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Green Fog Planning for Optimal Internet-of-Thing Task Scheduling

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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 paper, 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 two Integer Linear Programming (ILP) models to solve the fog planning 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 OPEX 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. 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.

INDEX TERMS Fog computing, cloud computing, IoT, network planning, energy efficiency.

I. INTRODUCTION

The 5^{th} 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.

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

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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. 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.

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 paper. 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 paper 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 ILP models with objectives of minimizing the OPEX and CAPEX overhead in fog planning, and minimizing the power consumption while maximizing the number of IoT tasks successfully served, respectively.

The rest of this paper is structured as follows. In section II, we discuss the related works. In section III, we review the iCloudFog framework and state the problems to be solved. In section IV, we introduce the proposed ILP models in details. In section V, we numerically evaluate the proposed ILP models via simulations. Section VI summarizes our work.

II. RELATED WORKS

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 patient's physical health and calling in an emergency [5]. *J. Wu, et al.* proposed a fog-computing-enabled cognitive network function virtualization (NFV) approach for an information-centric future Internet [6]. *Z. Zhou, et al.* believed that fog computing can effectively provide data processing methods to mobile crowd sensing [7].

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) [8]–[10]. *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 [11]. *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 [12]. *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 [13], [14].

Some other literature focused on addressing the challenges of fog computing in aspects of QoS guarantee [15]–[17], service latency [16], [18], blockchain [19], [20], energy efficiency [17], [21]–[23], machine learning [7], [24], cost management [25], data privacy and information security [22], [26], [27]. Most of the literature were based on the assumption of well-prepared fog networks (fogs). Very few of them addressed the fog planning and design issues, not to mention the solutions to a series of consequential issues [3], [4]. *F. Haider* and *A. Yousefpour's* have addressed similar issues by considering to interconnect fog nodes to form fogs that can be used to share resources and serve IoT tasks [3], [4]. Nonetheless, they have neither considered the different characteristics of wireless and wired candidate fog nodes nor the real-time and mobility requirements of IoT tasks.

III. ICLOUDFOG FRAMEWORK AND PROBLEM STATEMENT

A. ICLOUDFOG FRAMEWORK

The iCloudFog framework is shown in Fig 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.

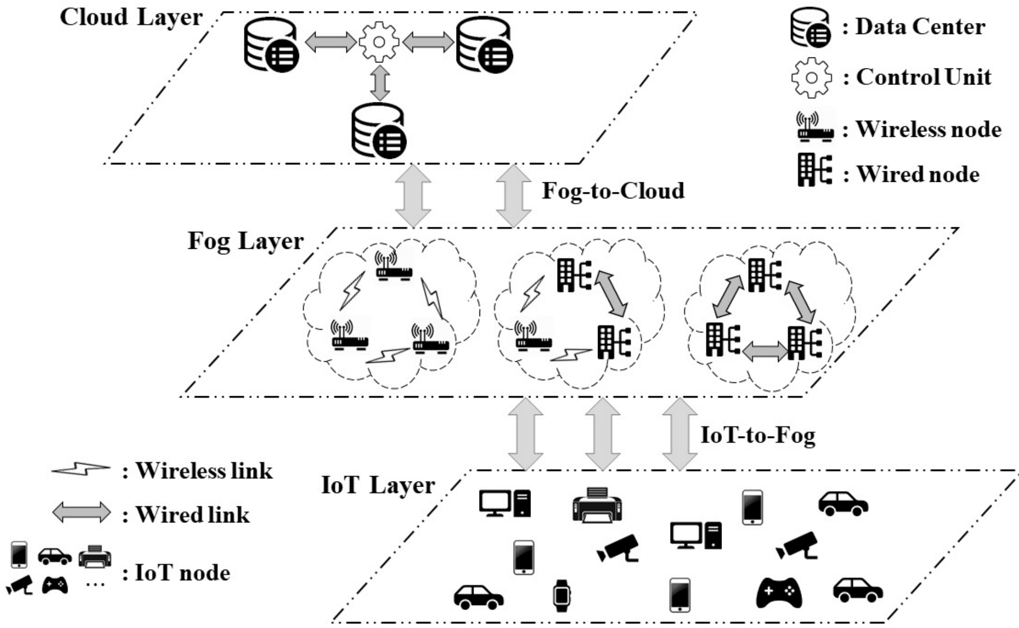

FIGURE 1. iCloudFog framework.

