ENERGENT: An Energy-Efficient UAV-Assisted Fog-IoT Framework for Disaster Management

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***Abstract*—In this paper, we propose ENergy-efficient disastER manaGmENT (ENERGENT) as a novel framework for disaster management in the unmanned aerial vehicle (UAV)-assisted Fog-Internet of things (IoT) networks. ENERGENT optimizes the energy consumption of the terminal nodes (TNs), as well as the UAVs, using three proposed algorithms. The first algorithm optimally adjusts the 3D placement of the UAVs such that these nodes consume the minimum energy to reach the desired cluster of the TNs. Besides, the transmit power and the transmission rate of the TNs are set in a way that their energy consumption is minimized and the outage probability requirements are met in the network. In the second algorithm, we propose an optimal task offloading scheme where tasks are offloaded to the UAVs in order to meet the network delay constraints. Finally, the third algorithm takes advantage of wireless power transfer to transfer energy to the TNs when their remaining energy degrades a predefined threshold. This scheme guarantees a minimum throughput for all TNs within a cluster by which the total network throughput is maximized. Simulation results reveal that ENERGENT outperforms the existing methods in terms of optimized network energy consumption, delay, and throughput.**

***Index Terms*—Disaster management, energy efficiency, fog-IoT networks, throughput optimization, unmanned aerial vehicle (UAV), wireless power transfer (WPT).**

I. INTRODUCTION

UNMANNED aerial vehicles (UAVs) or drones, which operate autonomously or are flown under remote control, have the characteristics such as versatility, mobility, and flexibility. These features give UAVs the potential to be widely used in different Internet of things (IoT)-based applications such as disaster management, agriculture, military, network communications, and smart healthcare [1]–[4]. The versatility of the UAVs becomes paramount when these nodes are adopted as fog nodes (FNs) that will fly over the terminal nodes (TNs) at the edge of the network (See Fig. 1). In such scenarios, UAVs can take advantage of either a relay (UAV-relay) or an FN (UAV-FN) to provide the required services to the TNs. Each UAV-relay is responsible for delivering the tasks to the nearby base stations (BSs) for further processing [2], whereas a UAV-FN receives the tasks from the TNs and processes them locally. The role of UAV-FNs is more significant than UAV-relays in scenarios, such as disaster management, where accessing the stationary BSs is difficult, challenging, or even impossible for the TNs. However, the computing capacity of UAV-FNs is limited. To cope with this shortcoming, UAV-FNs can cooperate with the terrestrial BSs or cloud servers [5].

The tasks generated by TNs are highly delay-sensitive, especially in disaster management scenarios such as fire and flood [6], wherein making urgent decisions is critical. Apart from the importance of the latency in such scenarios, the limited energy budget of TNs imposes a limitation on them for processing their tasks, locally. This is more significant for the highly important tasks, such as map navigation and exploring applications, which consume a remarkable amount of energy. To tackle the aforementioned issues, complementary resources need to be leveraged at the shortest distance with the TNs. UAV-FNs are suitable candidates in this regard thanks to their mobility and versatility. The UAV-FNs can hover in an optimal 3D position above TNs such that the TNs consume less energy for offloading the tasks to them. Besides, the shorter distance between the UAV-FN and TNs alleviates the transmission delay of the tasks [5]. However, managing network communications and computations to achieve the highest performance is always challenging. Thereby, schemes with optimal task offloading and energy consumption management are required to improve the efficiency of Fog-IoT networks.

A. Literature Review

The studies in the literature show a large research body in improving the efficiency of UAV-enabled IoT networks. For example, Wu *et al.* [7] investigate trajectory planning and communication power control for a multi-UAV multi-user system. This work aims to maximize the throughput over ground users in a downlink scenario. Similarly, in [8], the authors consider the energy efficiency of the UAV-assisted communication networks and propose a UAV trajectory planning for hovering above a single ground communication terminal. Tang *et al.* [9] study a game-based channel assignment scheme for UAVs in D2D-enabled communication networks. UAVs have also been utilized to enhance the flexibility of a mobile edge computing system in [10] and [11], where UAVs act as relay nodes to be involved in the computation of the offloading process. More recently, the researchers utilized UAVs as aerial cloudlets to provide edge computing services. For example, Jeong *et al.* [12] investigate the UAV's path planning to

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minimize the energy consumption of communication for task offloading at mobile users. This is while the energy budget of UAV cloudlet is constrained. In [13], the authors consider the computation offloading strategy in an IoT network when the UAV trajectories are pre-determined. The objective is to minimize the computing delay, user energy consumption, and server computing cost.

Pandey *et al.* propose a new method in [14] to address the seamless indoor IoT connectivity of the farthest multiple users. The method optimizes the transmission power of all users, which are randomly located in the network, such that all of them can receive the transmitted data from the UAV-FN with a minimum path loss. A joint offloading method is proposed in [15] for the hierarchical fog-cloud computing system, including multiple mobile users and multiple UAVs, to minimize the total weighted consumed power of the system. The authors in [16] consider a system model, including multiple UAVs and multiple TNs, in which TNs are activated randomly over time. Accordingly, a framework is proposed to jointly optimize 3D placement and mobility of the UAVs, device-UAV association, and uplink power control such that the total transmission power of TNs is minimized and the network path loss is alleviated. However, this approach suffers from large delay as it disregards the delay factor in allocating UAV-FNs to clusters.

Liu *et al.* [17] investigate the control of the power consumption of the IoT devices which is a challenge as most of the devices are battery-powered. They utilize a UAV to assist in a heterogeneous IoT for emergency communications. Hence, a distributed non-orthogonal multiple access (NOMA) scheme is proposed regardless of successive interference cancellation (SIC). To provide communication coverage for the alive users and IoT devices efficiently, a multi-objective resource allocation (MORA) scheme is proposed. Briefly, the initial MORA problem is formulated and decoupled with the user power initialization. A reweighted message-passing algorithm (ReMPA) is used to assign the sub-channels to the devices and the users step by step. Lastly, the transmitting power of users and devices are jointly fine-tuned using an iterative access control scheme.

The authors in [2] study an overview of different UAVs-based, IoT-based, and IoT, coupled with UAVs platforms to efficiently manage disasters. They propose an energy-efficient task scheduling scheme for UAVs to collect data from the ground IoT devices. The main contribution is to optimize the flight path of UAVs such that their energy consumption is minimized. To this end, the scheme analyzes the collected vital signs data by UAVs for people involved in disaster areas. Moreover, the decision tree classification algorithm is carried out to determine their health status.

Nowadays, wireless power transfer (WPT) has attracted the attention of many researchers, where the UAVs can wirelessly transfer power/energy to the TNs and hence, compensate for the shortage of the limited energy budget of the TNs. For instance, Iranmanesh *et al.* [18] consider a scheme in which the UAVs take over the parcel delivery. The authors propose a heuristic flight path planning (HFPP) scheme that utilizes wireless charging stations to prolong the flight time of UAVs for joint parcel delivery and data communication provisioning. Leng [19] analyzes the utilization of UAVs to charge wireless sensor networks using wireless power transfer. Moreover, the author evaluates the impact of different parameters on the networks' lifetime. In [20], the UAV is employed to charge the sensors to maximize the lifetime of the wireless sensor network. Basha *et al.* [21] also consider the benefit of leveraging the UAVs to power the sensors and the conditions needed. In both of these works, the authors only investigate a one-shot charging process. In [22], the UAVs are utilized as energy providers to charge the D2D pairs for which two phases are conducted in each time slot, namely the energy harvesting phase, and the information transmission phase. The energy required for the information transmission phase is limited by the energy received in the energy harvesting phase. However, the dynamic characteristic is not considered in the resource allocation problem. The authors in [23] introduce another UAV-enabled charging system in which the sum energy maximization problem and the minimum received energy maximization problem are optimized separately. Li *et al.* [24] address the problem of radio-frequency-based wireless charging for wireless sensor networks by considering energy harvesting and information transmission together. In their approach, frequency division multiplexing and time-division multiplexing are adopted. The authors mainly focus on the power allocation problem. In [25], the utilization of UAV-assisted wireless power transfer in mobile-edge computing is investigated, where UAVs are used to provide energy for the devices and perform computation-intensive tasks for the devices. However, the energy constraint of the UAV is not considered.

