A Mobile Edge Computing Model enabling efficient Computation offload-aware Energy Conservation

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ABSTRACT This paper elaborates on alleviating the energy conservation problem in wireless devices operating under Internet of Things (IoT) environments, by using machine-to-machine (M2M) communication mechanisms. Such IoT wireless terminals, like wearables, smart glasses and smart objects, are able to distress energy consumption levels of the IoT environments, playing a crucial role to the Quality of Service (QoS) or Quality of Experience (QoE) provision for end users under several high demand scenarios, while they are on the move. In this context, this paper proposes a new offload-aware recommendation scheme, towards allowing the effective monitoring of high energy consumption applications that run in the mobile devices of such IoT ecosystems. The proposed model enables mobile users having a nonstop provision of on-demand services, while such devices are able to provide the available required resources that are to be exploited in IoT environments. By taking into account this approach, this paper exploits an edge-based offloading M2M communication mechanism, towards enabling resource-aware recommendation. Performance evaluation results validate the proposed approach, by assessing the provided model in the framework of the reliability provision for IoT terminals under the use of the recommendation scheme, as well as the energy conservation provision for several mobile devices that are included in the IoT environment during the offloading procedure.

INDEX TERMS Edge Computing; Energy Conservation; IoT Offload Metrics; Offload Processing; Resource-aware Recommendation; Offload-oriented Mobile Cloud

I. INTRODUCTION

Resource hungry applications of IoT mobile devices can effectively run by exploiting cloud computing paradigm and related mechanisms. Mobile terminals that are on-the-move, are able to resourcefully create a cluster, while they can contact additional edge interconnected devices, like smart glasses, wearables, smart jewelry, smart shoes, and smart accessories. In this way, the target is to enhance services provision efficiency, as well as QoS (Quality of Service) requirements by each mobile device [1]. QoS in such IoT environments suggests an effective exploitation of the available resources in contrast to the power distribution management across the existing mobile terminals in the cluster. It is certainly correct that the mobile terminals QoS requests are of deterministic nature, as well as other QoS dimensions and levels, which are influenced by several performance metrics [2] are different of each other. The Edge
Computing [3] schemes and related paradigms, where the interconnected IoT mobile terminals, like smart appliances, smart glasses etc. can distress the QoS energy levels of all mobile devices in such ecosystems. Furthermore, it can be vital in terms of the QoS levels that are provided to the mobile terminals, for several services provision requests according to different power consumption considerations. The requests for acceptable QoS provision to every mobile terminal are exponentially growing [1], as well as in other cases [2], the processing abilities of the IoT terminals are not able handle with the processing necessity that is required by mobile applications, like real-time interactive games. This is because of the increased requests in processing power, where every mobile terminal has to able to offer a response in a specified time frame. Also, in every IoT terminal the increased energy consumption is a great problem for the mobile users and their high requests several time periods that intensively use the device to play real time games, as well as other energy hungry applications. It is true that total number of inter-connected devices is exponentially growing with incredible rates in such IoT environments, enabling a dense networking formation, where a joint increase in processing levels, by exploiting superposition offloading [3], as well as the expected energy levels, which are required by mobile terminals have to be related with the remote management of exploited resources.

The IoT environments of mobile interconnected devices can be an efficient solution for terminals with insufficiency of resources. Such mobile terminals are able to ‘host-run-execute’ processes, which belong to alternative devices, targeting to support accessibility of resources for ‘resource-starving’ end users and applications. Since, mobile devices in IoT environments are rare in resources, while many resource constraints exist, the energy maintenance along with the attainable consistency, position a challenge for the provision of QoS to the mobile users, as well as for the mobile services and applications. In this context, the edge computing environment is able to host high energy consumption applications towards operating the increased demanding processes, to fulfill the requests of the mobile end-users. This paper elaborates on a new resource offload scheme, which supports “resource-awareness” together with a recommendation mechanism of the interconnected devices that are aware of the resources, as well as the constraints within a proximity to allow the effective monitoring of energy demanding applications in such IoT networking environments. In addition, this paper elaborates on a new framework, to present the use, as well as the basic requests of such use-cases and reference scenarios. Several, processing parameters, metrics, as well as network, migration and recommendation-oriented parameters, have been exploited, to minimize the levels of energy consumption when energy hungry applications are provided and critical or delay-sensitive processes are applied. In this framework, the sections of the paper below present the related work, to demonstrate alternative solutions and the overall design principles of this work. A detailed performance evaluation is also presented, while the results extracted are indicating the effectiveness of the anticipated research approach, by exploiting both real-time emulator and by conducting simulation tests under specific networking specifications and scenarios.

