) of a planned fog is $\boldsymbol{N-1/N}$, which is approaching one when N is big enough. The coefficient value M here is used to balance objective (3.21) and objective (3.22).

Equation (3.22) is the multi-weighted objective, where a weight value of θ is used to integrate objective (3.20) and objective (3.21).

$$\sum_{h}\sum_{k} DC_{h,k} = \sum_{j}^{j\in FN}\sum_{j'}^{j'\in FN} y_{jj'} * \begin{pmatrix} DC_{WL,WD} ** \; DC_{WL,WD} * \left(FT_j * \left(1-FT_{j'}\right) + \left(1-FT_j\right) * FT_{j'}\right) \\ + DC_{WL,WL} * FT_j * FT_{j'} \\ DC_{WD,WD} * \left(1-FT_j\right) * (1-FT_{j'})\,) \end{pmatrix} \tag{3.23}$$

$$\sum_{i}\sum_{l} UC_{i,l} = \sum_{i}^{i\in IT}\sum_{j}^{j\in FN} (IC_i + IS_i) * \begin{pmatrix} x_{ij} * \left(UC_{i,WD} * \left(1-FT_j\right) + UC_{i,WL} * FT_{j'}\right) \\ + \\ z_{i,j} * UC_{i,cloud} \end{pmatrix}, \tag{3.24}$$

$$\frac{\frac{N-1}{N} + \frac{(N-2)*2+1}{N} * (N-1)}{N} = \frac{2(N-1)^2}{N^2}\ , \ (for\ Star) \tag{3.25}$$

$$\frac{0+1+2+\cdots+\frac{N-1}{2}+\frac{N-1}{2}+\cdots+2+1}{N} = \frac{N^2-1}{4N}\ , \ \ (for\ Ring,\ N \in Odd) \tag{3.26}$$

$$\frac{0+1+2+\cdots+\frac{N}{2}+\cdots+2+1}{N} = \frac{N}{4}\ , \ (for\ Ring, N \in Even) \tag{3.27}$$

Formula (3.25) shows the calculation process of the average hop count of a star fog plan. It is mainly to average the probability of the offload task of the central node and surrounding nodes of the star fogs.

Formula (3.26) and (3.27) represent the calculation process of the average hops of ring topology fogs programming. The odds and even fog nodes have different fogs average hop probability calculations, so they are shown separately.

3) Constraints

The constraints of fog planning based on the star and ring topologies are given in the following, respectively.

- Constraints on Star Topologies

$$\frac{N-1}{N} * \sum_{j}^{j\in FN} u_j = \sum_{j}^{j\in FN} \sum_{j'}^{j'\in FN} y_{jj'} \ , \tag{3.28}$$

$$u_j + u_j' \geq 2 * y_{jj'} \ , \quad \forall j, j' \in FN \, , \tag{3.29}$$

$$\alpha * \sum_{j}^{j\in FN} j \leq \sum_{j}^{j\in FN} u_j \leq \beta * \sum_{j}^{j\in FN} j \ , \tag{3.30}$$

$$(N-2) \geq \sum_{j''}^{j''\in FN} \left(y_{jj''} + y_{j'j''}\right) * y_{jj'} \ , \quad \forall j, j' \in FN \, . \tag{3.31}$$

- Constraints on Ring Topologies

$$\sum_{j}^{j\in FN} u_j * \frac{N}{N} = \sum_{j}^{j\in FN} \sum_{j'}^{j'\in FN} y_{jj'} \ ,$$

(3.32)

$$u_j * 2 - \sum_{j'}^{j'\in FN} y_{jj'} = 0 \ , \quad \forall j \in FN \ ,$$

(3.33)

$$u_j + u_j' \geq 2 * y_{jj'} \ , \quad \forall j, j' \in FN \ ,$$

(3.34)

$$\alpha * \sum_{j}^{j\in FN} j \leq \sum_{j}^{j\in FN} j \leq \beta * \sum_{j}^{j\in FN} j \ .$$

(3.35)

Constraints (3.28) and (3.32) ensure the conservation of the total number of links needed in a star and a ring, respectively. Constraints (3.29) and (3.34) ensure that if a link is selected in constructing a star or a ring, the fog nodes at both ends of the link must be selected too. Constraints (3.30) and (3.35) ensure that the system needs at least α (%) and at most β (%) fog nodes to participate in constructing a star or a ring. Constraints (3.31) and (3.33) ensure that the planned fogs are based on star and ring topologies, respectively. In constraints (3.31) and (3.33), $\boldsymbol{j}$, $\boldsymbol{j'}$ and $\boldsymbol{j''}$ are not equal.

- Constraints on IoT Tasks Provisioning

The constraints on Star and Ring Fogs' IoT task configuration are actually consistent with the fully-connected mesh topology. Therefore, the constraints here can refer to formula (3.9) to formula (3.15).

