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Full Length Research Paper

Group-Based Data Offloading Techniques Assisted by D2D Communication in 5G Mobile Network

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ABSTRACT

Machine type communication devices proposed as one of the substantial data collections in the 5G of wireless networks. However, the existing mobile communication network is not designed to handle massive access from the MTC devices instead of human type communication. In this context, we propose the device-to-device communication assisted a mobile terminal (smartphone) on data computing, focusing on data generated from a correlated source of machine type communication devices. We consider the scenario that the MTC devices after collecting the data will transmit to a smartphone for computing. With the limitation of computing resources at the smartphone, some data are offloaded to the nearby mobile edge-computing server. By adopting the sensing capability on MTC devices, we use a power exponential function to compute a correlation coefficient existing between the devices. Then we propose two grouping techniques K-Means and hierarchical clustering to combine only the MTC devices, which are spatially correlated. Based on this framework, we compare the energy consumption when all data processed locally at a smartphone or remotely at mobile edge computing server with optimal solution obtained by exhaustive search method. The results illustrated that; the proposed grouping technique reduce the energy consumption at a smartphone while satisfying a required completion time.

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INTRODUCTION

Advanced development of 5G overlay the emerging paradigm of the Internet of Things (IoT), which permits the objects to interface and cooperate with each other using the internet (Holler et al. 2014). The IoT is an expansion of existing internet that allows a real object such as sensors, RFID tags, actuators and Machine type communication (MTC) to access the internet and exchange the information with other objects (Al-Fuqaha et al. 2015). MTC considered as a building block of an IoT that permits smart objects to interact through the communication with or without human involvement. Related to human type communication (HTC), the MTC devices have low power and inexpensive usually deployed to accomplish or facilitate specific tasks collectively. Additionally, according to the Cisco report on 2016, by 2021 the monthly global mobile traffic is expected to reach 49 Exabyte, and the majority of traffic originated from smart devices (Cisco 2017).

Moreover, the growth of the traffic generated by MTC devices will increase pressure on the network operators especially for the delay-sensitive services, which needs to be handled within a short time. The data offloading, caching and edge computing are the recently promising solutions to deals with the massive growth of the data in future networks (Rebecchi et al. 2015, Li et al. 2018 and Khodashenas et al. 2017). While these efforts can potentially relieve the performance on the network operators by involving more energy consumption due to a delay tolerant occurred to targeted MTC services, the proposed results still having shortcomings of a suitable performance for many MTC services regarding a significant volume of data during processing. Nevertheless, the data aggregation approach proposed in (Guo et al. 2017) to reduce the network congestion due to massive of MTC devices. The authors consider the two-phase of data transmission, MTC devices transmit data to an aggregator and then relayed to the base station based on the scheduling schemes. The aggregator in cellular networks sometimes can be MTC gateway or user devices as used in (Rigazzi *et al*. 2015) not only reduce the network congestion but also reduce the power consumption of the MTC devices since the transmission distance for MTC devices become shortened.

In general, the mobile networks indicated as a suited candidate to handle the traffic generated from MTC devices due to their broad range of network coverage (Ali et al. 2015). However, the current mobile network systems are designed to sustain the quality of service required by human-to-human (H2H) communication, which depends on sessions with the objective of providing a higher data rate. Likewise, the MTC devices are lower powered devices transmitting the small amount of data periodically. With the massive MTC devices connected to the mobile networks which expected to be much larger than the mobile users in the future will lead to the congestion on the core network because of higher signalling overhead. This increases the number of challenges on mobile networks especially on the resource's allocation and management. To alleviate this challenge, the mobile networks can dedicate some data processed by the terminal devices or edge computing devices, as we know most of these data carried the contents that needs to be processed corresponding to the owner servers such as environment detection, health monitoring, and the object detection.

Besides, for delay-sensitive applications such as object detection at a surveillance camera or vehicular communication needs faster response compared to delay tolerant applications such as participatory sensing (Ra et al. 2010). As to fulfil the delay sensitive of the data collected by MTC devices some data should be processed to the powerful edge-computing device that allocated very close to the data sources, we propose a smartphone having computation capability assisting the mobile network. With the limitation of the computational resources on a smartphone, some data will be offloaded to the nearby access point such as Wi-Fi or base station, thus we consider the base station equipped with mobile edge computing server (Nishiyama et al. 2014). Then the results obtained after computation will return to the MTC devices for further actions.

