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Satellite-based assisted-offloading for energy-constrained edge networks

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ABSTRACT

As the need for global broadband internet connectivity increases, there is a need to consider the use of non-terrestrial networks (NTNs) to extend the network coverage to protected areas (e.g., national parks). Usually, protected areas are prohibited from having power lines thus lacking wireless connectivity. To overcome this challenge, energy can be provided through the use of green energy from a solar photovoltaic (PV) system. Then, a green energy-based base station (BS) can be deployed within the area in order to provide mobile connectivity to visitors, as well as also using the NTNs to handle excess traffic or take over the traffic in the event the BS does not have sufficient green energy from storage. In this paper, a hybrid wireless communication system is proposed to include BS sites located in a protected area and satellites in the low earth orbits (LEO), coupled with new offloading strategies, with the main goal of optimizing the trade-off between energy consumption and end-to-end delay for the green energy-based BS sites. For accuracy of our simulations, we consider real data from a solar photovoltaics system, traffic workloads, visitor's location data, and satellite orbits from Starlink constellations. Our results demonstrate that the co-existence of the BS and satellite achieve energy savings from 59 % to 34 %, with an average system delay of 0.83 seconds and a packet drop rate that ranges from 8.3 % to 2.7 %, when compared with our benchmark.

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1. INTRODUCTION

The urge for sensing, learning, and communication services in future mobile node (MN) is a key research area in 6G [1]. This is motivated by the need to have wireless communication systems in protected areas (e.g., national parks, nature reserves) to intelligently monitor the environment, provide mobile services to visitors, and also to track endangered species. Having the communication infrastructure will allow data processing at the edge, that is, within a base station (BS) empowered with computation capabilities or in remote clouds (satellites). The primary objective of having protected areas is to protect biodiversity and ecosystem functions, and through interactions with natural environments, people derive a variety of physical and psychological benefits [2]. Despite the benefits, according to government laws, electricity lines are not permitted thus limiting the provisioning of MN services [3]. To enable smart connectivity in protected areas, in the near future, it is expected that the combination of edge servers and green-powered BS will provide the capability to deploy communication sites without requiring electrical wiring for power supply. In this, the BS are equipped with energy harvesting (EH) equipments and computing capabilities [4]. The use of green energy to power the edge systems will reduce the carbon emissions and also to expand network coverage within protected areas [5].

The provision of network coverage in unserved areas, similar to protected areas, is also of great importance despite the terrain difficulties which hinders communication tower installations. Using non-terrestrial networks (NTN), which comprise satellites, unmanned aerial vehicles (UAVs), and high altitude platforms (HAPs), to supplement terrestrial networks or offer on-demand wireless access to places without infrastructure, is one potential remedy for this [6]. High television (TV) towers and large antenna arrays utilizing massive-MIMO are proposed to provide connectivity to sparse areas [7]. Here, the systems have the latest emerging antenna technologies and designs such as reconfigurable phased/inflatable/fractal antennas realized with metasurface material. In addition, NTN can also offer a connectivity service in the event of a natural disaster [8], that is, where the deployed network infrastructure or terrestrial towers are out of service.

Similar to Multi-access Edge Computing MEC platforms, NTN can offer communication-plus computation services in addition to expanding network coverage [9]. Here, they can accept offloaded delay-dependent tasks from energy-deficient or capacity-constrained BS sites. For example, within a protected area, visitors are served by the BS which are located along the perimeter of the area, which in turn drains the battery of the mobile devices when processing any data due to the larger separation distance. This avails the opportunity of using NTNs. Regarding offloading tasks to satellites in low earth orbit (LEO), Pietro [10] proposed the use of in-orbit computing to provide near real-time computing to areas where satellites are the only option and terrestrial connectivity is lacking in order to offload jobs to LEO satellites. Here, the author presented an algorithm for a LEO satellite constellation to handle tasks from different locations through the sharing of the computing platform, thus relieving ground resources from computing some of the workloads. Similarly, Soret [11] proposed the use of LEO satellite constellations for offloading workloads and also backhauling the traffic from remote terrestrial communication sites to the core network. Here, they evaluated their performance based on Age of Information, latency, and collision rate. Performance assessments of LEO satellites are provided in [12], where data offloading techniques are suggested within the framework of vehicular edge computing. In that paper, the delay-sensitive task is sent from the ground device directly to the satellite. The use of terrestrial networks and NTNs for ubiquitous coverage is proposed as a solution for multi-connectivity in rural areas [13]. Here, the research work focused on smart agriculture related use case and using latency as a performance metric. From the aforementioned papers, it is noted that more studies are required to measure the performance of the co-existence of LEO satellite computing platforms and green-powered BSs (empowered with computing capabilities), in order to guarantee the expected end-to-end delay. Moreover, this research article differs from [12] as the ground mobile devices send information to the BS first, and then the BS transmit the information to the satellite via a locally mounted Starlink antenna.