IV. Simulation and Results Analysis

4.1 Simulation Environment

The simulation settings are shown in Tables 4.1 and 4.2, where $\boldsymbol{U}(x, y)$ indicates a value that is randomly distributed between x and y. We assume there are sufficient computing/storage resources in the cloud layer. In the middle fog layer, we assume that there is a total of six wired fog nodes and six wireless fog nodes, which can be freely selected to form WDFs, WLFs, and HBFs to serve IoT tasks. We assume that fog nodes j and j' are distant from each other in the range of 5 to 10 Km, i.e., $D_{jj'}$. The number of candidate fog nodes allowed in a potential fog type is set to be 3, i.e. N = 3. The available computing/storage resource units of all wired and wireless fog candidate nodes randomly fall in the range of 20 to 30, i.e., FC_j or FS_j. The number of required computing/storage resource units by IoT tasks are randomly set in the range of 5 to 9, i.e., IC_i or IS_i.

We assume that the CAPEX cost between fog nodes $\boldsymbol{h}$ and $\boldsymbol{k}$, i.e., $\boldsymbol{DC_{h,k}}$, for homogeneous fog types (i.e., WLF and WDF) and heterogeneous fog types (i.e.,HBF) are numerically set to 100 and 200, respectively. The Utilization Cost to serve IoT task $\boldsymbol{i}$ on different fog nodes, i.e., $\boldsymbol{UC_{i,WL}}$ and $\boldsymbol{UC_{i,WD}}$, are 2 and 3 for wireless and wired fog nodes, respectively. The cost of accessing cloud resource units to serve IoT task $\boldsymbol{i}$ is set to 25, i.e., $\boldsymbol{UC_{i,Cloud}}$. The total available power of fog node $\boldsymbol{j}$, i.e., $\boldsymbol{FE_j}$, is randomly distributed between 150 and 250 joules. The packet size of an IoT task $\boldsymbol{i}$, i.e., $\boldsymbol{IP_i}$, is randomly distributed between 2 to 8 Kbytes. The power consumption to serve per Kbytes, i.e., $\boldsymbol{EC_l}$, is set to 3, 10, and 5 joules [31],[32], when $\boldsymbol{l}$ is a cloud node, a wireless fog node and a wired fog node, respectively.

Table 4.1 Characteristics of IoT tasks & fog nodes

Parameter	Ranges	References
# of wireless fog nodes	6	
# of wired fog nodes	6	
$\boldsymbol{D_{jj'}}$	$\boldsymbol{U}$(5,10) km	[2]
$\boldsymbol{N}$	3	
$\boldsymbol{IC_i}$ or $\boldsymbol{IS_i}$	$\boldsymbol{U}$(5,9)	[35]
$\boldsymbol{FC_j}$ or $\boldsymbol{FS_j}$	$\boldsymbol{U}$(20,30)	[36] , [37]

Table 4.2 Other parameters on cost and energy

Parameter	Ranges	References
$\boldsymbol{DC_{h,k}}$	100 (WL&WL or WD&WD), 200(WL&WD)	[38]
$\boldsymbol{UC_{i,l}}$	& 2(WL), 3(WD), 25(Cloud)	[35], [39]
FE_j	$\boldsymbol{U}$(150,250) joule	
$\boldsymbol{IP_i}$	$\boldsymbol{U}$(2,8) KByte	[40]
$\boldsymbol{EC_l}$	3(Cloud), 10(WL), 5(WD) joule/Kbyte	[31], [32]

The total number of IoT tasks considered in this dissertation is set to 36, with a ratio of 50% requiring real-time services, and a ratio of 50% requiring mobility services. Note that the requirements of real-time and mobility are independent and do not affect each other. An IoT task may simultaneously have the two requirements, one of them or none of them. A ratio of 25% to 50% IoT tasks requires no real-time or mobility services.

On the other hand, since not all the candidate fog nodes will be selected to form a fog, we set the lower boundary, α, and upper boundary, β, of candidate fog nodes that should participate in the overall fog planning as 40% and 80%, respectively.

In addition, for exploring different Fogs topologies, The coefficient and weight values, i.e., M and θ, respectively, in the multi-weighted objective of formula (3.22) are set to 7000 and 1 by default, which can be modified according to the importance of the average hop counts and the cost.

4.2 Result analysis

To explore the proposed ILP models, we used the modeling language AMPL and the solver Gurobi 8.1.0 [33],[34]. The time limit for each experiment is set to half an hour. Experiments show that it takes about 80 million simplex iterations and about 2 million branch-and-cut nodes to get a set of optimal solutions.

In this section, we summarize and explain the result analysis under different preconditions.

4.2.1 Objective1: Cost-Efficiency

Figures 4.1 to 4.4 show the numerical results for the first ILP-TotalCost model, which aims to minimize the total CAPEX and

Utilization Cost. The total number of candidate fog nodes is twelve and the ratio of wireless to wired fog nodes (WD:WL) changes as shown in the ***x***-axis of Figure 4.1 Note that real-time and mobility requirements are not evaluated simultaneously, i.e., when one requirement is considered, the other requirement is not considered. Figure 4.1 shows the performance of total cost for different β s, i.e., β = 80% and β = 100%, respectively, under different WD:WL ratios. It is observed that the total cost is the smallest when the ratio of WD:WL is 6:6 (i.e. six wireless and six wired fog nodes). In addition, the total cost is smaller when β is set to 100% compared to that when β is 80%. This indicates that the Utilization Cost caused by accessing cloud resources is dominant, and when β is set to 100%, more resources can be provided by the fog layer. The performance under different α s is not given since the results show that it does not affect the total cost.