II. Related work and frameworks

There is no research up to now associating directly edge computing with resource-recommendation mechanisms for mobile terminals in IoT environments. In this respect, this paper proposes a scheme that can help interconnecting IoT mobile terminals with resource-recommendation approaches. Other related works addressed only a few parts of the associated problem. Other authors usually assume that mobile users in each IoT environment can communicate locally at any level of relation and such devices are uniformly distributed in the local cell area of the mobile base station. However, this is not actually practical for actual Device-to-Device (D2D) applications. In such cases data is transferred according to the communication attributes of the mobile users, as well as the energy levels and efficiency of the D2D communications. Alternative methods have been proposed based on Similarity Computing (SC), to address the states of each mobile terminal according to network-oriented similarities in a cluster [4]. Mobile terminals are usually treated in this way as “same-level capability” nodes, in respect to processing power and other related metrics. In addition, Collaborative Filtering (CF) is an alternative method to recommend the highest Memory capability. In such a case, mobile terminals are able to exploit the referred user as a backup or as a prediction forecasting user for the availability of the resources [4-5]. In this framework, other authors have proposed social network information [6, 7], towards improving the accuracy of traditional recommendation [8]. Furthermore, works in [8, 9 and 10] have proposed a joint recommendation and socially-aware scheme, towards supporting the effective management of the available resources in mobile terminals. Authors in [10] used a social collaboration mechanism to enable a cooperative partial offloading of processes between the interconnected mobile terminals. By this way, energy usage per mobile terminal is maximized. Other social recommendation schemes were proposed in [11, 12, 13]. Such schemes prove via their corresponding tests and experiments that not always the recommender system outperforms without engaging the social data, which is provided by the mobile terminals.

In addition, an important amount of research approaches in edge computing were proposed recently, elaborating on the energy minimization mechanisms in mobile terminals operating within an IoT environment. Based on such approaches it is assumed that all mobile terminals operate in shared wireless environments, which feature unpredictable channel and connection variations. The density of mobile users enables the effective exploitation of dormant terminals.
Dormant resources of the mobile terminals may vary from smart accessories to smart appliances, which can process data, towards achieving optimized resource management via effective process offloading. Authors in [11] propose a resource allocation mechanism for IoT-enabled terminals, by exploiting local data stemming from the mobile users, as well as their local views. In this way, the energy management scheme is optimized. In addition, research approach in [12] adopts resource management, in respect to handling tasks, which are based on the energy optimization and applications. By this way, the accuracy of collaborative filtering is improved. Towards enabling real-time feedback provision, this paper presents a mechanism for efficient resource offloading, combined with an assistive recommendation model that enables energy monitoring of the running applications on the IoT-enabled mobile devices. This allows a continuous on-demand service provision where devices actively provide the available resources to be exploited in the IoT ecosystem. The proposed edge-based computing offloading scheme runs on the edge terminals under a M2M approach, providing resource-awareness via recommendation diversities. In order to evaluate the efficiency of the proposed framework, an experimental scenario has been adopted, towards demonstrating the offered reliability for delay tolerant and delay sensitive services. In this respect, the energy conservation is preserved for several mobile terminals that constitute the IoT-enabled environment. Section III presents the proposed system model and solution formulation, as well as introduces several notations that have been exploited to formulate the associated problem. Section IV presents the performance evaluation results of the proposed scheme, outlining the benefits in terms of energy conservation. It also provides a comparative evaluation of the proposed scheme in comparison to other similar schemes based on the recommendation mechanism. Finally, Section V summarizes our conclusions and presents future work.