B. Motivation

The existing schemes and frameworks in the literature optimize the energy consumption of all the UAVs and the TNs by adjusting the 3D placement of the UAVs, optimizing the transmit power of the TNs, or optimizing task allocation mechanisms in the UAV-assisted Fog-IoT networks. On the other hand, research efforts have been devoted to improving the UAV-assisted Fog-IoT networks in disaster management in terms of delay and energy consumption of nodes. However, in all of them, the UAVs are the main nodes for controlling the situation, collecting the data, and reducing the energy consumption of the TNs by optimally adjusting their 3D placement or efficiently flying over the TNs. This is while the UAVs suffer from the limited energy budget themselves. Moreover, the energy budget of TNs is limited, which leads to throughput degradation if the TNs need to process their tasks locally. Based on the aforementioned gaps in the literature, we take advantage of UAVs for charging the TNs, and their flexibility in optimizing the transmit power of the TNs.

C. Contribution

To deal with the challenges in the literature, for the first time, we propose a framework, named ENergy-efficient disastER manaGmENT (ENERGENT), wherein each TN takes over the processing of a portion or whole of a task in collaboration with the UAV-FNs. ENERGENT includes an energy harvesting scheme to transfer power to UAV-FNs and TNs to prolong the network lifetime. Overall, ENERGENT comprises three schemes as discussed below that aim to improve the energy efficiency of the Fog-IoT networks in disaster management while meeting the quality of service (QoS) requirements in the network. Specifically, the contributions of the paper are summarized as follows:

- An assignment scheme is proposed to optimally allocate each UAV-FN to a different and unique cluster of TNs such that the UAV-FNs consume the minimum energy to fly toward the corresponding cluster. Hence, an optimization problem is defined to optimize the 3D placement of the UAV-FNs so that the TNs reach their maximum transmission rate and transmit power while meeting the outage probability constraint in the network. Subsequently, the energy consumption of TNs is optimized.
- A task offloading scheme is proposed to boost the battery life of the TNs. In this scheme, which is a partial offloading scheme, each TN can process a portion of a task locally, and offload the rest to the corresponding UAV-FN. Therefore, the optimal partial amount of the tasks needs to be found in a way that the delay constraints are met and the TNs consume the minimum energy for processing the tasks.
- An energy harvesting scheme is proposed in which a UAV-FN transfers energy to the TNs belonging to the corresponding cluster when the available energy is below a predefined threshold. Moreover, a WPT-UAV with enough energy resources, e.g., the solar-powered Facebook Aquila, is used to transfer wireless power to the UAV-FNs when required.

D. Organization

The rest of this paper is organized as follows: Section II presents the system model, including channel model, outage probability model, delay model, energy model, and throughput model. Section III includes the proposed ENERGENT framework and the corresponding schemes. Numerical results are provided in Section IV. Finally, Section V concludes the paper.

II. System Model

We consider a system model shown in Fig. 1, including N UAV-FNs and M TNs. The set of UAV-FNs is shown by $\mathcal{V} = \{v_1, v_2, \cdots, v_N\}$. Moreover, there exists a WPT-UAV to transfer energy to the UAV-FNs when necessary. It is assumed that the TNs group together to form the clusters based on their location. The k-means clustering [26] method is used in this regard. Each cluster c is composed of $\mathbb{M}_c$ TNs, where $\text{TN}_{(i,c)}$ represents i-th TN belonging to cluster c. Without loss of generality, we assume that each $\text{TN}_{(i,c)}$ generates one task in each time slot with an average size of $L_{(i,c)}$. Every task can be partially/completely processed at the TN locally and/or offloaded to the corresponding UAV-FN. The transmission mode between the TNs and the corresponding

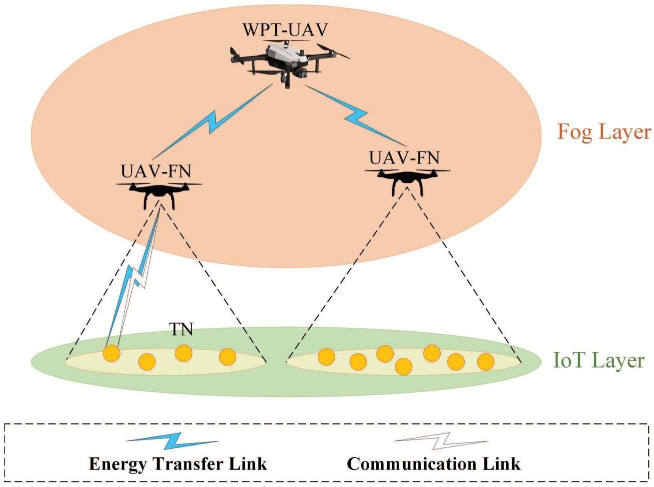

Fig. 1. System model.

UAV-FN is full-duplex. Also, multiple TNs within a cluster can simultaneously transmit their tasks to the UAV-FN. In light of that, the TNs utilize the frequency division multiple access (FDMA) method to access the shared channel. Among all available UAV-FNs in the network, only one UAV-FN is assigned to each cluster at a time slot. Besides, a cluster can only be assigned to one and only one UAV-FN at each time slot. Each UAV-FN covers an area with a radius of $\mathcal{R}$.

The 3D placement of the UAV-FNs, especially the flight altitude of the UAV-FNs, plays an important role in providing the QoS requirements in the network. For instance, by increasing the flight altitude, the outage probability of delivering the tasks generated by TNs to the corresponding UAV-FN increases. In such a situation, the TNs need to consume more energy to offload their tasks to the UAV-FN and suffer from larger delays. Therefore, optimizing the flight altitude of the UAV-FNs is an essential objective behind this work. In the rest of this section, we study the channel model of TN-UAV pairs, the outage probability model, the delay model, the energy model of nodes, and the throughput model in the network.

Notations: In this paper, scalars are denoted by italic letters. Boldface lower-case letters denote vectors. For a vector $\boldsymbol{a}$, $\|\boldsymbol{a}\|$, $\boldsymbol{a}^T$, and $\boldsymbol{a}^H$ represent its Euclidean norm, its transpose, and its conjugate transpose, respectively. $\Pr(\cdot)$ denotes the probability. $\Gamma(\cdot)$ and $\Gamma(\cdot,\cdot)$ denote the Gamma function and the upper incomplete Gamma function, respectively; Finally, $U[\cdot]$ indicates the uniform distribution.