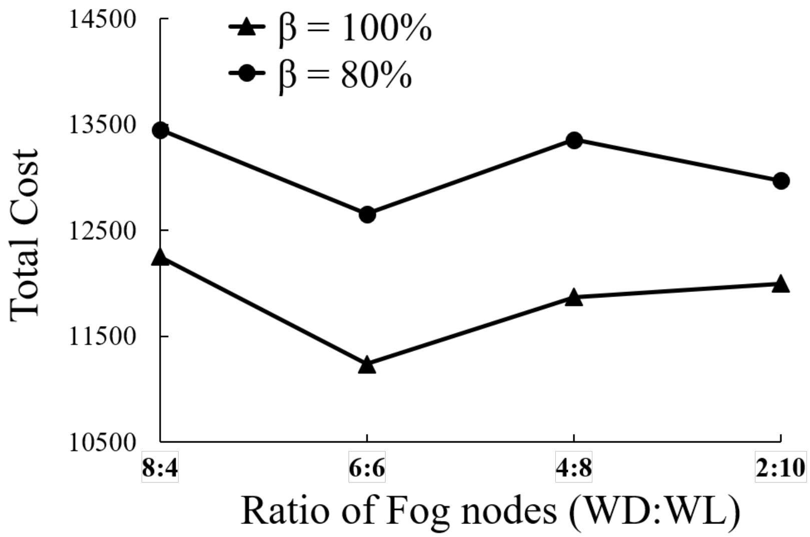


Fig 4.1 Total cost under different βs and different ratios of WD : WL.

Figure 4.2 shows the impact of fog size (i.e., the number of fog nodes participating in each fog) on the performance of the total cost. In this simulation, β is set to 80%. Since the total number of candidate fog nodes is twelve, the maximum fog nodes which can participate in fog planning is 9 (= 12*80%). The following observations can be obtained: 1) the optimal/smallest total cost occurs when N = 3, which implies a fog consisting of three fog nodes is the optimal scale under the current simulation settings. The total number of fogs planned is three when N = 3; 2) the total cost is the highest when N = 5 and decreases after that. The major reason lies in that when N is no less than 5, only one fog will be formed, considering nine as the maximum number of candidate fog nodes. Therefore, the total available resource units of the fog layer are minimum when N = 5, and many IoT tasks are uploaded to cloud for processing; 3) when N is 9, all the candidate fog nodes are selected to form one big fog which implies that the available fog resources is the same with that when N = 3. Nonetheless, since we consider fully-connected fog topology, the number of links deployed between fog nodes as well as the total cost are much more than that when N = 3.

Figure 4.3 shows the impact of different ratios of real-time and mobility IoT tasks on the performance of total cost. We can observe that the real-time requirement has less impact on the total cost when compared to that of the mobility. This is because real-time IoT tasks can be connected to both of wireless and wired fog nodes in either WLFs or HBFs but IoT tasks with mobility can only be connected to wireless fog nodes directly in WLFs or HBFs.

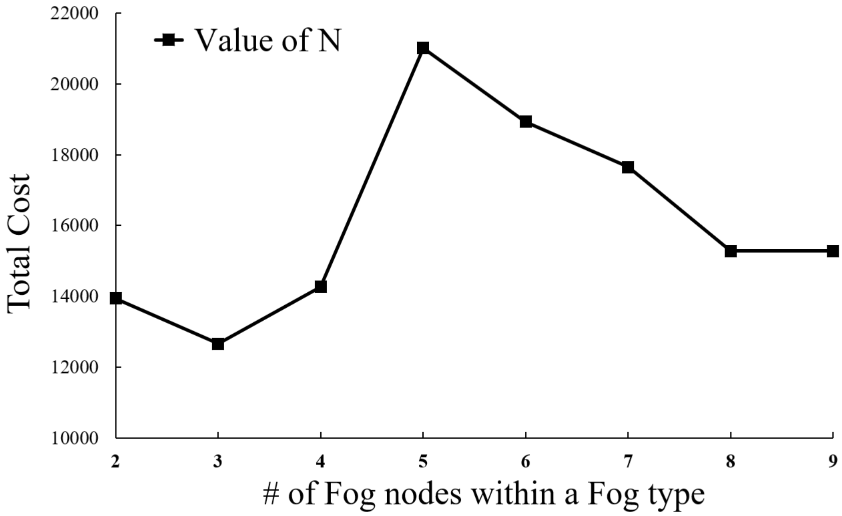


Fig 4.2 Total cost under different Ns.