However, the MTC devices usually deployed to perform specific tasks especially in high-density area, then the data collected from nearby MTC devices are not entirely independent rather spatially correlated (Vlajic N and Xia D 2006). For example, in the environment monitoring, the camera sensor devices that are proximally located are more likely to detect similar readings. To deals with spatial correlation at the MTC devices, we propose grouping techniques adopted from the clustering algorithms mentioned as the k-means and hierarchical algorithm. MTC devices are grouping based on nearby locations or spatially correlated and we assume the data collected by individual devices are statistically similar. In this case, instead of processing a data collected by an individual device, we consider the groups that combine only the MTC devices that spatially correlated. The main contributions of the paper explained as follows

- We use the correlation model to find a correlation coefficient based on the location coordinates of each MTC device
- We have proposed the two grouping techniques to group the MTC devices based on the spatial correlation to reduce the size of input data (redundancy) during the processing at the smartphone
- We apply a differential entropy framework to obtain the data size on each group
- We use Exhaustive Search Method (ESM) to find all the possible optimal solution that provides the minimum total energy cost on the smartphone device

The remaining parts of this paper organized as follows. Related work discussed in section 2. In section 3, we describe the system model together with details of the correlation model and the proposed grouping technique. The section 4 presents the theoretical concepts of computation, and we define the optimization problem for minimizing the energy consumption. In section, we evaluate the optimization problem using exhaustive search method, and Section 6 discusses the results to clarify our study and finally we conclude by summarizing the idea of the whole the paper.

METHODS AND MATERIALS

Related Works

Many research ideas have been proposed to improve the resources constrain in MTC communication and wireless networks. In (Park et al. 2015) a medium access control (MAC) protocol with low energy and latency proposed for hierarchical structured of M2M networks. It allows the effective data transmission originated from terminal nodes to a sink node through a cluster head and (3GPP Std. TR 37.868 2011) extended access barring (EAB) in LTE-A studied to deals with the overloaded problem originated from a large number of MTC devices compete to access the networks in a limited burst. The cloud-based lightweight investigated for mobile core networks devoted for MTC to improve challenges of network congestion and system overload (Taleb et al. 2014). An energy efficient data aggregation scheme was introduced (Malak et al. 2016) for M2M network with the objective of minimizing the average total energy expenditure and then the optimal data scheme based on coverage probability framework developed for MTC devices. As the massive traffic generated by machine-to-machine, the ultra-low-latency, and maintained minimal data rate as identified in (Dawy et al. 2017), and a cross-layer approach for MTC system proposed with appropriate channel coding to eliminate the data buffering and package generation at the transmitting device.

MTC data offloading through device user equipment (UE) is discussed in (Atat et al. 2017, Pratas et al. 2014 and Cao et al. 2017). From the results based on spectrum access, efficient of radio resources management and extended the battery life of the MTC devices due to a short distance through D2D links discussed in (Atat et al. 2017). The authors in (Pratas et al. 2014) designated on how to utilize underlay D2D communication on transmitting MTC data to the base station (BS) relayed through UE with successive interference cancellation. Similarly, in (Cao et al. 2017), the D2D communication has revolutionized the idea to deploy UE act as a relay based on relaying data from MTC devices using D2D communication links. The authors also developed a protocol to aggregate data from MTC devices at the UE and then transmit data to a BS together with the UE's own data.

Furthermore, many data aggregation algorithms need to know the information related to devices together with the targeted base station such as location, and signal strength for efficiently relaying the data through the intermediate devices. The benefit of the aggregation is to clarify the fact that the MTC devices that are very near to each other are collecting similar data (Song et al. 2015). It counted that the devices which are spatially correlated especially on the dense deployment of MTC devices, often transmit identical information (called redundancy) to the base station. To deals with this problem, the data-centric clustering approach proposed to improve the quality of the data transmitted to the base station (Juan et al. 2013). Additionally, clustering techniques used in many fields to control distributed user devices over wireless networks. In (Sasikumar P and Khara 2012) the k-means clustering algorithm discussed in a wireless network and the node that has the highest energy treated as a cluster head and then others node assigned to the nearest cluster based on the highest energy. In this case, when the node broadcast the information to all the nodes, the nodes that are in the coverage range of the cluster receiving it and broadcast again to the other nodes. In contrast with clustering, the grouping hierarchy structure technique is proposed in wireless sensor networks (Hawbani et al. 2015). The sensor nodes spitted according to their maximum covered regions of the geographical locations in such a way that each group consists of a number of leaders and number of nodes.

Although the grouping technique based on clustering algorithms is more explored in the field of data mining and wireless sensor networks but can be adapted to works in the communication systems. The authors in (Xu et al. 2014) discussed the user grouping for massive MIMO in frequency division duplexing systems. Two clustering algorithms were proposed K-Medoids and hierarchical clustering to groups user based on three similarity measures namely as a weighted likelihood, Fubini-Study and subspace projection. The results presented shows that the hierarchical clustering provides better performance compared with other in large capacity. Similarly, in this context we adopt the same approach to define the grouping technique by grouping MTC devices based on the spatial correlation.