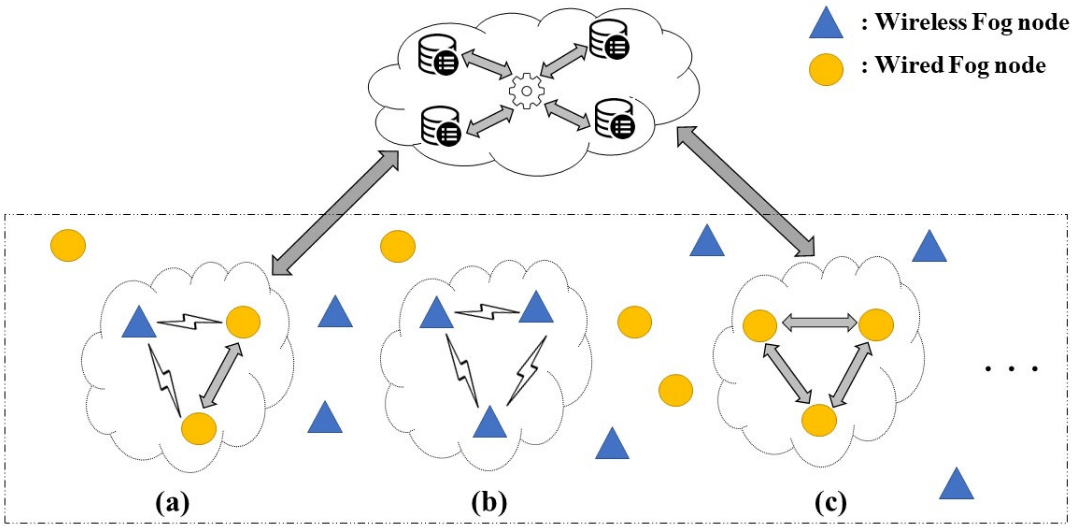

FIGURE 2. Fog types: (a) Wireless fog (WLF); (b) Hybrid Wired-Wireless fog (HBF); (c) Wired fog (WDF) [2].

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 Fig 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 heavy-weight cloud services that may require a large number of transmission bandwidth and computing/storage resources with no real-time or mobility requirements.

B. 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.

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 Fig 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., OPEX 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 OPEX 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 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.

IV. FOG PLANNING ILP MODELS

In this section, we introduce the proposed two ILP models in details. The first ILP model is proposed to minimize the planning overhead in terms of the CAPEX and OPEX cost and is named as ILP-CaOpEx. 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.

A. ILP MODEL FOR MINIMIZING CAPEX AND OPEX COST (ILP-CAOPEX)

The CAPEX cost in fog planning mainly comes from constructing different fog types using different links, such as wireless and wired links. The OPEX cost considered in this paper 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 j and the number of fog nodes that can participate in constructing any fog is identically set to 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 i, $i \in IT$
$\boldsymbol{IS_i}$	Total number of storage resources required by IoT task i, $i \in IT$
$\boldsymbol{IM_i}$	Binary parameter. One indicates IoT task i requires mobility; zero, vice versa, $i \in IT$
$\boldsymbol{IR_i}$	Binary parameter. One indicates IoT task i requires real-time; zero, vice versa, $i \in IT$
$\boldsymbol{FC_j}$	Total number of available computing resources in fog node j, $j \in FN$
$\boldsymbol{FS_j}$	Total number of available storage resources in fog node j, $j \in FN$
$\boldsymbol{FT_j}$	Binary parameter. One indicates fog node j is wireless one; zero indicates fog node j is wired one, $j \in FN$
$\boldsymbol{DC_{h,k}}$	CAPEX cost of deploying links between fog nodes h and k, $h, k \in FN$
$\boldsymbol{UC_{i,l}}$	OPEX cost of using fog node or Cloud node l to serve any IoT tasks i, $i \in IT$, $l \in CF$
$\boldsymbol{N}$	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 j and j', $j, j' \in FN$