A. Channel Model

According to assumptions of the considered system model, the line-of-sight (LoS) propagation is established between a TN-UAV pair. Among all available practical distributions for the LoS transmission, the Nakagami-m distribution with the shape parameter m is a well-known model which can capture a wide range of fading scenarios ($m < 1$ for Hoyt, $m = 1$ for Rayleigh, and $m > 1$ for Rician) [27]–[29]. Therefore, the channel capacity between a TN and the corresponding UAV-FN is defined as

$$C_{(i,c)j} = B\log_2\left(1 + \frac{P_{(i,c)}g_0\hbar_{(i,c)j}d_{(i,c)j}^{-\alpha}}{I_{(i,c)} + \sigma^2}\right), \quad (1)$$

where B is the bandwidth, $P_{(i,c)}$ is the transmit power of $\mathrm{TN}_{(i,\,c)}$, g_0 denotes the channel gain at the reference distance $d_m = 1$ m, α shows the path loss exponent, σ^2 is the additive white Gaussian noise (AWGN) power, and $\hbar_{(i,c)j}$ represents the fading coefficient of the channel, following Gamma distribution, with a mean of 1. $I_{(i,c)} = \sum_{\substack{i'=1\\ i'\neq i}}^{\mathbb{M}_c} P_{(i',c)}g_0\hbar_{(i',c)j}d_{(i',c)j}^{-\alpha}$ is the interference derived from interfering BSs. Finally, $d_{(i,c)j}$ stands for the distance between $\mathrm{TN}_{(i,\,c)}$ and v_j, which is given as

$$d_{(i,c)j} = \sqrt{z_j^2 + \|\boldsymbol{u}_j - \boldsymbol{u}_{(i,c)}\|^2}, \quad (2)$$

where z_j is the flight altitude of v_j, $\boldsymbol{u}_j = [x_j, y_j]^{\boldsymbol{T}}$ and $\boldsymbol{u}_{(i,c)} = [x_{(i,c)}, y_{(i,c)}]^{\boldsymbol{T}}$ are the horizontal coordinate of v_j and $\mathrm{TN}_{(i,\,c)}$, respectively. Moreover, the height of TNs is set to zero.

In the considered system model, the interference power produced by other transmitters is much larger than the AWGN. Hence, the interference is dominant over the noise, and the network performs in an interference-limited regime [30]. Accordingly, we ignore the noise in our calculations. Therefore, signal to interference ratio (SIR) is expressed as

$$C_{(i,c)j} = B\log_2\left(1 + \frac{P_{(i,c)}g_0\hbar_{(i,c)j}d_{(i,c)j}^{-\alpha}}{I_{(i,c)}}\right). \quad (3)$$

B. Outage Probability Model

In the considered system model, the outage probability happens when the transmission rate of a TN exceeds the channel capacity between the TN and the corresponding UAV-FN beyond which the UAV-FN cannot receive the tasks. Accordingly, considering $R_{(i,c)}$ as the transmission rate of $\mathrm{TN}_{(i,\,c)}$, the outage probability is defined as $P_{out} = Pr(C_{(i,c)j} < R_{(i,c)})$ [31], [32]. We assume that the fading coefficient of all channels in a cluster is the same, i.e., $\hbar_{(i,c)j} = \hbar, \forall\ \mathrm{TN}_{(i,\,c)} \in$ cluster c. By employing the methods and assumptions provided in [33], we have

$$\overline{P}_{out} = \frac{m^{(m-1)}A_1^{2m}\Gamma(2m, m\hbar^2)}{\Gamma^2(m)} - \frac{\Gamma(m, m\hbar^2)}{\Gamma(m)},$$
$$\text{where } A_1 = \frac{\left(2^{R_{(i,c)j}/B} - 1\right)d_{(i,c)j}^{\alpha}\sum_{\substack{i'=1\\ i'\neq i}}^{\mathbb{M}_c} d_{(i',c)j}^{-\alpha}}{P_{(i,c)}g_0}. \quad (4)$$

C. Delay Model

The delay model depends on the allocation scheme of the tasks. If the corresponding TN processes the task locally, the delay model is equal to the processing delay at the TN. We assume that the queuing model in the TNs follows the first in first out (FIFO) model. By considering t_0 as the time that a TN needs for processing one bit and $\hat{L}_{(i,c)}$ as the number of bits buffered at $\mathrm{TN}_{(i,\,c)}$, the processing delay of a task at $\mathrm{TN}_{(i,\,c)}$ is calculated as

$$D_{(i,c)}^{comp} = \hat{L}_{(i,c)}t_0 + L_{(i,c)}t_0. \quad (5)$$

In the case of offloading, a task suffers from two types of delay. The first delay is the transmission delay for sending the generated task from the corresponding TN to the corresponding UAV-FN; and the second type of delay, referred to as computing delay, is the required time for processing the task at the corresponding UAV-FN. The transmission delay of a task generated by $\mathrm{TN}_{(i,\,c)}$ is expressed as [34], [35]

$$D_{(i,c)}^{tx} = \frac{L_{(i,c)}}{R_{(i,c)}}. \quad (6)$$

By respectively considering μ_j, λ_j, and L_j as the service rate, the average traffic rate, and the average size of tasks per arrival at v_j, the computing delay for $L_{(i,c)}$ at v_j is calculated as [36]

$$D_{(i,c)j}^{comp} = \frac{L_{(i,c)}}{\mu_j - \lambda_j L_j}. \quad (7)$$

D. Energy Model

In the following, the energy models of TNs and UAV-FNs are represented separately.

1) Energy model of TNs: The energy consumption of TNs comprises three parts: the required energy for processing a task locally; the required energy for transmitting a task to the corresponding UAV-FN; and as a novel contribution of our proposed framework, the harvesting energy that the UAV-FN transfers to the TNs.

a) Task processing energy model: By considering e_0 as the energy for processing one bit by a TN, the task processing energy is expressed as

$$E_{(i,c)}^{comp} = L_{(i,c)}e_0. \quad (8)$$

b) Offloading energy model: The energy consumption for offloading a task to the corresponding UAV-FN depends on the transmit power, as well as the transmission rate of a TN, which is given as [35], [37]

$$E_{(i,c)}^{tx} = P_i\frac{L_{(i,c)}}{R_{(i,c)}}. \quad (9)$$

c) Energy harvesting model: When the remaining energy of TNs in a cluster degrades a threshold, E_{th}, the corresponding UAV-FN is responsible to transfer the energy to the TNs. The received power at $\mathrm{TN}_{(i,\,c)}$ is given by $P_{(i,c)}^{rx} = P_j\|\hbar_{(i,c)j}\|^2 d_{(i,c)j}^{-\alpha}$, where P_j is the transmit power of the UAV-FN. We adopt a piece-wise linear EH model [38], in which the harvested power is linearly boosted with the received power up to a threshold, called the saturation point. Let $\eta_{(i,c)}$ and P_{sat} show the linear energy conversion efficiency and the saturation power, respectively. Therefore, the harvested energy by $\mathrm{TN}_{(i,\,c)}$ is modeled as

$$P_{(i,c)}^{h} = \begin{cases} \eta_{(i,c)}P_{(i,c)}^{rx} & 0 \le \eta_{(i,c)}P_{(i,c)}^{rx} < P_{sat} \\ P_{sat} & \eta_{(i,c)}P_{(i,c)}^{rx} \ge P_{sat}. \end{cases} \quad (10)$$