III. System model and solution formulation

The development of a recommendation scheme comes over the current availability of the channels in the IoT environment. The proposed model does not adopt any central system or a central base station towards managing the coordination of the mobile terminals in the IoT-enabled clustered environment. The collaborative recommendation scheme is used to the participating mobile terminals in order to decrease the computational influence on resources that aggravates the consumption of the energy levels inside the devices. In recommender systems, the objects that are participating are as follows: for M mobile users in the system

\[ U_r = \{u_1, u_2, u_3, u_4, \ldots, u_M \} \] (1)

it means that the \( U_r \) recommendations for each mobile terminal represent the availability of the resources, as well as the system utility \( S_{U(t)} \) at time \( t \) for each user/device. The fairness index is based on the capacity availability \( C_{u(t)} \) and the battery level \( I_{u(t)} \) of device \( U_r \) at time slot \( t \).

The equivalent resource exchange network is defined as an undirected graph \( G = (U, E) \). In such a case, \( U \) is a set of user vertices and \( E \subseteq U \times U \) signifies the edge-oriented interconnecting terminals, which share the available resources. This concept is represented in Figure 1(a) above. In this respect, \( E \) denotes the mobile users, who exploit the same resources or share the common resource activities. Based on the second case, the resource similarity can be extracted by using the Jaccard coefficient [16], as follows:

\[ S_{u_i, u_j} = \frac{|N(u_i) \cap N(u_j)|}{|N(u_i) \cup N(u_j)|} \] (2.1)

\[ S(u_i) \geq 0, u_j \leq 1 \] (2.2)

It stems from Equation 2.1 that for greater values of \( S_{u_i, u_j} \), more common resources exist that are shared between the mobile terminals. This is assessed, by exploiting the Jaccard coefficient towards evaluating the common resources among the mobile terminals over the total number of shared resources. In turn, the similarity degree between user \( u_i \) and the other mobile terminals is obtained based on (2.1). Towards having capability in allocating resources, this paper generalizes the concept of Jaccard coefficient and Jaccard distance estimation as follows:

\[ S_G(u_i, u_j) = \frac{\sum_{i,j} \min(u_i, u_j)}{\sum_{i,j} \max(u_i, u_j)} \] (2.3)

with distance \( d_{i,j|S_G(u_i, u_j)} = 1 - S_G(u_i, u_j) \) (2.4)

where the \( d_{i,j|S_G(u_i, u_j)} \) represents the guaranteed resources/applications etc., that are jointly exploited by the users/members for time \( t \). This specifies that the longer the distance is, the shared/commonly used resources are less.

The mobile terminals are separated into alternative virtual communities dynamically, based on their preference sequences. To further exploit the resource exchange...
relationship scheme, as well as employ the task offloading accordingly, the coalition game model is exploited, towards describing the resource exchange between mobile terminals to decrease the virtual community difference. In such a case, a mobile node that has redundancy of resources can be represented, by assessing the $S_{u_i u_j}$ for larger values and evaluating the eligibility criteria to be satisfied as follows:

$$\forall S_{u_i u_j}(t) \max(S_{u(t)}, C_{u(t)}) \exists \min l_{u(t)}, a_j \mid S_{u_i}$$ (3)

where $S_{u(t)}$ represents the system utility at time $t$, $C_{u(t)}$ is the available capacity and $l_{u(t)}$ battery level of device $U_t$ at time $t$.

In addition, this work defines the offloading capability as follows:

$$K_{um} = \frac{\sum_{a_j} \max(S_{u(t)}, C_{u(t)}) \exists \min l_{u(t)}, a_j \mid S_{u_i}}{\sum_{a_j} \max(S_{u(t)}, C_{u(t)}) \exists \min l_{u(t)}, a_j \mid S_{a_j}}$$ (4)

where $K_{um}$ indicates the offloading capability provided the maximum possible system utilisation given the maximum available capacity $C_{u(t)}$ and battery threshold $l_{u(t)}$ of device $U_t$ at time $t$ for a respective offloaded process $a_j$.