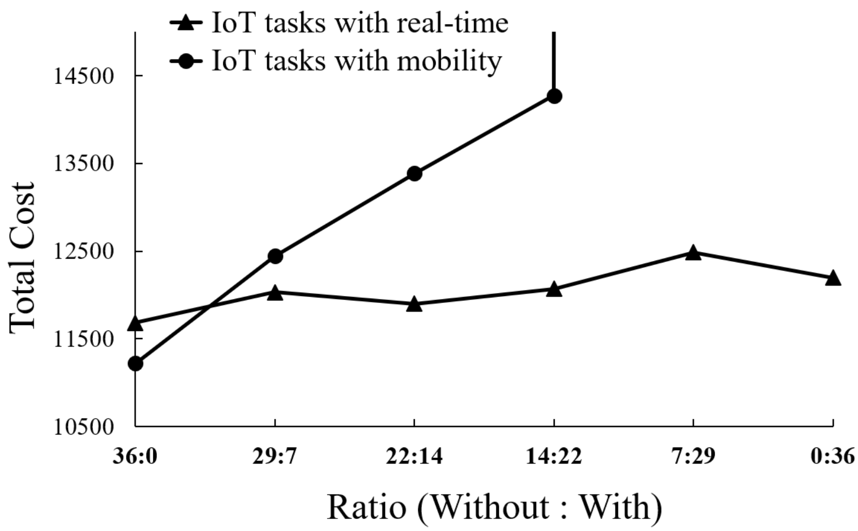
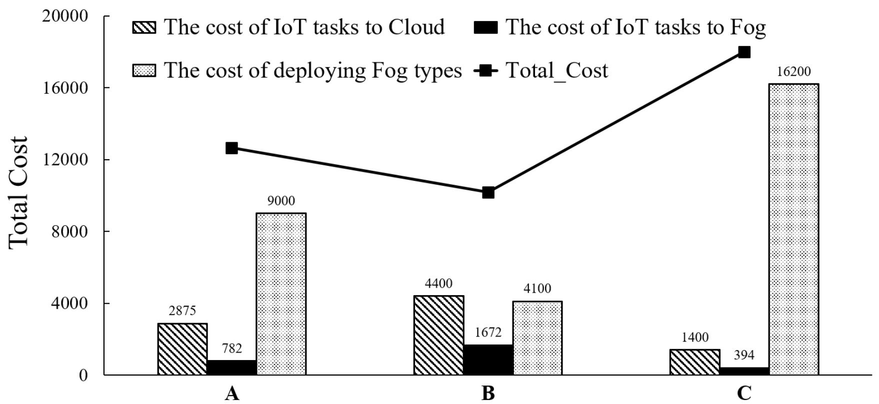


Fig 4.3 Total cost under different ratios of real-time/ mobility IoT tasks.

Figure 4.4 gives a detailed vision on how the Utilization Cost and CAPEX vary under different simulation settings, say A, B, and C. The Utilization Cost is further divided into the fog and cloud parts, respectively. More specifically, in scenario A, $DC_{WL,WL}$ = $DC_{WD,WD}$ =100, $DC_{WL,WD}$ = 200 and FC_{WL} =2, FC_{WD} =3,

$UC_{i,Cloud}$=25. In scenario B, $DC_{WL,WL} = DC_{WD,WD}$= 50, $DC_{WL,WD}$ =100 and FC_{WL} = 4, FC_{WD} =6, $UC_{i,Cloud}$ =50. In scenario C, $DC_{WL,WL}$ = $DC_{WD,WD}$=200, $DC_{WL,WD}$ =400 and FC_{WL} =1, FC_{WD} = 1.5, $UC_{i,Cloud}$ = 12.5. The results show that under scenario ***A***, the CAPEX cost is the dominant component of total cost, and the Utilization Cost of cloud and fogs is relatively small. In scenario ***B***, although the Utilization Cost of cloud is nearly doubled, the total cost is reduced, reflecting that the dominant component in this case is CAPEX cost. In scenario ***C***, the CAPEX cost due to deployment is the key factor that iCloudFog needs to consider.



A: $DC_{WL,WL} = DC_{WD,WD} = 100$, $DC_{WL,WD} = 200$, $FC_{WL} = 2$, $FC_{WD} = 3$, $CC = 25$
B: $DC_{WL,WL} = DC_{WD,WD} = 50$, $DC_{WL,WD} = 100$, $FC_{WL} = 4$, $FC_{WD} = 6$, $CC = 50$
C: $DC_{WL,WL} = DC_{WD,WD} = 200$, $DC_{WL,WD} = 400$, $FC_{WL} = 1$, $FC_{WD} = 1.5$, $CC = 12.5$

Fig 4.4 Total cost under three different initial settings for CAPEX and Utilization Cost.

Figure 4.5 and Figure 4.6 show similar results to that of Figure 4.3 differing in that they simultaneously consider the requirements of real-time and mobility. From the results, we can observe that: 1) with the increasing number of mobile and real-time IoT tasks, the total cost increases significantly; 2) the requirement of mobility has a more significant impact on the performance of total cost than the requirement of real-time does. Therefore, the maximum number of IoT tasks with mobility requirement served by iCloudFog is less than that of the real-time IoT tasks.