2) Energy model of UAV-FNs: The energy consumption of a UAV-FN is composed of two parts. The major part is the propulsion energy, i.e., the energy that the UAV-FN consumes to fly towards the corresponding cluster and hover there. The minor part is communication-related energy, i.e., the energy consumption for processing the tasks. Since the propulsion is dominant on the communication-related energy, the latter is usually ignored in the calculations [39]. However, according to the assumption of the proposed framework in this paper, the communication-related energy can affect the optimal association of the UAV-FNs and the clusters. Hence, we consider both energy consumption of the UAV-FNs for flying toward the corresponding cluster. It is worth mentioning that, the UAV-FNs are responsible for transferring energy to the TNs within the corresponding cluster during the computing time, which leads to the reduction of the UAV-FNs' energy budget. To compensate for such a reduction, the WPT-UAV takes over to recharge the UAV-FNs when their energy budget degrades a predefined threshold.

a) Propulsion energy model: We assume that each UAV-FN moves with a constant speed V towards the corresponding cluster. The center of a cluster shows the horizontal coordinate of the cluster, which is defined as the mean of coordinate of the TNs belonging to the cluster, i.e., $\boldsymbol{u}_c = [x_c = \sum_{i=1}^{\mathbb{M}_c} x_{(i,c)}/\mathbb{M}_c, y_c = \sum_{i=1}^{\mathbb{M}_c} y_{(i,c)}/\mathbb{M}_c]^{\boldsymbol{T}}$. Accordingly, the energy consumption of v_j to flight toward cluster c in d_{cj} meters is calculated as

$$E^{f}_{(i,c)j} = E_0 d_{cj}, \tag{11}$$

where E_0 is the required energy for flying per meter unit which is given as [39]

$$E_0 = P_0\left(\frac{1}{V} + \frac{3V}{U_{tip}^2}\right) + P_{in}\left(\sqrt{V^{-4} + \frac{1}{4V_0^4}} - \frac{1}{2V_0^2}\right)^{\frac{1}{2}} + \frac{1}{2}d_0 \rho s A V^2, \tag{12}$$

where P_0 and P_{in} are the blade profile power and induced power in hovering status, respectively; V_0 denotes the mean rotor induced velocity in hover; ρ and A are known as the air density and rotor disc area, respectively. U_{tip} represents the tip speed of the rotor blade; d_0 stands for the fuselage drag ratio; and finally, s is the rotor solidity.

After arriving above cluster c, the UAV-FN must adjust its flight altitude for which the UAV-FN changes its altitude for $\tilde{z}_j$ meter. It also can stay for a time period with fixed power consumption above the cluster to process the tasks generated by TNs. By respectively considering e_{fa} and P_h as the required energy for adjusting one meter and the power consumption of the UAV-FN for hovering in Watt, the energy consumption for flight altitude adjustment and hovering by v_j is calculated as

$$E^{alt}_j = \overbrace{e_{fa}\tilde{z}_j}^{adjusting} + \underbrace{P_h \tau}_{hovering}, \tag{13}$$

where τ shows the time that v_j spends to hover, which is known as the time-slot duration in this paper. Overall, the total energy consumption of v_j for flying toward the corresponding cluster c and hovering there is given as

$$E^{t}_{cj} = E_0 d_{cj} + e_{fa}\tilde{z}_j + P_h \tau. \tag{14}$$

b) Communication-related energy model: Let $\tilde{e}_0$ indicate the energy that a UAV-FN consumes to process one bit. Hence, the total energy for processing a task with a size of $L_{(i,c)}$ is expressed as

$$E^{comp}_j = L_{(i,c)}\tilde{e}_0. \tag{15}$$

E. Throughput Model

In a time slot with a duration of τ, the system throughput is defined as the total number of bits that the TNs offload to the corresponding UAV-FN. Therefore, the throughput of $\text{TN}_{(i,\,c)}$ with respect to v_j is defined as

$$\mathcal{T}_{(i,c)j} = B\log_2\left(1 + \frac{P_{(i,c)} g_0 \hbar_{(i,c)j} d_{(i,c)j}^{-\alpha}}{I_{(i,c)}}\right)\tau. \tag{16}$$

III. PROPOSED ENERGENT FRAMEWORK

The ENERGENT framework is proposed in this section to improve the energy efficiency of the Fog-IoT networks in disaster management. In this regard, the ENERGENT employs three schemes, which are optimal UAV-FN assignment scheme, optimal task-offloading scheme, and optimal energy transferring scheme. The schemes are explained in the following sub-sections.

A. UAV-FN Assignment Scheme

The main objective of this scheme is to assign the UAV-FNs to the clusters in a way that each UAV-FN consumes the minimum energy for flying toward the corresponding cluster. Thereafter, the 3D placement of the UAV-FN is optimized with respect to the TNs within the corresponding cluster such that the TNs reach the optimal transmission rate, as well as transmit power, while the network outage probability constraint is met. As a result, the TNs will consume less energy to offload the tasks to the corresponding UAV-FN with respect to the obtained optimal transmission rate and transmission power. Therefore, the UAV-FN assignment scheme is divided into two phases: the allocation phase and the 3D placement phase.

1) Allocation phase: The main objective of the allocation phase is to assign the UAV-FNs to the clusters so that each UAV-FN flies toward the corresponding cluster with the least energy consumption. We define a_{cj} to be an indicator function, which is equal to one if v_j is assigned to cluster c, and zero otherwise. Let assume that the optimal number of clusters in the network is N_c, where $N \geq N_c$. By considering E^{av}_j as the available energy of v_j, the allocation problem is formulated as

$$\text{(P1): } \underset{a_{cj}}{\text{minimize}}\ E_0 d_{cj} a_{cj}, \tag{17}$$

s.t.

$$\sum_{c=1}^{N_c} a_{cj} = 1,\ 1 \le j \le N, \tag{17a}$$

$$\sum_{j=1}^{N} a_{cj} = 1,\ 1 \le c \le N_c, \tag{17b}$$

$$\sum_{i=1}^{\mathbb{M}_c} L_{(i,c)} \tilde{e}_0 a_{cj} \le E_j^{av}, 1 \le j \le N,\ 1 \le c \le N_c, \tag{17c}$$

$$a_{cj} \in \{0,1\},\ 1 \le j \le N,\ 1 \le c \le N_c. \tag{17d}$$

Constraint (17a) implies that each UAV-FN can be assigned to one and only one cluster. According to (17b), that is complementary of (17a), each cluster is associated with only one UAV-FN. Constraint (17c) emphasizes that the available energy of the candidate UAV-FN must be greater than the total energy for processing the incoming tasks from the corresponding TNs. Finally, (17d) indicates that a_{cj} is a binary variable.

a) Convergence, optimality, and complexity: P1 is linear in terms of a_{cj}. Moreover, since a_{cj} is a Boolean, P1 is Boolean linear programming (LP) problem. To solve P1, we use relaxation method, by which $a_{cj} \in \{0,1\}$ is relaxed to $0 \le a_{cj} \le 1,\ 1 \le j \le N,\ 1 \le c \le N_c$. The relaxed problem is convex, thus the convex optimization toolbox, namely CVX, is used to solve it [40]. The relaxed problem is solved in a polynomial time in terms of the number of clusters and the UAV-FNs, i.e., $\mathcal{O}(N \times N_c)$.

2) 3D placement phase: After successful association between the UAV-FNs and the clusters, each UAV-FN needs to optimally adjust its 3D placement with respect to the corresponding cluster. Accordingly, the TNs within the cluster reach their optimal transmission rate and transmit power by which the energy consumption of the TNs for offloading the tasks to the UAV-FN is minimized. Moreover, the outage probability requirement is met in the network.