Managing green-powered communications sites is also important as they are dependent on the amount of green energy that can be harvested per time instance. In order to handle dynamic workload offloading, an efficient reinforcement learning-based resource management algorithm is proposed and in this paper green energy sources were integrated into a MEC system [14]. Then, in our previous paper, we suggested a new network design where a controller manages the EH BSs [4]. To manage the computing resources (Virtual machine (VM) and BS), we selectively turn them on and off over a constrained prediction horizon. By redistributing the network load among the BSs and taking advantage of the spatial diversity of the available green energy, the green-based load balancing technique is suggested, in order to maximize the edge system performance [15]. Here, containers were considered as computing resources within the MEC server. Overall, it should be stated that the aforementioned research works lack the consideration of off-grid BS systems for protected areas and the use of LEO satellite to complement the BSs located in such areas.

The main contributions of this paper are summarized as follows: (i) we propose a novel edge computing framework for ground mobile devices that include mechanisms to dynamically offload tasks to LEO satellites via the BS if there is a guarantee of near real-time communications-plus-computation processes, or prioritize the use of a local edge platform. This framework also make use of admission control procedures within the BS, as well as in the satellites; (ii) To evaluate the network performance, we jointly consider the use of green-powered BSs and LEO satellites for offloading the delay-sensitive tasks from a protected area. Here, our main goal it to optimize the trade-off between energy consumption and the end-to-end delay, through the use of limited liability company (LLC) principles and the use of green energy as a performance metric. Real-world harvested energy, traffic load traces, visitor's location data, orbital traces and parameters, are used to evaluate the performance of the proposed optimization strategy. The numerical results obtained through simulation show that the proposed optimization strategies are able to efficiently manage the communication sites, as well as allowing processing of tasks in LEO satellites.

The remainder of this article is organized as follows: Section 2 presents our system model, section 3 provides the mathematical formulation of the problem and the offloading strategies, section 4 discuss the simulation results, and section 5 summarizes our conclusion.

2. SYSTEM MODEL

This section describes the scenario section 2.1, the satellite orbit and channel model section 2.2, the energy consumption model for the BS site section 2.3, and the delay model section 2.4.

2.1. Scenario description

Our considered scenario is depicted in Figure 1. Here, we consider $n \in \mathcal{N}$ BSs deployed in a protected area (in our instance, a national park is considered) and each is equipped with computing capabilities (i.e., each EH BS has a local computing platform that runs containers). A set of u ground mobile devices, from visitors who prefer walking within the park, offload their delay-sensitive or delay-tolerant tasks to BS n, (in our case direct offloading to the satellite is not allowed). The BS are within the coverage of LEO Starlink satellites. Visitor's current locations (mobility patterns) are known through the location service application programming interface (LS API) [16], which is a service that supports the mobile device location retrieval mechanism and then passing the information to authorized applications within the MEC platform. Here, we emulate the user equipment (UE) location lookup procedure between the edge server the subscribed mobile users using the location dataset from [17].