2) Decision variables

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

3) Objective

Minimize (Total_Cost):

$$Minimize(\sum_h \sum_k DC_{h,k} + \sum_i \sum_l UC_{i,l}), \quad i \in IT, h, k \in FN, l \in CF \tag{1}$$

The above equation expresses the first objective. It aims at minimizing the total CAPEX and OPEX cost, where the first item, say $\sum_h \sum_k DC_{h,k}$, indicates CAPEX cost due to deploying link between fog nodes $\boldsymbol{h}$ and $\boldsymbol{k}$; while the second item, say $\sum_m \sum_n UC_{i,l}$, indicates OPEX cost due to serving IoT task $\boldsymbol{i}$ via cloud or fog node $\boldsymbol{l}$. The specific calculation of the two items are given in equations (2) and (3).

$$\sum_h \sum_k DC_{h,k} = \sum_j^{j \in FN} \sum_{j'}^{j' \in FN} y_{jj'} * \begin{pmatrix} DC_{WL,WD}*(FT_j*(1-FT_{j'})+(1-FT_j)*FT_{j'}) \\ +DC_{WL,WL}*FT_j*FT_{j'} \\ +DC_{WD,WD}*(1-FT_j)*(1-FT_{j'}) \end{pmatrix}, \tag{2}$$

$$\sum_i \sum_l UC_{i,l} = \sum_i^{i \in IT} \sum_j^{j \in FN} (IC_i + IS_i) * \begin{pmatrix} x_{ij}\begin{pmatrix} UC_{i,WD}*(1-FT_j)) \\ +UC_{i,WL}*FT_{j'} \end{pmatrix} \\ +z_{i,j} * UC_{i,Cloud} \end{pmatrix}. \tag{3}$$

4) Constraints

- Constraints on fog planning

$$0.5 * (N-1) * \sum_j^{j \in FN} u_j = \sum_j^{j \in FN} \sum_{j'}^{j' \in FN} y_{jj'}, \tag{4}$$

$$u_j * (N-1) - \sum_{j'}^{j' \in FN} y_{jj'} = 0 \quad \forall j \in FN, \tag{5}$$

$$u_j + u_{j'} \geq 2 * y_{jj'} \quad \forall j, j' \in FN, \tag{6}$$

$$\alpha * \sum_j^{j \in FN} j \leq \sum_j^{j \in FN} u_j \leq \beta * \sum_j^{j \in FN} j, \tag{7}$$

$$y_{jj'} + y_{jj''} + y_{j'j''} = \begin{cases} 0 \\ 1 \\ 3 \end{cases} \quad \forall j, j', j'' \in FN. \tag{8}$$

Since we consider to plan fogs with full connection, constraint (4) ensures that the total number of links in all the planned fogs is conservative while satisfying the fully-connected condition.

Constraint (5) ensures that the total number of links in a single fog type is conservative while satisfying the fully-connected condition.

Constraint (6) restricts that if any two fog nodes are selected, the link between them should also be selected.

Constraint (7) limits the lower and upper bound ratios of the number of candidate fog nodes that should participate in constructing fogs.

Constraint (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

$$\sum_j^{j \in FN} (x_{i,j} + z_{i,j}) = 1 \quad \forall i \in IT, \tag{9}$$

$$x_{ij} + z_{ij} \leq u_j \quad \forall j \in FN, \tag{10}$$

$$\sum_j^{j \in FN} x_{ij} * FT_j \geq IM_i \quad \forall i \in IT, \tag{11}$$

$$\sum_j^{j \in FN} \sum_{j'}^{j' \in FN} x_{ij} * (FT_j + y_{jj'} * FT_{j'}) \geq IR_i \quad \forall i \in IT, \tag{12}$$

$$z_{ij} \leq (1 - IR_i) * (1 - IM_i) * (1 - FT_j) \quad \forall i \in IT, j \in FN, \tag{13}$$

$$FC_j + \sum_{j'}^{j' \in FN} y_{jj'} * FC_{j'} \geq \sum_{j'}^{j' \in FN} \sum_i^{i \in IT} (x_{ij} + x_{ij'} * y_{jj'}) * IC_i \quad j \in FN, j \neq j', \tag{14}$$

$$FS_j + \sum_{j'}^{j' \in FN} y_{jj'} * FS_{j'} \geq \sum_{j'}^{j' \in FN} \sum_i^{i \in IT} (x_{ij} + x_{ij'} * y_{jj'}) * IS_i \quad j \in FN, j \neq j'. \tag{15}$$

Constraint (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 (10) restricts that if an IoT task is served by a fog node, the node must be selected in any planned fog.