The average signal to noise ratio (SNR), $\overline{\Omega}$, is defined as [41]

$$\overline{\Omega} = \frac{P_{(i,c)} d_{(i,c)j}^{-\alpha}}{\sigma^2} E[\hbar_{(i,c)j}] = \frac{P_{(i,c)} d_{(i,c)j}^{-\alpha}}{\sigma^2}. \tag{18}$$

According to the assumptions provided in [42], $\overline{\Omega}$ is bounded as

$$\frac{P_{(i,c)}^{\min}}{P_{(i,c)}^{\max}} \overline{\Omega} \ge \Omega_{th}, \tag{19}$$

where Ω is the SNR threshold. Therefore, the transmit power of $\text{TN}_{(i,\,c)}$ is calculated as [41]

$$P_{(i,c)} \ge \underbrace{\sqrt{\frac{P_{(i,c)}^{\max} d_{(i,c)j}^{\alpha} \sigma^2 \Omega_{th}}{P_{(i,c)}^{\min}}}}_{P_{(i,c)}^{lb,1}}. \tag{20}$$

On the other hand, the outage probability must be less than a threshold, β, i.e., $\overline{P}_{out} \le \beta$. By substituting the obtained value from (4) in the aforementioned inequality and solving it in terms of $R_{(i,c)}$, we have

$$R_{(i,c)} \le \underbrace{B \log_2 \left(1 + \frac{\Gamma^{1/m}(m) \left(\beta + \frac{\Gamma(m, m\hbar^2)}{\Gamma(m)} \right)^{1/2m} A_4}{m^{\left(\frac{m-1}{2m}\right)} \Gamma^{1/2m}(2m, m\hbar^2)} \right)}_{R_{(i,c)}^{up}}, \tag{21}$$

where $A_4 = P_{(i,c)} g_0 d_{(i,c)j}^{-\alpha} / \sum_{\substack{i'=1 \\ i' \ne i}}^{\mathbb{M}_c} d_{(i',c)j}^{-\alpha}$.

According to the energy model defined for the UAV-FNs, each v_j consumes $e_{fa} |z_j^{\text{init}} - z_j|$ energy unit for adjusting its altitude, where z_j^{init} is the initial non-optimal altitude of v_j. We consider the aforementioned energy consumption in the proposed optimization problem for the 3D placement scheme. Therefore, for each v_j and the corresponding cluster c with $a_{cj} = 1$, we have

$$\text{(P2):} \quad \underset{P_{(i,c)}, R_{(i,c)}, z_j}{\text{minimize}} \sum_{i=1}^{\mathbb{M}_c} \frac{P_{(i,c)} L_{(i,c)}}{R_{(i,c)}} + e_{fa} |z_j^{\text{init}} - z_j|, \tag{22}$$

s.t.

$$z_j^2 + \| \boldsymbol{u}_j - \boldsymbol{u}_{(i,c)} \|^2 \le \mathcal{R}^2,\ \forall i \in c, \tag{22a}$$

$$P_{(i,c)} \ge \sqrt{\frac{P_{(i,c)}^{\max} d_{(i,c)j}^{\alpha} \sigma^2 \Omega_{th}}{P_{(i,c)}^{\min}}},\ \forall i \in c, \tag{22b}$$

$$R_{(i,c)} \le R_{(i,c)}^{\text{up}},\ \forall i \in c, \tag{22c}$$

$$P_{(i,c)} \le P_{(i,c)}^{\max}, R_{(i,c)} > 0,\ \forall i \in c; z^{\min} \le z_j \le z^{\max}. \tag{22d}$$

According to (22a), the optimal flight altitude of v_j must be set so that all TNs belonging to the cluster are under the coverage of v_j. Constraint (22b) indicates the minimum value of the transmit power for each TN that meets the QoS requirements. Constraint (22c) implies that the transmission rate of a TN should not exceed the obtained value in (21). Finally, (22d) shows the boundaries of the decision variables.

a) Convergence, optimality, and complexity: The objective function provided in (22), constraint (22b), and constraint (22c) all are non-convex because the objective variables $P_{(i,c)}$ and $R_{(i,c)}$ are functions of the other objective variable, i.e., z_j. However, it can be found that the objective function is minimized if $P_{(i,c)}$ and $R_{(i,c)}$ reach their minimum and maximum value, respectively. Moreover, the minimum value of z_j results in minimizing the objective function. On the other hand, it can be concluded from (22b) and (21) that the minimum value of z_j leads to the minimum value of $P_{(i,c)}$ and the maximum value of $R_{(i,c)}$. Therefore, the optimal value of z_j is the solution of P2. After obtaining the optimal value of z_j, the optimal value of $P_{(i,c)}$ is found for a given value of $R_{(i,c)}$. By manipulating (21), we have

$$P_{(i,c)} \geq \overbrace{\left(2^{R_{(i,c)}/B} - 1\right) A_5}^{P^{lb,2}_{(i,c)}}, \tag{23}$$

where $A_5 = \dfrac{m^{\left(\frac{m-1}{2m}\right)} \Gamma^{1/2m}(2m, m\hbar^2) \sum_{\substack{i'=1 \\ i' \neq i}}^{\mathbb{M}_c} d^{-\alpha}_{(i',c)j}}{\Gamma^{1/m}(m) \left(\beta + \frac{\Gamma(m, m\hbar^2)}{\Gamma(m)}\right)^{1/2m} g_0 d^{-\alpha}_{(i,c)j}}$.

Therefore, the optimal value of $P_{(i,c)}$ is given as

$$P^*_{(i,c)} = \min\left\{\max\left\{P^{lb,1}_{(i,c)}, P^{lb,2}_{(i,c)}\right\}, P^{\max}_{(i,c)}\right\}. \tag{24}$$

Thereafter, the optimal value of the transmission rate of $\mathrm{TN}_{(i,\, c)}$ is calculate as

$$R^*_{(i,c)} = B \log_2\left(1 + A_6 P^*_{(i,c)}\right),$$

$$A_6 = \frac{\Gamma^{1/m}(m) \left(\beta + \frac{\Gamma(m, m\hbar^2)}{\Gamma(m)}\right)^{1/2m} g_0 d^{-\alpha}_{(i,c)j}}{m^{\left(\frac{m-1}{2m}\right)} \Gamma^{1/2m}(2m, m\hbar^2) \sum_{\substack{i'=1 \\ i' \neq i}}^{\mathbb{M}_c} d^{-\alpha}_{(i',c)j}}. \tag{25}$$

We adopt the proposed algorithm in [43], where a bisection algorithm has been designed to find the optimal flight altitude of the UAV-FN such that the transmit power and the transmission rate of the TNs reach the optimal values. Algorithm 1 shows the procedure of obtaining the optimal transmission rate, as well as transmit power, for TNs and the optimal flight altitude for the corresponding UAV-FN by using the bisection algorithm. The algorithm first finds the optimal flight altitude of the UAV-FN such that all TNs are within its coverage area. Then, it calculates optimal transmit power and transmission rate for all TNs. By considering $\epsilon = \mathbb{M}_c - covered$, the complexity of Algorithm 1 will be $\mathcal{O}(\mathbb{M}_c(\log \epsilon)/2)$.

B. Task-Offloading Scheme

Due to the delay constraints and limitations in the computation capacity of the TNs, a task can be partially offloaded to the corresponding UAV-FN. The optimal portion of the task for offloading can significantly improve the energy efficiency of the TNs. This can be achieved because the TNs consume more energy to process the tasks locally than offloading them to the corresponding UAV-FN. To this end, we define $\rho_{(i,c)}$ as the portion that needs to be offloaded to the UAV-FN. Let D_{th} indicates the delay threshold of processing a task. Therefore, for every task generated in the network, the optimal offloading portion is obtained by solving the following optimization problem.