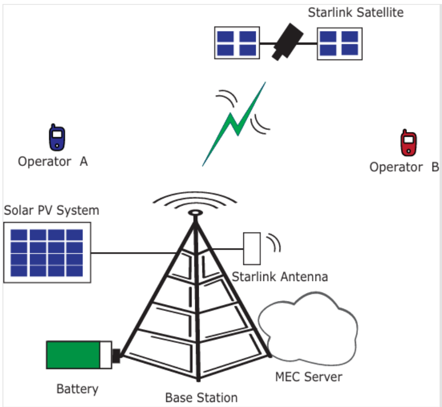

Figure 1. The BS system being complemented by a satellite

The BS infrastructure is shared between mobile operators, in order to avoid crowding the protected site, and it is powered by energy harvested from a solar photovoltaic (PV) system. Here, the use of wind turbines as a source of energy is neglected due to its noise pollution which has an effect to wildlife [18]. The obtained energy then supplies the computing platform, BS communication infrastructure, as well as Starlink antenna mounted onsite to provide satellite-based Internet services. Any traffic that is going to be offloaded to the satellite, will pass through the mounted Starlink antenna. In addition, the battery bank of size $\Upsilon_{\max}$ stores the excess energy, and for the satellite we assume that there is enough energy within its battery bank as there exist a direct line of sight (LOS) with the sun. On the MEC server of capacity C_{loc}, there is an access control application that is responsible for admitting and forwarding workloads to its active G computing resources (containers) or to a set of s visible LEO Starlink satellites that are each running G containers onboard, with each having a capacity C_{sat}, for processing the offloaded data taking into account the delay constraint σ.

2.2. Orbital and channel model

Generic orbital model: The ground mobile devices offload their tasks to the BS, and the BS location is determined by its latitude l_u and longitude L_u, and the satellite's position in space is defined by its altitude

l_h, latitude l_s and longitude L_s. To accurately determine the location of a Starlink satellite on its orbit, we make use of the two-line element (TLE) data from [19], which provides an up-to-date trajectory and orbital parameters. Similar to [12], the separation distance d (in km) from the BS and the generic satellite as follows,

$$d = (l_h + r_e)\left[1 + \left(\frac{r_e}{l_h + r_e}\right)^2 - 2\left(\frac{r_e}{l_h + r_e}\right)\cos(\psi)\right]^{1/2} \tag{1}$$

where r_e is the radius of the earth (i.e., 6378.137 km), and ψ represents the angle between the BS and the satellite as observed from the earth's center, and it is related using the following equation,

$$\cos(\psi) = \cos(l_s)\cos(l_u)\cos(L_u - L_s) + \sin(l_u)\sin(L_s) \tag{2}$$

From [20], the angle of elevation θ is obtained from the following relationship,

$$\cos(\theta) = \frac{(l_h + r_e)\sin(\psi)}{d} \tag{3}$$

For a satellite to be visible to the BS, its elevation angle must be above some minimum value and it is upper bounded by some value, i.e., $\theta \leq 81.3°$ [20].

Wireless channel model: The channel model for the BS to satellite connectivity can be obtained from the 3GPP specifications [21], where we assume the LOS and let the signal-to-noise ratio (dB) between BS n and the visible satellite (in log) to be,

$$\Gamma_{n,s} = \mathrm{EIRP}_n + (G/T)_n - P_n - k - B_n, \tag{4}$$

where EIRP_n is the effective isotropic radiated power of the transmitter in W, $(G/T)_n$ is the received antenna gain to noise temperature ratio (sometimes called figure of merit), P_n is the path loss which constitute of free space path loss, pointing loss, polarization loss, and loss due to the atmosphere, k is the Boltzmann constant and B_n is the bandwidth is Hz. The free space path loss, P_n^{FS}, is given by [20],

$$P_n^{\mathrm{FS}} = 92.45 + 20\log(f_c) + 20\log(d) \tag{5}$$

where f_c is the carrier frequency in GHz.

2.3. BS consumption model

The total energy consumed [J] by each BS site, denoted by $\beta_n^{\mathrm{site}}(t)$, consists of the wireless communications processes, denoted by $\beta_n^{\mathrm{bs}}(t)$, and the edge server processes, which includes computing, caching, and communication activities within itself, is denoted by $\beta_n^{\mathrm{edg}}(t)$. Thus, at slot t, the energy consumed can be formulated as follows [15],

$$\beta_n^{\mathrm{site}}(t) = \beta_n^{\mathrm{bs}}(t) + \beta_n^{\mathrm{edg}}(t) \tag{6}$$

The transmission process drains energy from the BS site. Here, we let β_0 represent the operating energy neglecting workloads, $\beta_{ld}(t)$ is the task dependent transmission power to-and-from the ground mobile devices and also to the satellite at a target rate of r_0 which guarantees the low latency threshold, $\beta_{sat}(t)$ is the energy used by the Starlink antenna for uplink (UL) and downlink (DL) data transfer, and $\beta_{dt}(t)$ is the inter-communication energy cost [J/byte] for passing data to the edge server interfaces for processing. Since the BS transmission power is adaptive, we let $\eta(t) \in \{0, 1\}$ be the switching status indicator. Thus, the BS consumption is as follows,

$$\beta_n^{\mathrm{bs}}(t) = \eta(t)\beta_0 + \beta_{ld}(t) + \beta_{sat}(t) + \beta_{dt}(t) \tag{7}$$