A. Energy-consumption model using Machine-to-Machine recommendation mechanisms

The set of $U_t = \{u_1, u_2, u_3, u_4, ..., u_m\}$ is representing the mobile terminals, which are exploiting within a virtual cluster, a computationally intensive and delay sensitive task [17]. This task has to be completed within a specified time-frame $\tau_j$. The total transmission offload-completion time should satisfy $\tau_j > \tau_{a_j}$ while the energy of the mobile user $u_m$ for offloading the set of offloaded tasks of size $B_j$ can be estimated as follows:

$$E_{um} = \frac{\min(P_j) \max(B_j)}{\sup(\lambda(a_j))}$$ (5.1)

$$T_{um} = \frac{B_j}{\max(\lambda(a_j))}$$ (5.2)

where $a_j$ is an executable partitionable task that will be potentially offloaded and $\lambda$ is the uplink data rate for computation offloading of mobile device user $i$ for the minimized $\min(P_j)$ transmission power of device $j$. The uplink data rate for computation offloading can be evaluated using:

$$\lambda_i = BW_i \log_2 \left(1 + \frac{P_i H_{ILBTS}}{\omega_i + \sum_{c_i \in N_i(j): a_i = 1} P_i H_{ILBTS}} \right)$$ (5.3)

In Equation 5.3, $BW$ is the channel bandwidth and $P_i$ is user $i$’s transmission power, which is determined by the

wireless access base-station based on several power control algorithms, such as ones in [17], [18]. The parameter $H_{ILBTS}$ denotes the channel gain between the mobile device user $n$ and the base-station, and $\omega_i$ represents the background interference power, including the noise power and the interference power from other mobile device users. Such users carry out wireless transmission, but they are not actively involved in the $d_{i,j}$. Equation 5.3 states that if many wireless devices select the offloading process for conserving their energy for their computational resources, will impact the interference parameter, which in turn ends with low data rates.

The $a_j$ executable partitionable task that will be potentially offloaded, is executed on the mobile device in an opportunistic manner provided that Eq. 4 can be satisfied for the $K_{um}$. This is evaluated considering that there is adequate bandwidth $B_j$ for this offload to occur so that the minimum $T_{um}$ for the $a_j$ executable partitionable task is satisfied. By considering the $\Omega_m$ as the clock frequency of the mobile processing unit in $U_t$ the process time cost for offloading $a_j$ is $T_{um}(a_j) = w_{a_j} \cdot \Omega_m \exists \min l_{u(t)} a_j \mid S_{u_i}$

where $w_{a_j}$ is the computing workload needed for this offload.

In turn, the total Energy cost for the entire offload process can be evaluated by:

$$E_{umTotal} = \sum_{a_j} \frac{\min[P_j] \max(B_j)}{\sup(\lambda(a_j))} \max(S_{u(t)}, C_{u(t)})$$ (6)

The Equation 6 represents the total Energy cost [19] for the entire offload process can be decreased once the subsequent energy is further minimized in the virtual communities according to the device’s offload sequences for the minimized $\min(P_j)$ transmission power of device $j$ for any given task $a_j$. The complete steps in the form of pseudocode along with the sequence that these occur are appearing in Table I.

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**Table I. Pseudocode for the offloading process using the proposed scheme.**

| 1: Inputs: $U_t, S_{G(u_i u_j)}$, resources $r_{x, y}$-MobileDevice |
| 2: for each $U_t$ evaluate $S_{u(t)}$ provided that $\forall S_{u_i u_j}(t)$ $\max(S_{u(t)}, C_{u(t)}) \exists \min l_{u(t)}, a_j \mid S_{u_i}$ |
| 3: while $(a_i l = 0)$ |
| 4: evaluate Virtual Community $K_{um}$ |
| 5: for each $a_j$, $K_{um}$ evaluate $Y_{(u_t), Y_{(u_j)}}$ |
| 6: estimate $T_{um} E_{umTotal}$ |
| 7: offload $(a_j)$ |
| 8: end for |
| 9: end while |
| 10: end for |