Constraint (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 (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 (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 (14) and (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.

B. ILP MODEL FOR 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-CaOpEx 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-CaOpEx model are required here. The additional ones are shown as follows.

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

2) Objective

$$Minimize(\sum_{l}\sum_{i}(EC_l * IP_i)), \quad l \in CF,\ i \in IT, \tag{16}$$

$$\sum_{l}\sum_{i}(EC_l * IP_i) = \sum_{i}^{i\in IT}\sum_{j}^{j\in FN} IP_i * \begin{pmatrix} x_{ij} * \begin{pmatrix} EC_{WD}*(1-FT_j) \\ +EC_{WL}*FT_j \end{pmatrix} \\ +z_{ij} * EC_{Cloud} \end{pmatrix}. \tag{17}$$

In objective (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 (17).

In addition, we also consider to unify the two objectives, i.e., (1) and (16), and propose the weighted sum objective as shown in (18), where θ is the weight value that is used to adjust the significance of cost and energy efficiency in the combined objective.

$$Minimize(\sum_{h}\sum_{k} DC_{h,k} + \sum_{i}\sum_{l} UC_{i,l} + \theta * (\sum_{l}\sum_{i}(EC_l * IP_i))),\ i \in IT,\ h,k \in FN,\ l \in CF. \tag{18}$$

3) Constraints

$$\sum_{i}^{i\in IT} x_{ij} * IP_i * (EC_{WD} * (1 - FT_j) + EC_{WL} * FT_j) \leq FE_j \quad \forall j \in FN. \tag{19}$$

Note that all the constraints from (9)-(15) are required here. Constraint (19) restricts that the total power consumed in serving the IoT tasks in a fog node should not exceed the fog's 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.

V. NUMERICAL EVALUATION

A. SIMULATION ENVIRONMENT

The simulation settings are shown in tables 1 and 2, where $U(x, y)$ 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 $\boldsymbol{j}$ and $\boldsymbol{j'}$ are distant from each other in the range of 5 to 10 Km, i.e., $\boldsymbol{D_{jj'}}$. The number of candidate fog nodes allowed in a potential fog type is set to be 3, i.e. $\boldsymbol{N}$ = 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., $\boldsymbol{FC_j}$ or $\boldsymbol{FS_j}$. The number of required computing/storage resource units by IoT tasks are randomly set in the range of 5 to 9, i.e., $\boldsymbol{IC_i}$ or $\boldsymbol{IS_i}$.

We assume that the CAPEX cost between fog nodes h and 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 OPEX cost to serve IoT task 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 i is set to 25, i.e., $\boldsymbol{UC}_{i,Cloud}$. The total available power of fog node j, i.e., $\boldsymbol{FE_j}$, is randomly distributed between 150 and 250 joules. The packet size of an IoT task 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 [28], [29], when l is a cloud node, a wireless fog node and a wired fog node, respectively.

The total number of IoT tasks considered in this paper 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, $\boldsymbol{\alpha}$, and upper boundary, $\boldsymbol{\beta}$, of candidate fog nodes that should

TABLE 1. Characteristics of IoT tasks & fog nodes.

PARM	RANGES	REFS
# of wireless fog nodes	6	
# of wired fog nodes	6	
$D_{jj'}$	U(5,10) km	[2]
N	3	
IC_i or IS_i	U(5,9)	[32]
FC_j or FS_j	U(20,30)	[33], [34]

TABLE 2. Other parameters on cost and energy.