Algorithm 1 Optimal 3D placement of the UAV v_j

```
Input: ε > 0, R, z_j^max, z_j, M_c, 1 ≤ c ≤ N_c;
z_min = z^min;
z_max = z^max;
repeat
    z_m = ⌊(z_min + z_max)/2⌋;
    covered ← total # of TNs under coverage of v_j;
    if covered == M_c then
        z_min = z_m;
    else
        z_max = z_m;
    end if
until (covered − M_c < 0)
z_j^* = z_m;
for i = 1 : M_c do
    Calculate P_(i,c)^* by using (24);
    Calculate R_(i,c)^* by using (25);
end for
Return u_j^*, z_j^*, P_(1,c)^*, ···, P_(M_c,c)^*, R_(1,c)^*, ···, R_(M_c,c)^*;
```

$$\text{(P3)}: \underset{\rho_{(i,c)}}{\text{minimize}}\ (1 - \rho_{(i,c)}) L_{(i,c)} e_0 + \rho_{(i,c)} \frac{P_{(i,c)} L_{(i,c)}}{R_{i,c}}, \tag{26}$$

s.t.

$$\left(\hat{L}_{(i,c)} + (1 - \rho_{(i,c)}) L_{(i,c)}\right) t_0 + \rho_{(i,c)} \left(\frac{L_{(i,c)}}{R_{(i,c)}} + \frac{L_{(i,c)}}{\mu_j - \lambda_j L_j}\right) \leq D_{th}, \tag{26a}$$

$$0 \leq \rho_{(i,c)} \leq 1,\ 1 \leq i \leq \mathbb{M}_c,,\ 1 \leq c \leq N_c. \tag{26b}$$

Constraint (26a) implies that the optimal portion should be set in a way that the sum of the processing delay at the corresponding TN locally and the offloading delay does not exceed the predefined delay threshold. Constraint (26b) indicates the boundaries of $\rho_{(i,c)}$.

1) Convergence, optimality, and complexity: P3 is an LP problem with respect to $\rho_{(i,c)}$. Therefore, the CVX toolbox is used to solve the problem. The time complexity of the problem is linearly increased with the number of TNs in the network, i.e., M.

C. Energy Transferring Scheme

In time slot k, when the average available energy consumption of the TNs reaches below a predefined threshold, the corresponding UAV-FN starts its mission to transfer energy to

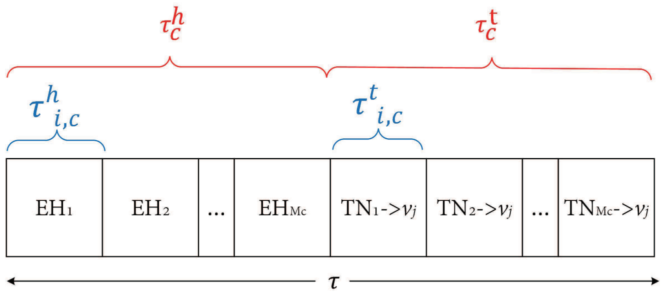

Fig. 2. Block structure of the considered system model.

the clusters. Fig. 2 shows the block structure of the considered system model. At the beginning of a time slot, the UAV-FN transfers energy in a time duration τ_c^h; Thereafter, the cluster starts transmitting data to the corresponding UAV-FN within the time duration τ_c^t. It is noticeable that each τ_c^h and τ_c^t for cluster c are divided into $\mathbb{M}_c$ parts, respectively termed as $\tau_{(i,c)}^h$ and $\tau_{(i,c)}^t$, corresponding to the TNs within the cluster. However, the UAV-FNs consume a lot of energy by transferring power to the TNs. Therefore, the WPT-UAV is employed to compensate for the energy reduction of the UAV-FNs by transferring energy to them when required.

The main objective of the proposed scheme is to find the optimal information transfer duration, as well as the optimal harvested energy, for each cluster in a way that a minimum throughput is guaranteed for all TNs in the cluster. Therefore, the corresponding problem with respect to cluster c is formulated as

$$\text{(P4)}: \underset{\tau_{(i,c)}^t, P_{(i,c)}^h, \mathcal{T}}{\text{maximize}} \ \mathcal{T}, \tag{27}$$

s.t.

$$B\log_2\left(1+\frac{P_{(i,c)}^h g_0 \hbar_{(i,c)j} d_{(i,c)j}^{-\alpha}}{I_{(i,c)}}\right)\tau_{(i,c)}^t - \mathcal{T} \geq 0, \tag{27a}$$

$$\sum_{i=1}^{\mathbb{M}_c}\left(\tau_{(i,c)}^h + \tau_{(i,c)}^t\right) \leq \tau, \tag{27b}$$

$$\tau_{(i,c)}^h P_{(i,c)}^h \geq (1-\rho_{(i,c)})L_{(i,c)}e_0 + \rho_{(i,c)}\frac{P_{(i,c)}L_{(i,c)}}{R_{i,c}}, \quad 1 \leq i \leq \mathbb{M}_c, \tag{27c}$$

$$P_{(i,c)}^h \leq \min\{\eta_{(i,c)}P_{(i,c)}^{rx}, P_{sat}\}, \ 1 \leq i \leq \mathbb{M}_c, \tag{27d}$$

$$\tau_{(i,c)}^t, P_{(i,c)}^h > 0, \ 1 \leq i \leq \mathbb{M}_c, \mathcal{T} > 0. \tag{27e}$$

Constraint (27a) ensures a minimum throughput for all TNs within the cluster. Constraint (27b) indicates that the sum of the time duration for harvesting the energy and transmitting the data to the corresponding UAV-FN for a cluster must be equal to the time slot duration. According to (27c), the harvested energy must be equal to or greater than the required energy for offloading the task to the UAV-FN. Constraint (27d) implies that the harvested power cannot exceed the minimum value of the saturation power and a predefined threshold. Finally, (27e) shows the lower bound of the objective variables.

a) Convergence, optimality, and complexity: The main objective of the proposed model P4 is to jointly optimize the information transfer duration and the harvested energy in each time slot such that a minimum throughput is guaranteed for each cluster. To solve P4, we first assume that $\tau_{(i,c)}^t$ is fixed for all TNs within the cluster c. Hence, we find the optimal value of the corresponding harvested power, i.e., $P_{(i,c)}^{h,*}$. Then, the optimal information transfer time, i.e., $\tau_{(i,c)}^{t,*}$, is obtained. Since P4 is an epigraph problem form [44], the CVX toolbox is used to solve P4 and obtain the results.

Table I
SYSTEM SETUP FOR NUMERICAL SIMULATIONS.

Parameter	B	α	β	P_{sat}	$z^{\max}$	$z^{\min}$
Value	10 MHz	3	0.01	1 W	120 m	30 m

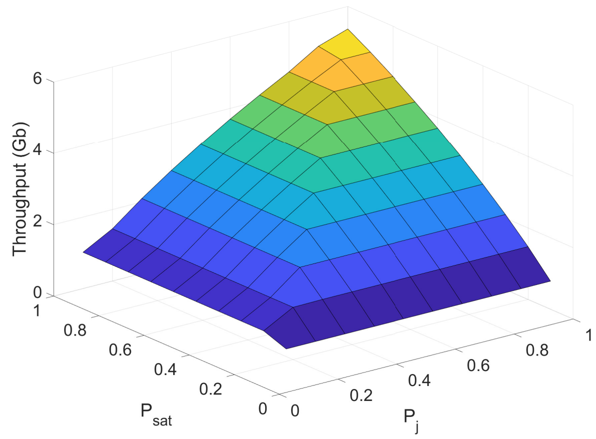

Fig. 3. Impact of saturation power and transmit power of UAV-FNs on the network throughput.