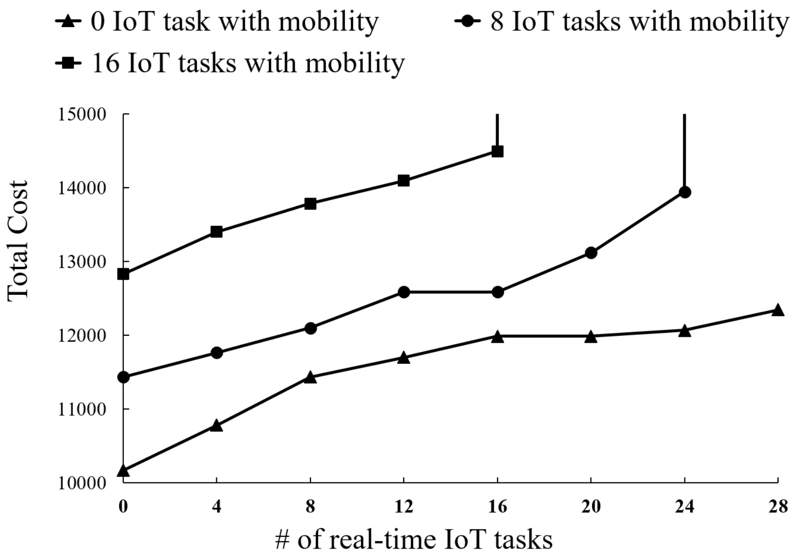


Fig 4.5 Total cost under different number of real-time IoT tasks.

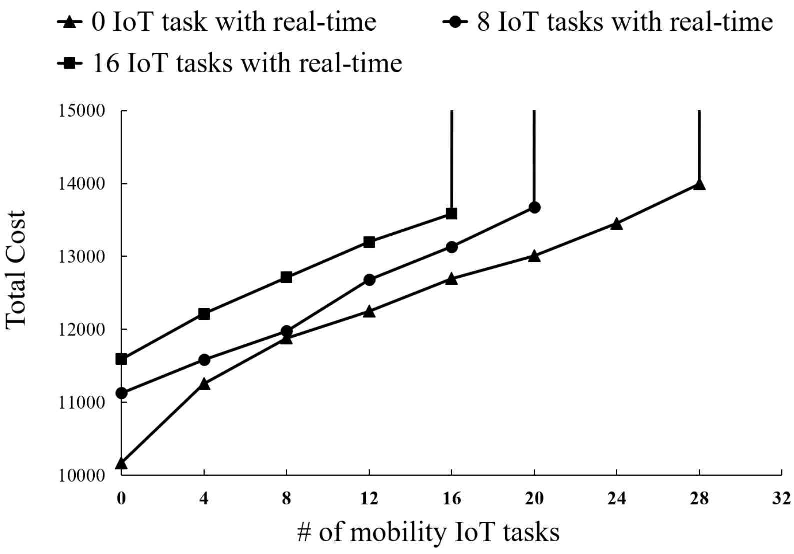


Fig 4.6 Total cost under different number of mobility IoT tasks.

4.2.2 Objective2: Power Consumption

In this section, we investigate the power consumption when serving IoT tasks. Figure 4.7 mainly considers the optimization of a single objective (Total_Energy) given in equation (3.16) under different requirements of real-time and mobility IoT tasks. We can find that mobility requirement affects the performance of power consumption more than the real-time requirement does. This mainly lies in that real-time tasks can be connected to both of wired and wireless fog nodes, while mobile tasks can only be connected to wireless fog nodes.

Figure 4.8 evaluates the weighted objective in equation (3.18) under different weight values of θ. We found the power consumption under all θs does not decreases even when we increase the weight value of it.

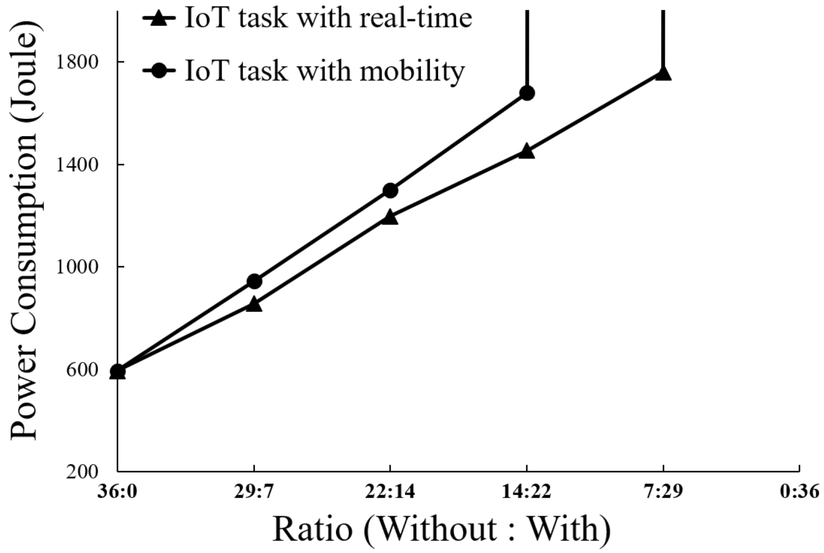


Fig 4.7 Total power consumption under different ratios IoT tasks.