The energy consumed by the softwarized computing platform (in the satellite or MEC server) is dependent on the total number of active containers at time t. The CPU utilization share is denoted by $\beta_{cp}(t)$, then the resource scheduler will activate and de-activate containers based on-demand, through a reliable intra-communication link operating at rate of $r_g(t)$ bits/s, in order to allocate tasks of size $\gamma_g(t)$ and such incurs a cost denoted by $\beta_{sw}(t)$. Then, the tasks are queued before processing and dequeue after processing, thus the input-output buffer activities incurs an energy cost and it is denoted by $\beta_{qu}(t)$. Since some of the viral Internet content can be cached locally, the caching process contributes an amount of energy drained and it is denoted by $\beta_{ch}(t)$. The total energy drained within the computing platform is as follows,

$$\beta_n^{\text{bs}}(t) = \eta(t)\beta_0 + \beta_{ld}(t) + \beta_{sat}(t) + \beta_{dt}(t) \tag{8}$$

Within the computing platforms, the maximum per-slot communication rate is limited to a pre-assigned value $r_{\max}$, thus the following hard constraint must hold: $\sum_{g=1}^{G(t)} r_g(t) \leq r_{\max}$.

The energy that is used for BS operations is from a solar PV system Figure 2 for harvested energy traces from [22]) and the battery. At each time instance, the amount of energy drawn from the battery, for communication-plus-computing activities, must be less than the amount required by the communication site and it is defined as $\Upsilon_n(t) \geq \beta_n^{\text{site}}(t)$. Thus, the amount of the green energy demanded per site is as follows,

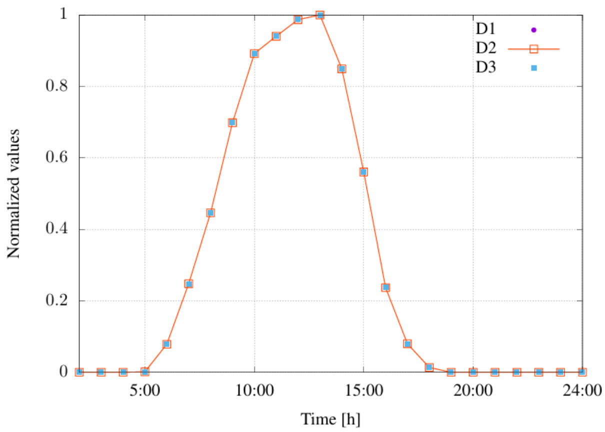

Figure 2. Solar energy traces from a PV system for day 1 (D1) to day 3 (D3)

$$\upsilon_n(t) = \upsilon_n^c(t) + \upsilon_n^o(t) \tag{9}$$

where $\upsilon_n^c(t)$ is the fractional energy that is for charging the battery and $\upsilon_n^o(t)$ is the share that is used immediately for supporting local operations. Per each time slot t, it is important to note that the actual amount of energy (denoted by $E_n^{\max}$) that can be extracted from the environment is limited, thus we have an energy harvesting constraint as,

$$\upsilon_n^c(t) + \upsilon_n^o(t) \leq E_n^{\max}\,, \forall n, \forall t. \tag{10}$$

During the day, the storage device level fluctuates according to the following equation,

$$\Upsilon_n(t) = \zeta_n(\Upsilon_n(t-1) - \beta_n^{\text{site}}(t)) + \Phi(\upsilon_n^c(t))\,, \tag{11}$$

where $\zeta_n \in (0, 1]$ represents the battery self-discharging behavior, and $\Phi \in (0, 1]$ represents the incurred losses during the charging phase.