IV. NUMERICAL RESULTS

We consider a system in which $M = 100$ TNs are uniformly distributed in a region with a radius of $r = 2000$ m. Each $\text{TN}_{(i,c)}$ generates a task in each time slot, where the task's size follows a uniform distributed value of $U[60, 80]$ KB. All TNs have the same maximum transmission power, which is equal to 23 dBm [31]. The rotary UAV-FNs are considered with a coverage radius of $\mathcal{R} = 200$ m, where $E_0 = 55$ J/m and $P_h = 170$ W [45]. The following setup is used for other network parameters: $\mu_j = 100$ Mbps, $P_j = 0.1$ W $\forall j$; $\eta_{(i,c)} = 0.2 \forall i, c$ [46]; The CVX toolbox of MATLAB is used to develop the simulation models. It is worth mentioning that the simulations are performed for 15 replicas. The rest of simulation parameters are given in Table I.

We compare ENERGENT with the proposed method in [25], which is called "Baseline" in this paper. The main objective of the Baseline is to maximize the total weighted network throughput, where a weight factor is assigned to each

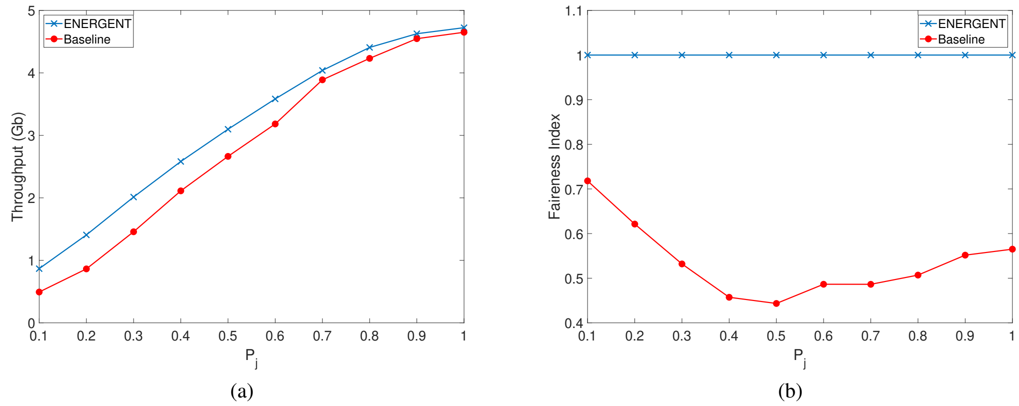

Fig. 4. Comparison of the proposed ENERGENT and the Baseline method with respect to different values of the transmit power of UAV-FNs, P_j: (a) throughput and (b) fairness index, $\mathcal{F}$.

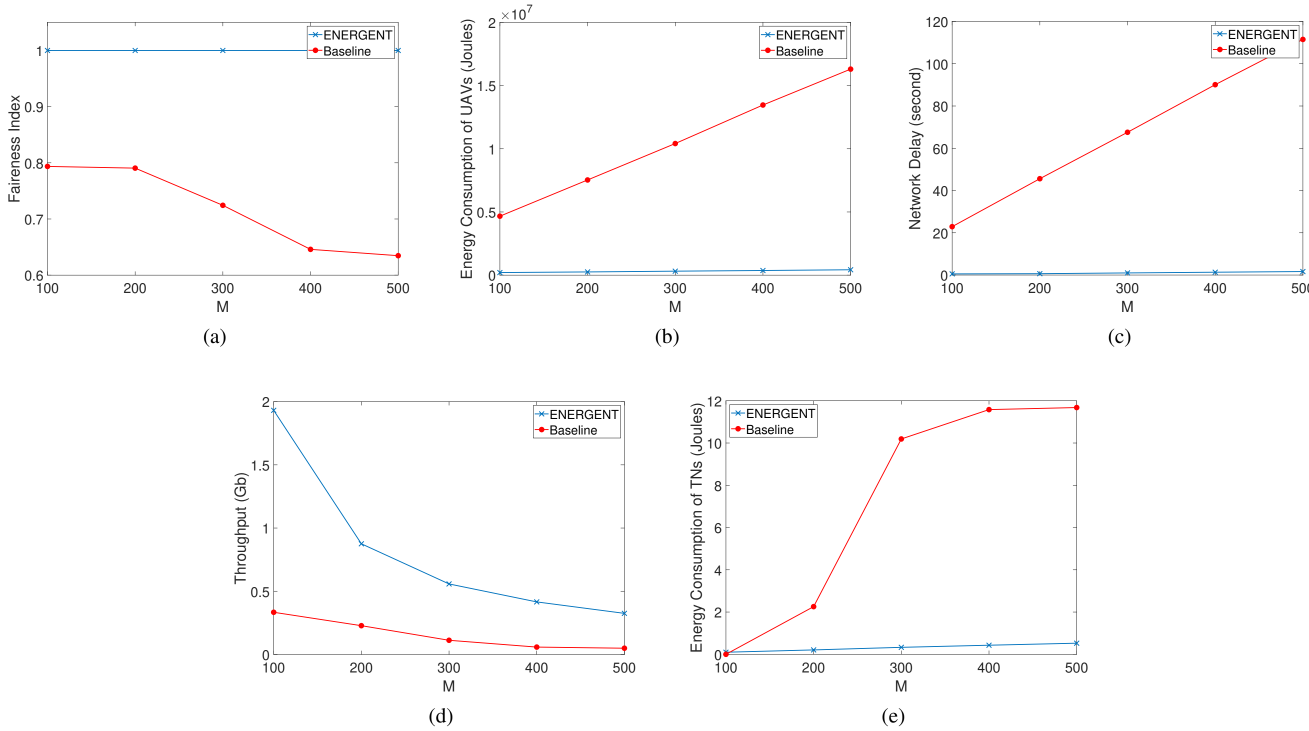

Fig. 5. Comparison of the proposed ENERGENT and the Baseline method with respect to different numbers of TNs: (a) fairness index, (b) energy consumption of UAV-FNs, (c) network delay, (d) throughput, and (e) energy consumption of TNs.

TN belonging to a cluster. To this end, Baseline optimizes the transmit power of TNs with respect to the harvested power, as well as their central processing unit (CPU) frequency. It is noticeable that Baseline has been designed for a network including one UAV-FN and multiple TNs, in which the UAV-FN flies toward the TNs at the minimum altitude and assumes that there is no interference among TNs.

Fig. 3 shows the impact of saturation power and transmit power of UAV-FNs on the network throughput. Since the harvested power of each TN is bounded to the minimum of the saturation power and the received power from the corresponding UAV-FN, by increasing the saturation power, the minimum value is also increased. Hence, the TN can harvest more power which accordingly results in more throughput.

The next step is to evaluate the impact of the transmit power of UAVs on the network throughput. In this regard, we perform simulations for different values of the transmit power of UAV-FNs, P_j. Fig. 4 includes the corresponding results. Fig. 4(a) shows that by increasing the saturation power of the UAVs, TNs can harvest more energy to process more bits, and hence, the network throughput increases.