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B. Machine-to-Machine offloading mechanisms

When the above thresholds cannot be met, the offloading methodologies can be applied using the mechanisms described in this section. During the offload period, there are $n$ devices that make computation offloading requests to these infrastructures. The computation task of device $i$ is:

$$ u_i, i \in U_r = \{u_1, u_2, u_3, u_4, \ldots, u_M\} \quad (7) $$

The above equation 7 cannot be split into sub-tasks [20] and belongs to a single device. Each task $u_i$ is characterized by a tuple $\{w_i, d_i, p_i^d, \delta_{u_i}\}$, where the $w_i$ is the workload, i.e., the amount of computing resources required to accomplish a specified task, $d_i$ is the size of the data that is required for the computation process, $p_i^d$ ($p_i^d > 0$) is a device-oriented parameter that indicates the device capability or how much prone is, when the task process takes place and indicates the delay [8], and $\delta_{u_i}$ is the anticipated delay of the task. When a task is completed within the expected time $\delta_{u_i}$ then $\delta_{u_i} = 0$ and has zero delay cost. Each device can perform the task locally using its own resources that exist on the device. Let $f_{u_i}$ denote the local computing capability of device $i$ so the completion time of executing the task locally is:

$$ \Delta_{u_i} = \frac{w_i}{\sup(f_{u_i})} \quad (8) $$

Hence the offloading capability in this case becomes:

$$ K_{um} = \frac{\left| \sum_{i} \min\{w_i, d_i, \min\{\delta_{u_i}, \max\{C_{ui}(t)\}\}\} \right| \min\{w_i, d_i\} p_i^d}{\sum_i \max\{p_i^d, \delta_{u_i}, \mathcal{C}_u(t)\}^\gamma \Delta_{u_i}} \quad (9) $$

Equation 9 above is valid only for offloading, when there is no clear recommendation via the methodology introduced above (Equations 2-6) and the $\Delta_{u_i} < T_{um}(a_j)$ for offloading $aj$ where $T_{um}(a_j) = w_{a_j} \Omega_m \geq \min \{u_i(t), a_j\} S_{u_i(t)}$ provided that there is available adequate capacity and $l_{u_i(t)}$ battery level of device $U_r$ at time $t$.

The total offloading capability becomes:

$$ \sum_{i=1}^{n} \sum_{j=0}^{m} X_{ij} f(E_{um}, T_{um}) $$

$$ = \sum_{i=1}^{n} \sum_{j=0}^{m} X_{ij} f(E_{um}, T_{um}) \in \min (E_{um}^\text{Total}) \quad (10) $$

For the minimum Energy consumption during the offloading process on different nodes, Equation 10 provides a precise estimation of tuning the parameters for increasing the offloading capability of the node, and allow more data to be offloaded when $\Delta_{u_i} < T_{um}(a_j)$.

Figure 1(b). Ecosystem encompasses the IoT devices that can either offload locally within Virtual Communities or to remote devices.

1) Stochastic estimation of the workload model

The workload model in this research is considered as stochastic and independent whereas the number of computation jobs per time slot follows an independent and identical distribution [21], and the sizes of jobs belonging to the same type also follow an independent and identical distribution. The size of a job ($S_{aj}$) is measured in bits and based on the recent approaches in [6], [8], the CPU cycles required to execute a job with size $S_{aj}$ can be derived by $\text{Cycles}_{CPU} = \psi S_{aj} \exists T_{um}(a_j)$, where $\psi$ is the number of CPU cycles required to process 1 bit of a task. For a given workload $w_{a_j}$ the number of computation jobs within a different virtual community provided that $\Delta_{u_i}$ is satisfied. To model and evaluate the stochastic estimation by using the system of Figure 1(b), let $X_{aj}(t)$ be the number of computation jobs generated from the $i$th IoT virtual communities that arrive at edge node $i$ in slot $t^2$, and $WX_{aj}(t) = \sum_{i=0}^{n} X_{aj}(t) S_{aj}^k$ be the corresponding workload, $S_{aj}^k$ is the size of the $k$th task with $\xi_i = E(X_{aj}(t))$ be the task generation rate in $i$th community. Considering the latter let $Y_{(l,j)} Y_{(l,i)}$ and $Y_{(l,C\text{server})}$ where $Y_{(l,j)} Y_{(l,i)}$ are the computation on local edge and on virtual community respectively, and $Y_{(l,C\text{server})}$ is the computation performed on assistive Cloud, then the corresponding workload is evaluated by using:

$$ WY_{a(i,j)}(t) = \sum_{i=0}^{n} Y_{a(i,j)}(t) S_{aj}^k $$

$$ WY_{a(i,C\text{server})}(t) = \sum_{i=0}^{n} Y_{a(i,C\text{server})}(t) S_{aj}^k $$

and for the assistive Cloud it stands

$$ WX_{a(i,C\text{server})}(t) = \sum_{i=0}^{n} X_{a(i,C\text{server})}(t) S_{aj}^k $$

Form the above Equations (11) and (12) it becomes evident that for $WX_{aj}(t)$, it stands:

$$ WX_{aj}(t) = WY_{a(i,j)}(t) + WY_{a(i,C\text{server})}(t) $$

The pseudocode along with the different inputs and the corresponding steps are set in Table II.
### III. Performance assessment, experimental results analysis and discussion

This section of the paper elaborates on the performance evaluation of the proposed scheme, in respect to the diversity characteristics of the associated networking mechanisms, as well as the social recommendation impact that is adopted in this work. The performance evaluation results are focused on the offloading methodology to incorporate a “resource-awareness” coalition mechanism together with the recommendation scheme. It has also been taken into account that the nearby IoT-enabled mobile terminals are aware of the resources and the related constraints within a proximity. This paper also elaborates on the offloading capability by the mobile terminals considering that the maximum possible system utilisation and the maximum available capacity is assessed over a battery threshold $l_{U_r}(t)$ of device $U_r$ at time $t$. The conducted simulation experiments were conducted in a Java Simulator to encompass comparisons with other existing models. The experimental tests consider interactive applications, like interactive games to run during the evaluation process. The proposed scheme was implemented by exploiting an Android-based interface for the low-level process-assessment of each application. This interface was inter-connected with sockets of the simulator to support the responses in real-time of the offloading and recommendations, based on the proposed model that is described in Section III. In addition, the uplink data rate for the computation offloading is evaluated in real-time. The assessment of the performance, as well as the simulation experiments are associated to the context of executing the same kind of resources or share common resource activities in contrast to the energy conservation efficiency (Energy cost for the entire offload process) as described in proposed scheme. The mobility model which mobile terminals follow is the probabilistic Fractional Brownian Motion (FBM) adopted in [9]. The Energy cost was assessed in comparison to the offloading capability $K_{um}$ (Equation 4) is tuned with the $S_{umj}$ for large values while the system achieves the maximum possible utilisation with utilisation of the maximum available capacity $C_{u(t)}$ at time $t$ for a respective offloaded process $a_j$.

#### TABLE II. Pseudocode using the Machine-to-Machine offloading mechanisms and workload model.

1. **Inputs:** $U_r, S_{U_r(a_j)} \forall X_{a_j}(t)$
   - resources: $r_1, r_2, \ldots, r_n$ MobileDevice
2. for each $U_r$: evaluate $S_{U_r(a_j)}$ provided that $\forall S_{umj}(t)$
   - max($S_{umj}, C_{u(t)}$) $\leq$ min $l_{U_r(a_j)}$ $S_{umj}$
3. while ($a_j! = 0$)
4. evaluate $V_{(a_j)}$, $Y_{(a_j)}$ and $Y_{(a_{server})}$ $\forall X_{umj}$
5. for each $\lambda_i$, $K_{um}$ evaluate $W_{Y_{(a_j)}}(t), W_{Y_{(a_{server})}}(t)$
6. estimate $T_{umj}, E_{umj}$
7. minimize $W_{X_{a_j}}(t)$
8. offload ($a_j$)
9. end for
10. end while
11. end for

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Figure 2. Comparative evaluations and results obtained for the assistive recommendation offloading compared with two different schemes in contrast to the average node’s lifetime extensibility with the number of mobile devices (evaluated for the most energy draining applications).