2.4. Delay model

The input/output (I/O) queue of the system are assumed to be loss-free such that the time evolution of the backlogs queues follows Lindley's equations [23]. For intra-communication within the computing platform, we note that there exist a two-way per task execution delay (task to-and-from the container) where each link delay is denoted by $\rho_g(t) = 2\gamma_g(t)/r_g(t)$. Then, the computation processing duration that depends on the CPU cycles denoted by $t_{cp} = |G(t)|/C_{\text{loc}} = |G(t)|/C_{\text{sat}}$, queuing delay of the task on the input-output buffer, assuming the existence of a congestion handling mechanism, denoted by t_{qu}. Thus, the delay on the computing platform, denoted by t_d, is as follows,

$$t_d = \rho_g + t_{cp} + t_{qu}. \tag{12}$$

Since the tasks are either offloaded to the BS site for local computation or forwarded to the satellite edge computing platform, the time delay due to access decision making (accepting or forwarding) is denoted by t_{ac}. The ground mobile device offload the task to the BS, and the UL and DL delays are denoted as t^u_{ul} and t^u_{dl}, which are dependent on the transmission rate r_0 that guarantee the expected delay threshold and the size of the tasks as $t^u_{ul} = \gamma_g(t)/r_0$ and $t^u_{dl} = \gamma'_g/r_0$, where γ'_g is the computed results from the BS. Thus, for tasks offloaded to the BS for local computation, the total delay (denoted by t_{loc}) is as follows,

$$t_{loc} = t^u_{ul} + t^u_{dl} + t_{ac} + t_d + 2\, t_{pg}, \tag{13}$$

where t_{pg} is the propagation delay.

If the offloaded tasks are transmitted to the selected satellite from the BS, then there is the UL and DL delay due to the transmission rate denoted by $r^s_n(t)$ which is related to (4) through shannon capacity and the size of the transmitted tasks (denoted by $\gamma_n(t)$) as $t^{ul}_{n,s} = \gamma_n(t)/r^s_n$, and $t^{dl}_{n,s} = \gamma'_n(t)/r^s_n$, where γ'_n is the computed results from the satellite to BS n. Then, the total delay for tasks offloaded to the satellite (denoted by t_{sat}) is given as follows,

$$t_{sat} = t^{ul}_{n,s} + t^{dl}_{n,s} + t_d + 2\, t_{pg}. \tag{14}$$

To guarantee low latency for applications in MNs, we have to make sure that the following conditions hold for delay-sensitive tasks: $t_{loc} \leq \sigma$ and $t_{sat} \leq \sigma$.

3. BS-SATELLITE OFFLOADING FRAMEWORK

Data processing involves local BS computation or satellite-based computation, followed by tasks dropping if all the options are not available. Cases of dropping tasks are dependent on the available stored energy and the loading of the input-output queue. In terms of resource allocation within the computing platform, the container provisioning and load allocation over them, at t, is performed similar to [15].

In general, local computation is more convenient, provided that sufficient green-energy is available, as well as the computing resources. The energy to be harvested and the tasks to be offloaded are accumulated over the time slot, and they can only be known at the end of it. This implies that the amount of harvested energy and the tasks from the ground mobile devices can only be estimated using the LSTM neural networks [24], i.e., $\hat{\Upsilon}_n(t)$ and $\hat{\gamma}_n(t)$.

In order to manage the offloading process, using green energy as a performance metric, we propose a framework that will identify if the BS will compute the tasks locally or it will steer part of the offloaded tasks to the satellite edge system. To achieve this, the communication-plus-computing interval is defined as the ratio of the next time slot available green energy and the expected total energy consumption (recall that the harvested energy and tasks are forecasted), per BS site, as $J_n(t) = \frac{\Upsilon_n(t+1)}{\beta^{\text{site}}_n(t+1)} \geq 1$. For offloading decision making, we employ the following strategies:

Strategy 1 (Local offloading (LO)): If $J_n(t) \geq 1$ and $\hat{t}_{loc} < \sigma$, the site energy will be sufficient to handle the expected tasks with the guarantee of a low latency, otherwise if $J_n(t) < 1$ the communication site will not be able to handle the expected tasks, thus the strategy is to offload the tasks to the visible satellites or drop them. Here, we assume the ground mobile devices offload their delay-sensitive tasks to the BS with the highest signal strength.

Strategy 2 (Assisted-offloading (AO)): For $J_n(t) < 1$, the tasks will be offloaded to the satellite via the Starlink antenna. Here, the BS selects a serving satellite from a set of visible satellites. The set consist of satellites whose SNR (defined in (4)) is above a set threshold Γ^{th}. To select the satellite that will serve the BS from the set, the BS make use of a feedback mechanism that monitors the evolution of each satellite queue system, in a round robin manner. The feedback provides the state of the input queues for each satellite, and then the BS estimate the queuing duration's $\{\hat{t}_{qu}\}$ followed by checking if $\hat{t}_{sat} < \sigma$. Then, the satellite with the least value of $\{\hat{t}_{qu}\}$ from the set, also fulfilling the latency constraint, offloading the tasks to the satellite, denoted by s', will be prioritized, otherwise the data will be dropped and the communication with the satellite will be deactivated.