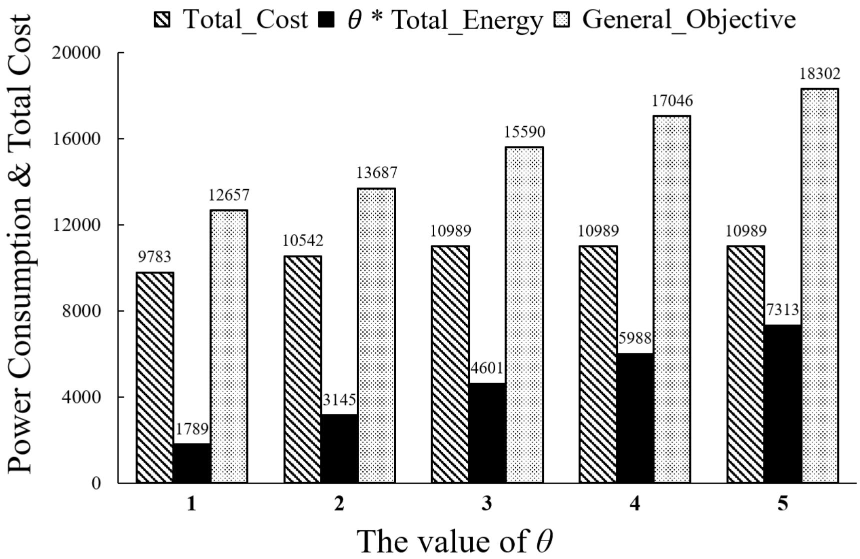


Fig 4.8 Multi-Objective in Equation(3.18) under different weight values θ.

4.2.3 Objective3: Different Topologies

Figure 4.9 shows the total cost under different numbers of candidate fog nodes for fully-connected mesh, ring and star fogs. Since the upper bound of β is set to 80% for a total of twelve candidate fog nodes, a total number of nine fog nodes are selected in the fog planning. With this setting, all the three different topologies achieve the optimal performance in terms of total cost when $N = 3$. The total cost of all the three topologies increases dynamically until $N = 5$, and decrease after that due to the fact that when $\boldsymbol{N} = 5$, four fog nodes out of nine cannot participate in forming any fog and a lot of tasks are offloaded to cloud. When $\boldsymbol{N} > 5$, the participation ratio of candidate fog nodes is increased and thus lead to decreased total cost. Among all the three topologies, star performs the best in terms of the total cost, followed by ring, and fully-connected mesh.

Figures 4.10 and 4.11 show the impact of real-time and mobility requirements of IoT tasks on the performance of total cost for star and ring topologies. From the results we can see that the star topology performs slightly better in serving both of real-time and mobile IoT tasks since it requires less total cost. The total costs for serving real-time IoT tasks are less than that when serving mobile IoT tasks for both topologies, due to the fact that real-time IoT tasks can be offloaded into fogs via both wired or wireless fog nodes, but mobile IoT tasks can only be offloaded to wireless fog nodes.

Figure 4.12 shows the change in the average hops of the three topologies with increasing number of fog nodes n. We can find that for fully-connected meshes, the average hops is the lowest of the three which is approaching one, which implies the biggest number of links required in each planned fog. Although the number of links for ring and star fogs is the same, when $N < 6$, the average hops of star fogs is greater than that of ring fogs, but when $\boldsymbol{N} \geq 6$, the average hops of star fogs starts to be lower than Ring, and the growth rate is moderate.

Figure 4.13 shows the performance for the total cost and the multi-weighted general objective. From the results, we can see that star performs the best in terms of the total cost, followed by ring, and fully-connected mesh. For the general objective, star performs the best, followed by fully-connected mesh and ring. Although fully-connected mesh fogs have the largest number of links in planning a fog, it is superior to ring, due to the fact that the number of average hops in a ring increases more dynamically with increasing N than that of fully-connected mesh.

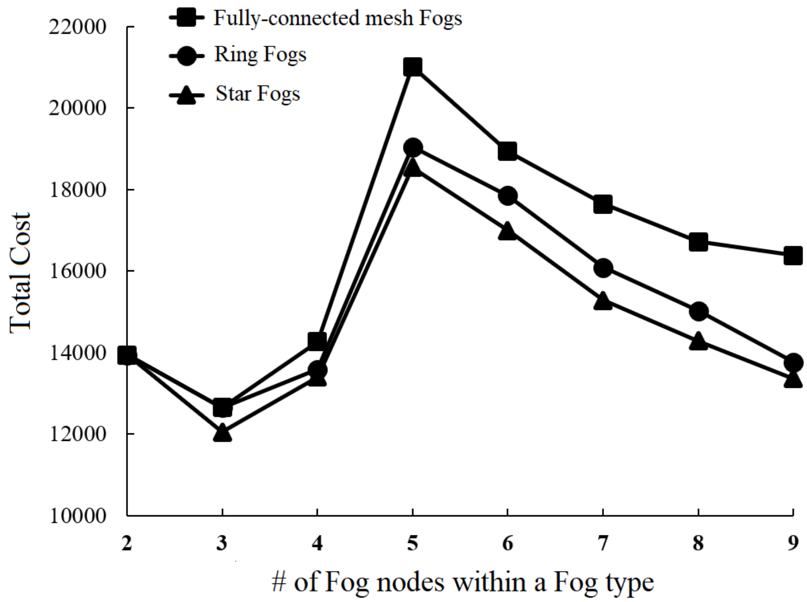


Fig 4.9 Total cost of three different topologies under different Ns.