Other objective of ENERGENT is to ensure a minimum throughput for all TNs belonging to a cluster. For this reason, we define the fairness index as $\mathcal{F} = \frac{\left(\sum_{i=1}^{\mathbb{M}_c} \mathcal{T}_{(i,c)}\right)^2}{\mathbb{M}_c \sum_{i=1}^{\mathbb{M}_c} \mathcal{T}^2_{(i,c)}}$ [47] for every cluster c, where $\mathcal{T}_{(i,c)}$ is the throughput of $\text{TN}_{(i,\,c)}$. The

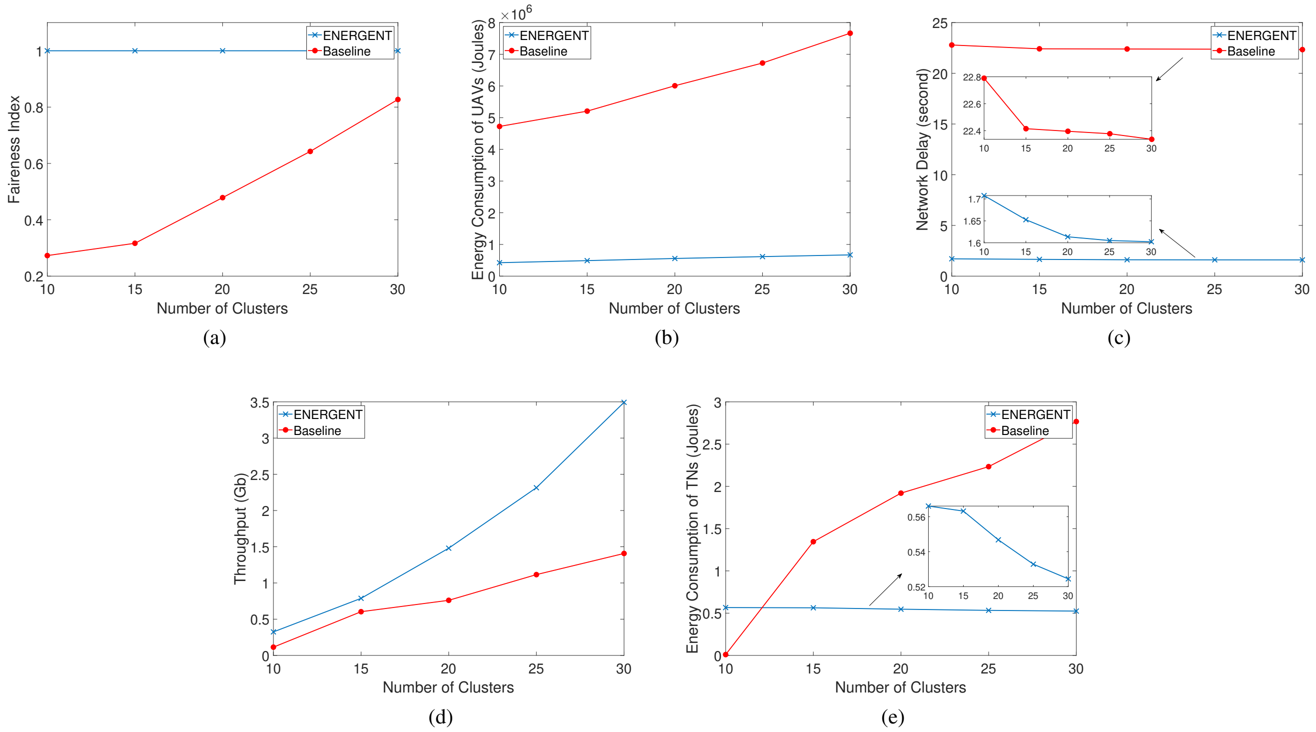

Fig. 6. Comparison of the proposed ENERGENT and the Baseline method with respect to different numbers of clusters: (a) fairness index; (b) energy consumption of UAV-FNs; (c) network delay; (d) throughput; and (e) energy consumption of TNs.

results obtained in Fig. 4(b) indicates that ENERGENT can provide a minimum throughput for all TNs belonging to a cluster as the index value is equal to 1. This is while the fairness index is less than 1 for the Baseline, which means there is no trade-off for the throughput of TNs.

In another scenario, the simulations are fulfilled for different numbers of TNs, whereas the number of clusters in the network is fixed. This leads to the fixed number of UAV-FNs, where $N = 10$. Fig. 5 indicates the results corresponding to the fairness index, the energy consumption of UAV-FNs, the network delay, the network throughput, and the energy consumption of TNs. Fig. 5(a) shows that ENERGENT could provide the throughput fairness among TNs, whereas Baseline is not successful in this regard. According to Fig. 5(b), the energy consumption of UAV-FNs in ENERGENT is much less than the Baseline's because the Baseline does not consider the optimal assignment of UAV-FNs to the clusters. Moreover, according to assumptions of the Baseline, UAV-FNs move toward each TN within a cluster to minimize their distance with the TNs. Fig. 5(c) indicates that ENERGENT could alleviate the network delay compared to the Baseline as the ENERGENT optimizes the transmit power, as well as the transmission rate, of TNs alongside the offloading portion of tasks with respect to the delay constraint in the network. This is while the Baseline mainly focuses on optimizing the transmit power of TNs with respect to the harvested power. Fig. 5(d) illustrates that by increasing the number of TNs for a fixed number of clusters, the network throughput is decreased. However, ENERGENT outperforms the Baseline in providing more network throughput. Finally, Fig. 5(e) shows the energy consumption of TNs affected by increasing the number of TNs in the network.

In the end, we compare ENERGENT and the Baseline method for different numbers of UAV-FNs, where there exist 500 TNs in the network. Fig. 6 illustrates the corresponding results. Fig. 6(a) shows that ENERGENT still ensures a minimum throughput for all TNs within a cluster in the network. Also, it can be seen that the fairness index value is increased for a larger number of clusters because by increasing the number of clusters for a fixed number of TNs, there would be fewer TNs within a cluster. Therefore, the probability of existing a trade-off between TNs is increased. However, this value is still less than 1. With the same reasons provided for Figs. 5(b) and 5(c), Figs. 6(b) and 6(c) imply that ENERGENT could outperform Baseline in terms of the energy consumption of UAV-FNs and network delay, respectively. Fig. 6(d) indicates that by increasing the number of clusters for a fixed number of TNs, less number of TNs remain in each cluster, which leads to the increment of the network throughput. According to Fig. 6(e), by decreasing the number of TNs within a cluster, the interference between TNs decreases. Accordingly, the transmission rate of TNs is boosted and the TNs need to consume less power to transmit their data. Hence, the energy consumption of TNs is alleviated. This is while the energy consumption of TNs increases in the Baseline as the TNs have been designed so that they harvest power as much as possible without considering the transmission rate of TNs and the interference among them. Fig. 6(e) also implies that the proposed offloading scheme in ENERGENT is more efficient than Baseline.

V. CONCLUSION

This paper proposed a novel framework, named ENERGENT, for disaster management in the UAV-assisted Fog-IoT networks. ENERGENT aims to optimize the energy consumption of all TNs and UAV-FNs. For this reason, three algorithms proposed to optimally adjust the 3D placement of the UAV-FNs for minimizing energy consumption, offload the tasks to the UAV-FNs in order to meet the network delay constraints, and prolong the network lifetime through witlessly transferring power to the TNs when their remaining energy degrades a predefined threshold. Simulation studies show that ENERGENT ensures a minimum throughput for all TNs within a cluster, which results in maximizing the total network throughput. In future work, we focus on the flight path planning of the WPT-UAV in the network.

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