To handle congestion in the computing platform input buffers, the proposed strategies make use of a soft-dropping policy. Here, the tasks are dropped at the satellite edge system when $\hat{t}_{sat} \geq \sigma$ and in the BS the tasks are also dropped when $\hat{t}_{loc} \geq \sigma$. When the tasks have been dropped, the mobile devices will back-off for a random period of time denoted by Δ, and when Δ expires the device can retry to offload their tasks. This allow the input buffers to decongest and prevent the edge systems' queues from overloading. In such cases, the data will be dropped with a probability of $q_{drop} = (\hat{t}_{sat}/\sigma)^{\delta} = (\hat{t}_{loc}/\sigma)^{\delta}$, where δ is a parameter that describes the steepness of q_{drop}.

The online algorithm: The distributed process of the online algorithm is as follows: The online algorithm starts with the initial state and builds a tree with all potential future states up to the prediction depth in a breadth-first manner.

The current system state is then initialized to create a search set, which is then accumulated while the algorithm iterates through the tree, taking into consideration predictions (energy, traffic), accumulated workloads at the output buffer, previous outputs, and controls. The collection of states that are reached at each prediction depth, taking into account the performance metric $J_n(t)$.

In order to generate the next set of reachable control actions, we first estimate the traffic load, delay-dependent tasks, locally acceptable computational load, harvested energy, and $J_n(t)$. Base on $J_n(t)$, the offloading strategy is then selected and any expected delay on the forecasted BS load and the buffers

Next, the energy cost $\beta_n^{\mathrm{bs}}(t)$ for every created state is calculated. After examining the prediction horizon, a series of achievable states with the lowest energy use is found. The system receives an input control action, which corresponds to the first state in the sequence; the others are discarded. For every time slot t, the procedure is repeated.

4. PERFORMANCE EVALUATION

4.1. Simulation setup

A BS system empowered with computation capabilities deployed in a protected area, and the Starlink constellation, is considered in this setup. The parameters that were used in the simulations are listed in Table 1. Our time slot duration τ is set to 15 min and the time horizon is set to 2 time slots. Datasets for traffic loads from [25], visitor's location from [17] for emulating the LS, harvested energy from [22], were used in our setup. For simulation, Python is used as the programming language.

Table 1. System parameters

Parameter	Value
Figure of merit $(G/T)_n$	15.84 dB/K
Carrier frequency, f_c	30 GHz
Bandwidth, B_n	10 MHz
EIRP Satellite antenna, EIRP$_n$	34.9 dBW
Earth radius, r_e	6378.137 km
Satellite height, l_h	$350 - 600$ km
SNR for AO policy, Γ^{th}	10 dB
Satellite capacity, C_{sat}	1 TB
Starlink antenna power, β_{sat}	50 W
BSs total , N	20
BS operating power β_0,	10.6 W
MEC capacity, C_{loc}	40 GB
Number of containers, G	20
Application time constraint, σ	0.8 s
Battery self-charging, ζ_n	0.9999
Energy storage capacity, Υ_{max}	100 kJ
Uplink task size γ_n	3 MB
Downlink task size γ_n'	0.1 MB
Target transmission rate, r_0	1 Mbps

4.2. Numerical results

In Figure 3, the real and predicted values for the harvested energy are shown. Here, the forecasting algorithm tracks each value and predict it over one-step. From the obtained results, the prediction variations are observed between $\Upsilon(t)$ and $\hat{\Upsilon}(t)$, the obtained root mean squared error (RMSE) values are 0.050 for one-step, 0.070 for the second-step. The obtained accuracy is good enough for our simulation setup.

For performance evaluation, we compare the two offloading methods: (i) the ground mobile device directly offloads the data to the satellite (DO) without any short-term future knowledge, similar to [12], and (ii) our proposal of sending data via the BS for local computation (LO) or satellite-based computation (AO), utilizing short-term future knowledge.