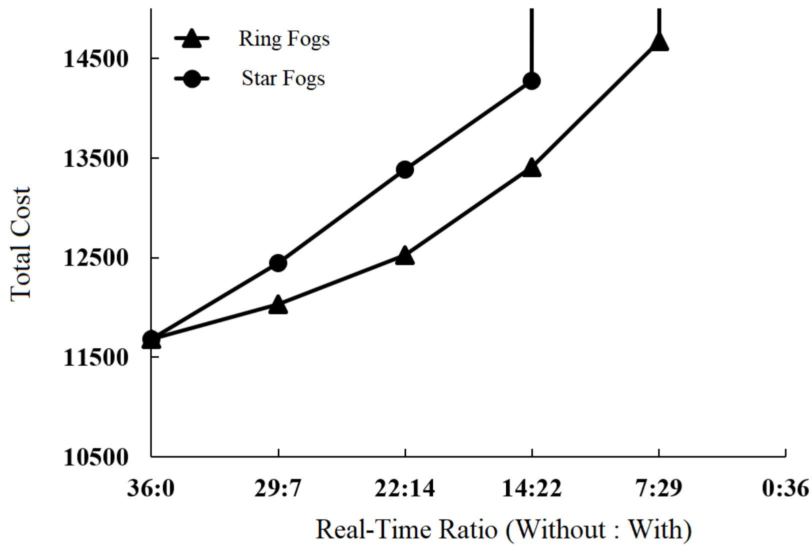


Fig 4.10 Total cost of ring and star topologies under different ratios of real-time IoT tasks.

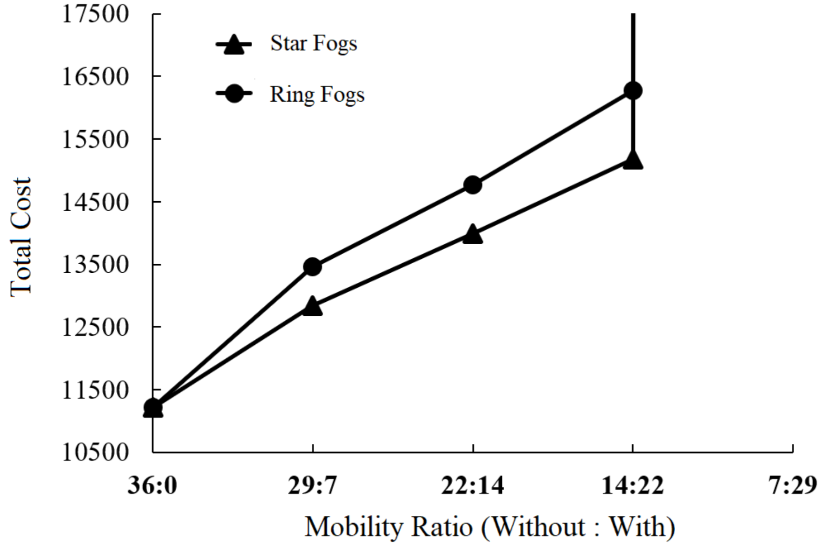


Fig 4.11 Total cost of ring and star topologies under different ratios of mobility IoT tasks.

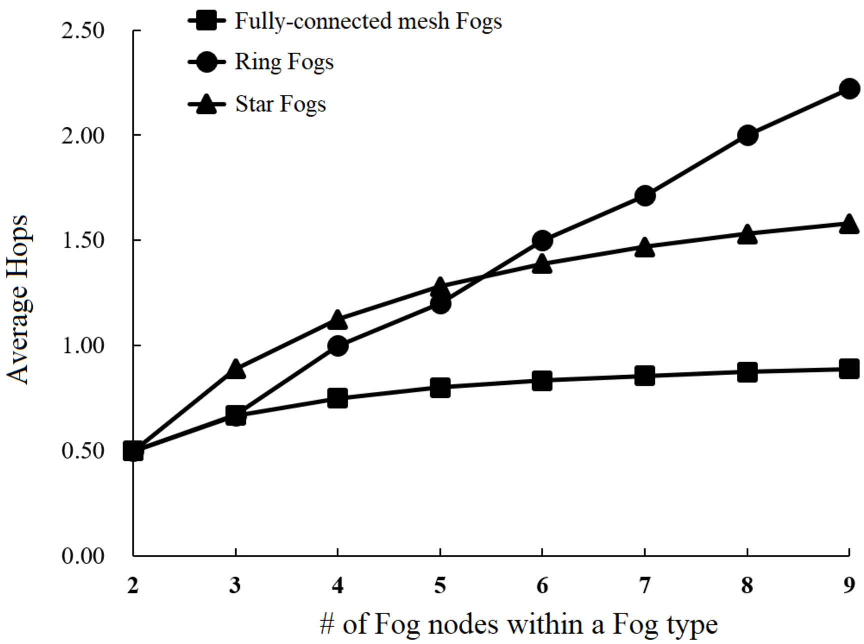


Fig 4.12 Average hops of three different topologies under different Ns.