PARM	RANGES	REFS
$DC_{h,k}$	100 (WL&WL or WD&WD), 200(WL&WD)	[35]
$UC_{i,l}$	2(WL), 3(WD), 25(Cloud)	[35], [36]
FE_j	U(150,250) joule	
IP_i	U (2,8) KByte	[37]
EC_l	3(Cloud), 10(WL), 5(WD) joule/Kbyte	[28], [29]

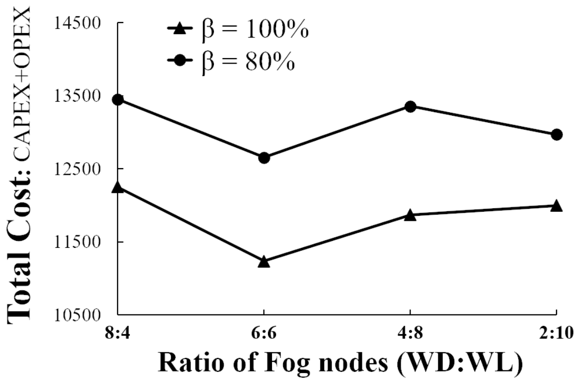

FIGURE 3. Total cost under different βs and different ratios of WD: WL.

participate in the overall fog planning as 40% and 80%, respectively.

B. NUMERICAL RESULTS AND ANALYSES

To explore the proposed ILP models, we used the modeling language AMPL and the solver Gurobi 8.1.0 [30], [31]. 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.

1) NUMERICAL RESULTS FOR ILP-CAOPEX

Figs. 3 to 6 show the numerical results for the first ILP-CaOpEx model, which aims to minimize the total CAPEX and OPEX 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 Fig. 3. Note that real-time and mobility requirements are not evaluated simultaneously, i.e., when one requirement is considered, the other requirement is not considered. Fig. 3 shows the performance of total cost for different β s, i.e., $\beta = 80\%$ and $\beta = 100\%$, 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,

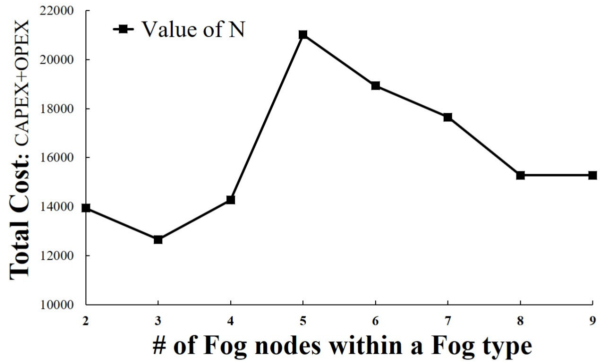

FIGURE 4. Total cost under different Ns.

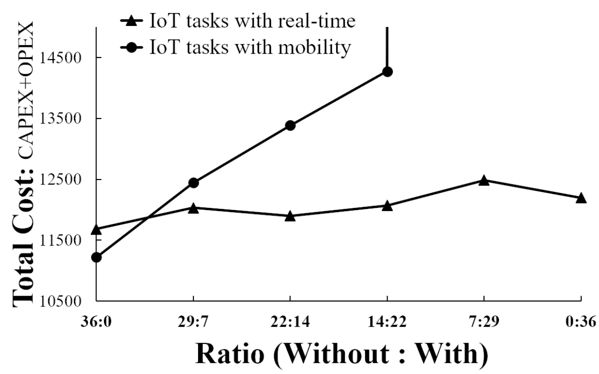

FIGURE 5. Total cost under different ratios of real-time/mobility IoT tasks.

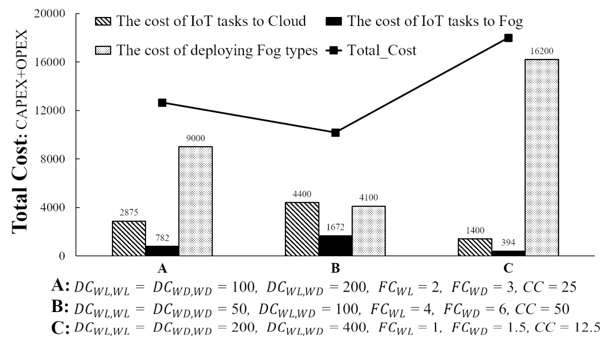

FIGURE 6. Total cost under three different initial settings for CAPEX and OPEX.

the total cost is smaller when β is set to 100% compared to that when β is 80%. This indicates that the OPEX 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 αs is not given since the results show that it does not affect the total cost.