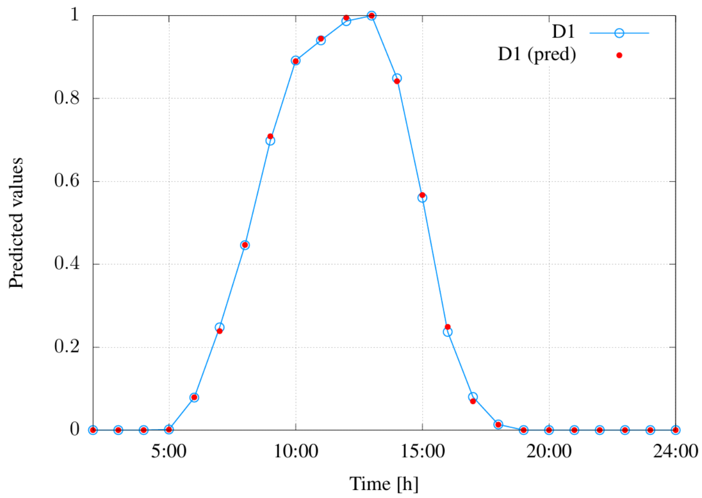

Figure 3. Solar energy traces for day 1 (D1) and its predicted values (D1(pred))

In Figure 4, we compare the energy savings that can be obtained when *partially some* of the offloaded tasks are forwarded by the BS to the selected LEO satellite for computation (LO + AO) and other tasks computed locally, and cases where all the tasks are computed locally (LO). It is observed that in the early hours of the morning (before 8 am), there are few visitors in the national park (low activity), thus the BS site is not much utilized as the energy is used for operation activities. Between 9.00 am - 15.00 pm, there is high activity within the park. This period corresponds to periods where there is sufficient amount of energy that can be harvested, as well as the arrival and departure of visitors from the national park. After 15.00 pm, the visitors will start to leave the park, then the energy savings increases. The energy savings obtained by LO + AO ranges from 59% to 34% and LO ranges from 52% to 30%. From the obtained results, it is observed that partial offloading to the satellite is beneficial as it relieve the BS site from computing everything locally, that is, fractional computing is better than computing everything locally.

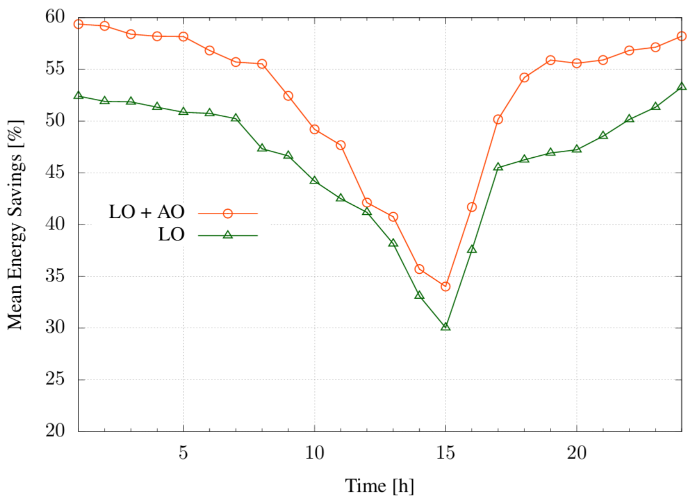

Figure 4. Energy savings within the BS site

The time-average system delay cost is shown in Figure 5, where the computational duration is observed over a number of time slots. It is observed that local computation (LO) bears a near real-time delay of 0.83 seconds when compared to the application delay requirement of 0.8 seconds (σ). In addition, we observed that assisted-offloading (where some of the tasks are partially offloaded to the satellite) is beneficial as it offers delays of 0.82 seconds which is as close to local computation on average. This is due to the fact that a portion of the tasks are offloaded to the satellite if computational resources are available on the satellite and congestion is not expected in the next time slot. The performance for direct offloading (DO) is low (when compared to assisted-offloading) as the men delay is 0.84 seconds. By offloading some of the tasks to the satellite, via the BS, helps in that the BS (acts as relay or sink) decide on the share that can be forwarded to the satellite platform, taking into account the amount of green energy to be harvested and the expected tasks.