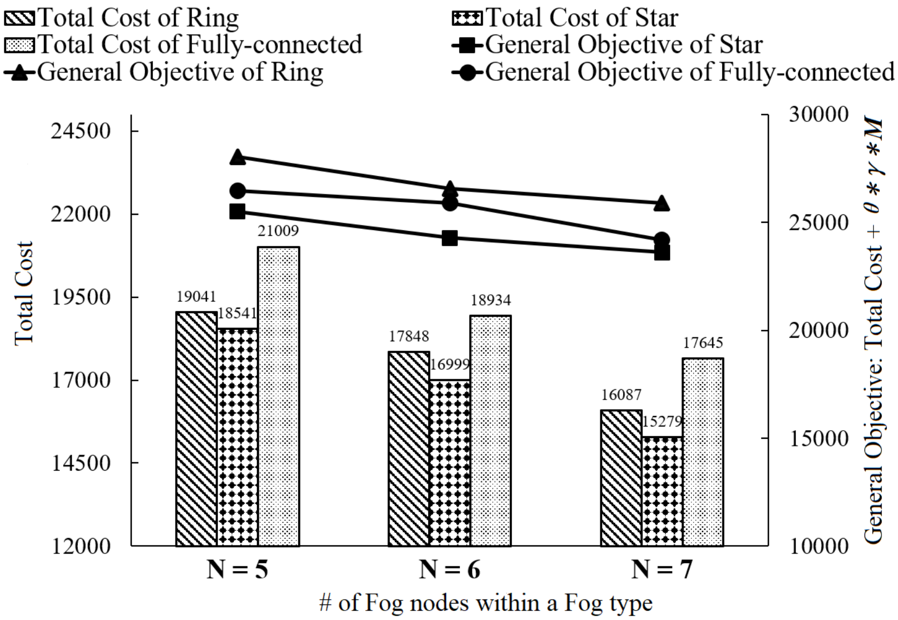


Fig 4.13 Multi-weighted objective in Equation (3.22) under different Ns.

V. Conclusions

In this dissertation, we first addressed the issue of fog planning under the framework of iCloudFog by investigating the total CAPEX and Utilization Cost and the power consumption when provisioning the IoT tasks upon the planned fogs. Specifically, we proposed two ILP models with objectives of minimizing the total cost and the power consumption, respectively, when serving IoT tasks w/o requirements of real-time and mobility. Extensive numerical simulations have been conducted to investigate the factors that would affect the overall performance of iCloudFog in terms of the total cost and total power consumption. From the numerical results, we can observe that the size of each fog affects the total cost significantly. Besides, the QoS requirements in terms of real-time and mobility affect both of the total cost and power consumption significantly. The optimal size of each fog in the fog planning process can be found based on the proposed models. Note that, both ILP models are based on fully-connected mesh Fogs.

Secondly, we also investigated the impact of different fog topologies, i.e., fully-connected, star, and ring, in fog planning on the performance of CAPEX and Utilization Cost. Specifically, we proposed two additional ILP models, with the objective of minimizing the total cost by considering the average hop count. Numerical simulations were carried out and the results were compared with the fully-connected mesh in our previous work. Results showed that fully-connected mesh topology had the highest cost and star topology performed the best in serving real-time and mobile IoT tasks.

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국문 요약

최적의 사물 인터넷 작업 예약을 위한 녹색의 효율적인 포그 계획

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(초록)

들어오는 5G 기술은 레거시 클라우드 서비스와는 매우 다른 실시간 및 이동성 요구 사항으로 엄청난 IoT (Internet-of-thing) 서비스를 확산시킬 것으로 예상됩니다. 원격 데이터 센터에 의존하는 중앙 집중식 관리로 인해 클라우드 컴퓨팅은 매우 낮은 대기 시간, 이동성 등과 같은 엄격한 IoT 요구 사항을 충족시키지 못합니다. 대신 포그 컴퓨팅과 같은 분산 에지 컴퓨팅은 유망한 접근 방식으로 만들어졌습니다. 최근 몇 년 동안 엄청난 주목을 받았습니다. 이 백서에서는 방대한 양의 IoT 서비스를 매우 다양하게 최적으로 프로비저닝하기 위해 네트워크 에지에서 레저 네트워크 장치를 효율적으로 구성하여 포그 네트워크 (안개)를 형성 한 다음 클라우드와 통합하여 스토리지 및 리소스를 제공합니다.

특히, 통합 구름 안개 (iCloudFog) 프레임 워크에서 포그 계획 및 포그 토폴로지 문제를 해결하기 위해 4 개의 Integer Linear Programming (ILP) 모델을 제안합니다. 첫 번째 ILP 모델에서 목표는 계획 안개로 인한 CAPEX 비용과 계획 안개로 인한 Utilization Cost 비용을 최소화하는 것입니다. 두 번째 ILP 모델에서 목표는 계획된 포그에서 성공적으로 프로비저닝 된 IoT 작업 수를 최대화하면서 전력 소비를 최소화하는 것입니다. 위의 두 가지 ILP 모델은 완전히 연결된

메시 토폴로지를 기반으로합니다. CAPEX 및 Utilization Cost 비용의 성능에 미치는 영향을 연구하기 위해 링 및 스타 토폴로지에 대해 각각 세 번째 및 네 번째 ILP 모델이 제안됩니다.

제안 된 ILP 모델은 실시간 및 이동성과 같은 다양한 IoT 작업 요구 사항을 고려하여 수치 적으로 평가됩니다. 수치 결과는 효율적으로 계획된 포그가 다양한 IoT 작업 요구 사항을 충족시키면서 계획 오버 헤드를 줄이는 데 도움이 될 수 있음을 보여줍니다. 또한 스타 토폴로지 포그는 네트워크 성능을 향상시키기위한 최적의 선택입니다.