Fig. 4 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

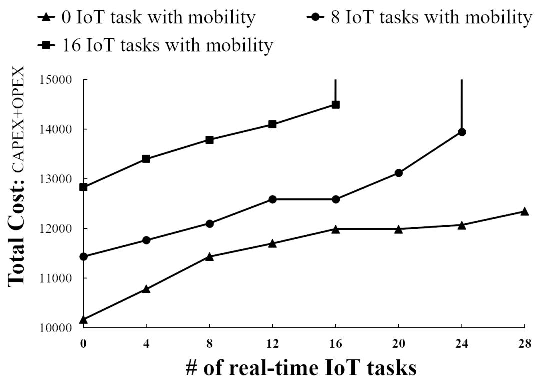

FIGURE 7. Total cost under different number of real-time IoT tasks.

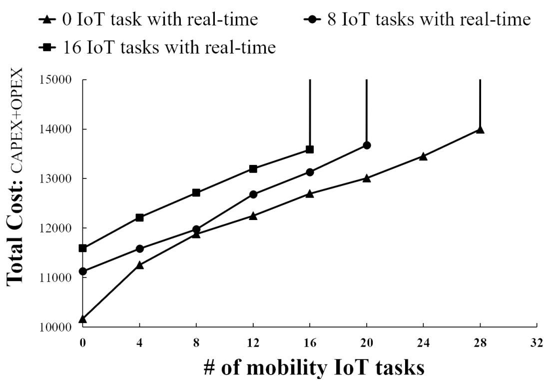

FIGURE 8. Total cost under different number of mobility IoT tasks.

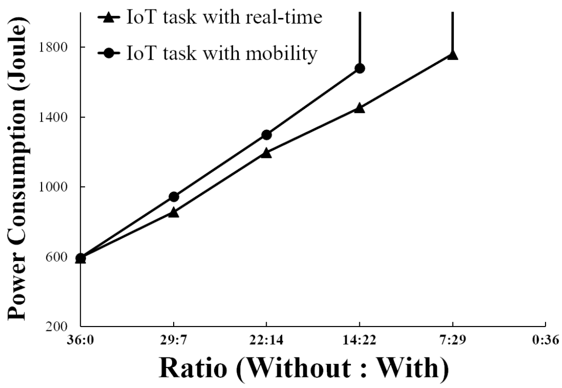

FIGURE 9. Total power consumption under different ratios IoT tasks.

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 $N = 3$.

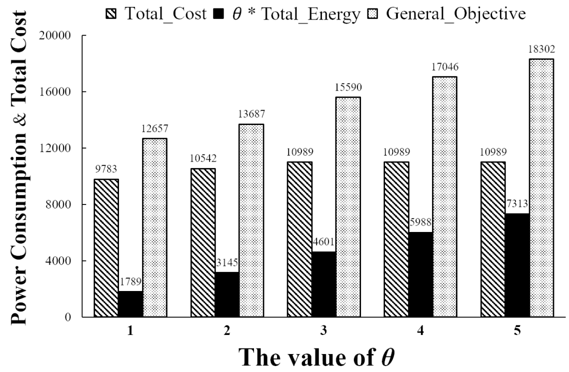

FIGURE 10. Multi-Objective in Equation(18) under different weight values θ.

Fig. 5 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. 6 gives a detailed vision on how the OPEX and CAPEX vary under different simulation settings, say A, B, and C. The OPEX 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 OPEX cost of cloud and fogs is relatively small. In scenario B, although the OPEX 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.

Fig. 7 and Fig. 8 show similar results to that of Fig. 5 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.