Figure 3. Execution time during simulation for interactive commonly used applications for all participating devices, evaluated for three different schemes.

The performance evaluation results that are presented in Figure 3 demonstrate how the proposed scheme performs in a network-oriented way, by comparing to alternative research approaches as indicated in [22]. Figure 3 presents the execution time during the simulation experiments for the mobile terminals, by exploiting alternative mobility patterns with emphasis to the connectivity channel, like GSM/GPRS, Wi-Fi/WLAN, and WLAN to another WLAN communication. The presented scheme is demonstrating important decrease, in respect to the execution time duration, in comparison to the other schemes. The performance
evaluation results that are presented in Figure 4 demonstrate the supremacy of the proposed model, by expressively rising the average lifetime of mobile terminals when the number of end users increases. It is important to mention here that by exploiting the proposed scheme, the average lifetime of the mobile terminals rises. Also, in contrast to the number of the end users, it progressively reaches the maximum increase when this number reaches the number of 150. Figure 5 shows the data offloading ratio, as well as the effects in the increase of participating mobile terminals in comparison to the other alternative schemes. The experimental results show that the proposed model performs expressively better when the number of the mobile terminals grows, as well as the level of data offloading is increased. Following the second case, Figure 6 represents the data offloading ratio with the number of commonly used by the user’s applications, for duration t. The adequacy in sharing resources is estimated using Jaccard coefficient and Jaccard distance estimation where the $d_{ij} = |X_i \cap X_j| / |X_i \cup X_j|$ in Figure 6 is evaluated for commonly used applications by the members.

Figure 4. Comparative evaluations of the average node lifetime extensibility with the number of the mobile devices.

Figure 5. Data offloading ratio and the effects in the increment of the number of participating users.

Figure 6. Data offloading ratio with the Number of commonly used by the users applications for time t.

Figure 7. Energy conservation (gain) with the commonly used by the members applications for a timeframe t.

Figure 8. Offloading Utility with the number of participating mobile users nodes utilizing a common interactive gaming procedure.

Figure 9. Task Delay Cost (ms) with the Input Size (Mb).
The proposed framework proves its supremacy when it comes to delay cost as well as the offloading capability of the scheme. Average End-to-End delay (msec) with the Jobs(tasks) per msec is presented in Figure 11 with the proposed offloading scheme exhibiting the minimum end-to-end delay while tasks are offloaded.

V. Conclusion

This paper elaborates on model to support real-time feedback provision, enabling efficient offloading. The proposed model, combined with an assistive recommendation scheme, enables for energy-efficient monitoring of running applications on mobile terminals that operate within an IoT-enabled environment. The mechanism enables a non-stop service provision, where mobile devices dynamically deliver the existing resources to be exploited in the IoT-enabled environment. The proposed recommendation scheme exploits an edge-based computing offload mechanism that is able to be adopted by any infrastructure, providing resource-awareness through recommendation diversities. In order to evaluate the efficiency of the proposed scheme, a simulated scenario has been proposed, showing the existing consistency for the offloaded delay-sensitive services, as well as the energy conservation for several mobile terminals establishing the IoT-enabled environment. The demonstrated results validate the benefits in respect to energy conservation and reliability of the proposed data offloading process. In addition, the comparative assessment of the proposed model with other similar ones expresses the supremacy in terms of energy gain.

Future research elaboration by authors include the development of an opportunistic mobile cloud that hosts ubiquitous IoT-enabled services, like game players, to be able offloading their resources. In this way, they will make full exploitation of the fog computing paradigm. This will encompass the abilities of a reflective Software Define Network (SDN) middleware, where decisions regarding the processing and holding times can be provided based on the access priority and recommendation level of each user.

REFERENCES