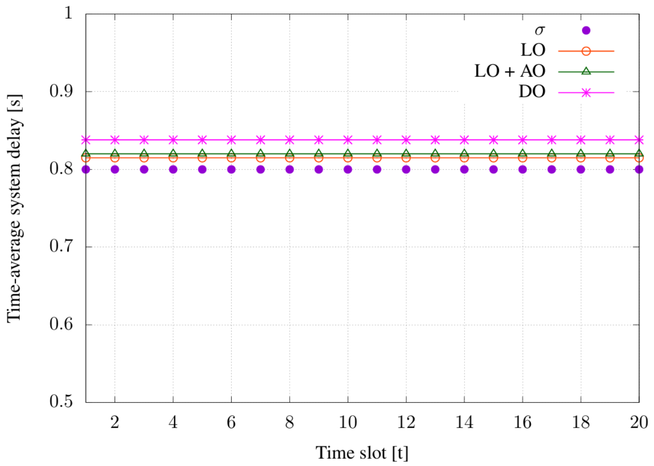

Figure 5. Time average system delay

The drop rate from the queues is illustrated in Figure 6. Here, assisted-offloading (LO + AO) is compared with full offloading to the satellite (DO), and LO + AO achieves a maximum drop rate of $8.3\,\%$ and a minimum of $2.6\,\%$ whereas DO achieves a maximum drop rate of $12.9\,\%$ and minimum of $9.9\,\%$. It is observed that our proposed strategies perform better (drop rate of $< \ 10\,\%$) when compared to direct offloading to the selected satellite. This is due to the loading of the input buffer of the satellites in the case of forwarding all the tasks to the satellite and the expected harvested energy.

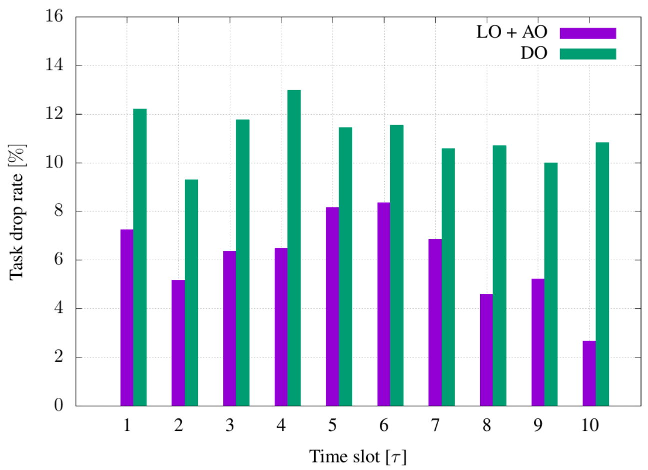

Figure 6. Task drop rate over a number of time-slots

5. CONCLUSIONS

In this paper, we propose a hybrid wireless communication system consisting of a base station empowered with computing capabilities, energized using green energy, and a LEO satellite system for providing mobile services to visitors within a protected area. The main goal of this research was to minimize the energy consumption per communication site with a guarantee of the expected end-to-end latency. In this work, we put forward a new tasks offloading strategy whereby the BS can handle some of the delay-sensitive tasks locally or offload the task to the visible satellite, using green energy as a performance metric. To save energy, the BS system forecast the short-term energy availability and then provision the computing resources base on the forecasted energy, and to guarantee the end-to-end delay the access control application on the edge server decide on the fraction of workloads to be computed locally or offloaded to the satellite. Our numerical results, obtained with real-world datasets, show via simulations that our proposed offloading strategy (LO + AO), which makes used of foresighted optimization in terms of green energy to be harvested, provision of computing resource, and the expected tasks, can be able to guarantee the end-to-end delay expected from applications when compared with our benchmark. The energy savings obtained by LO + AO ranges from $59\,\%$ to $34\,\%$ and LO ranges from $52\,\%$ to $30\,\%$. It is observed that local computation (LO) bears a near real-time delay of 0.83 seconds when compared to the application delay requirement of 0.8 seconds (σ). In terms of drop rate, LO + AO achieves a maximum drop rate of $8.3\,\%$ and a minimum of $2.6\,\%$ whereas DO achieves a maximum drop rate of $12.9\,\%$ and minimum of $9.9\,\%$. It is observed that our proposed strategies perform better (drop rate of $<\ 10\,\%$) when compared to direct offloading to the selected satellite.

As part of our future work, we will design more sophisticated offloading strategies that include long term dependencies in terms of energy forecasting, other forecasting methods, and the consideration of other NTNs such as high altitude platforms.

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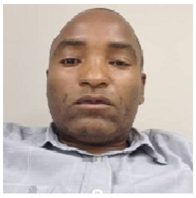

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