2) RESULTS FOR ILP-ENERGY

In this section, we investigate the power consumption when serving IoT tasks. Fig. 9 mainly considers the optimization of a single objective (Total_Energy) given in equation (16)

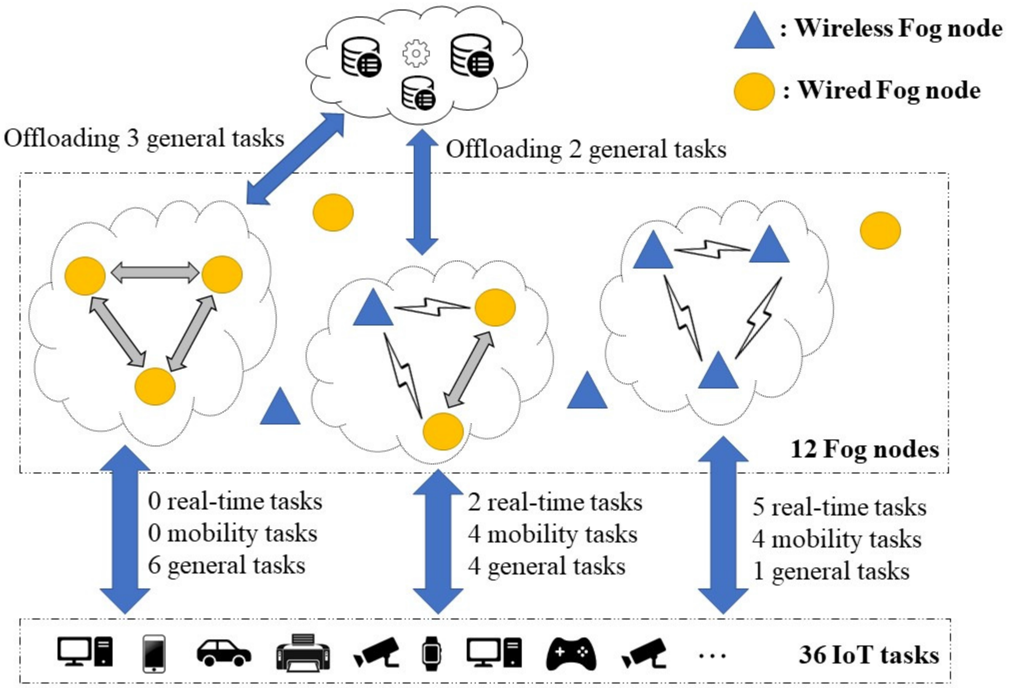

FIGURE 11. The result graph under default settings.

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.

Fig. 10 evaluates the weighted objective in equation (18) under different weight values of $\boldsymbol{\theta}$. We found the power consumption under all $\boldsymbol{\theta}$s does not decreases even when we increase the weight value of it.

C. TOPOLOGICAL RESULTS

To give an illustrative explanation, we show a topological result in Fig. 11, which is obtained under the objective of ILP-CaOpEx model and the scenario A (i.e., $\boldsymbol{DC}_{\boldsymbol{WL},\boldsymbol{WL}} = \boldsymbol{DC}_{\boldsymbol{WD},\boldsymbol{WD}} = 100$, $\boldsymbol{DC}_{\boldsymbol{WL},\boldsymbol{WD}} = 200$ and $\boldsymbol{FC}_{\boldsymbol{WL}} = 2$, $\boldsymbol{FC}_{\boldsymbol{WD}} = 3$, $\boldsymbol{UC}_{i,Cloud} = 25$.) of Fig. 6. A total of twelve candidate fog nodes are optimally planned into three fogs. The rest three fog nodes do not participate in planning. We can see that one WLF, one WDF and one HBF are formed. The three fogs together with the cloud handle a total number of 36 IoT tasks, with seven and eight of them requiring real-time and mobility services, respectively.

Specifically, we can see that the planned WDF on the left side does not handle real-time and mobility tasks. Instead, it provisions six general tasks and offloads three general tasks to the cloud layer for processing. The HBF in the middle handles two real-time tasks, four mobility tasks, four general tasks, and offloads two general tasks to the cloud layer for processing. The WLF on the right side handles five real-time tasks, four mobility tasks and one general task. Since a WLF is composed of only wireless fog nodes, it cannot offload IoT tasks to the Cloud.

VI. CONCLUSION

In this paper, we addressed the issue of fog planning under the framework of iCloudFog by investigating the total CAPEX and OPEX 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 in this paper, we mainly considered planning fogs with fully-connected architecture as a case study. In the future, we will evaluate the impact of various fog topology, such as ring, star, etc., on the network performance of iCloudFog framework.

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