System model and theoretical Descriptions

Consider the scenario whereby the sequence of the MTC devices $M = \{m_1, m_2, ..., m_N\}$ that having the sensing capability are randomly distributed at the event-based area to detect the object. After sensed each MTC transmits data to nearby user equipment U assisted by D2D communication link for processing or (computing). Then the results transmitted back to the MTC device for further action. With the limits of computation resources at U to process the data, some data are offloaded to the nearby Base Station equipped with mobile edge computing server (MECS) for further processing as shown on the Figure 1. Based on the statistical nature of the source and coverage the data collected by devices may have a high degree of the correlation.

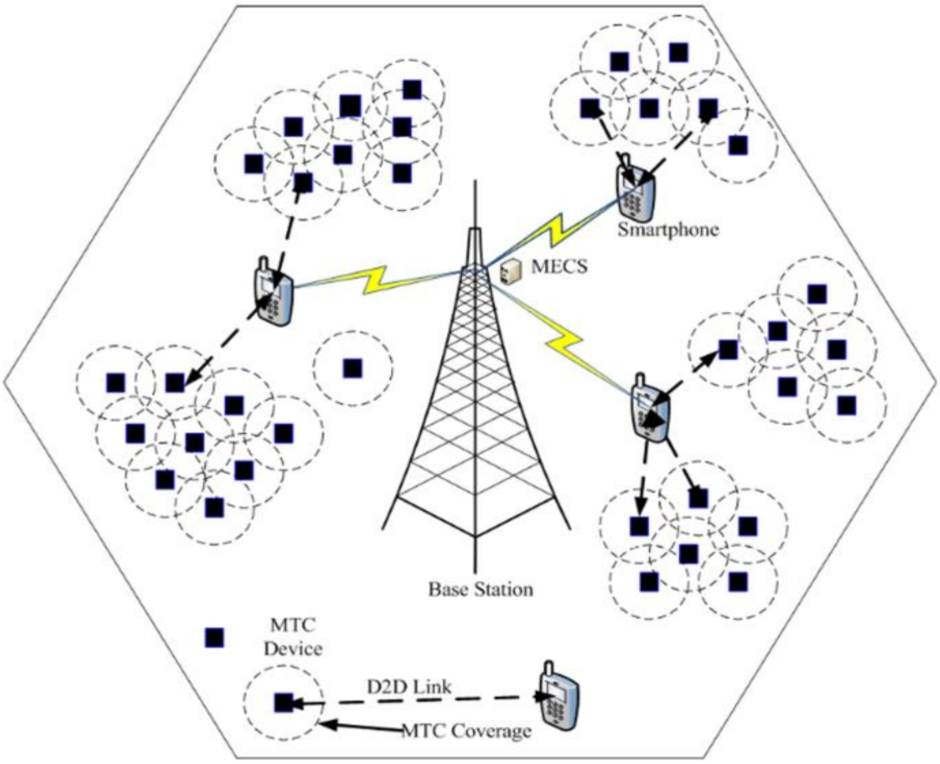


Figure 1. System Model

Analysis of Correlation Model

The intuition of a correlation in data computing is to shows the existence of data dependencies or similarity that collected from the different MTC devices. It implies that a smartphone wastes the computation resources to process similar data independently at the same time, instead, we can use some techniques to identify the presence of data correlation and then process together, thus helps to reduce the data redundancy. In our model, we adopt the Wireless Sensor Networks to compute the correlation coefficient with assumption that our devices are spatially correlated at event-based area such as surveillance cameras, environment-monitoring area etc. Such kind of correlation usually validated using non- negative covariance function decreasing with Euclidean distance of 1 at $d=0$ and 0 at $d=\infty$, where d denotes the Euclidean distance between the MTC devices. In addition, the data collected by the MTC device represented as $W=\{w_1, w_2, ..., w_N\}$ follows the multi-variate Gaussian distribution with mean μ and variance σ.

Then, the expression of covariance between the MTC device m_i and m_j evaluated based on (Vuran et al. 2004) with the position of coordinates C_i and C_j respectively is given by

$$\mathrm{cov}(m_i, m_j) = \sigma_i \sigma_j corr(m_i, m_j) \tag{1}$$

Furthermore, we can simplify as

$$corr(m_i, m_j) = \frac{E(m_i, m_j)}{\sigma_i \sigma_j} = K_\vartheta(\|C_i - C_j\|) = K_\vartheta(d_{i,j}) \tag{2}$$

where $K_\vartheta(.)$ represents the correlation function with correlation parameter ϑ and $d_{i,j}$ denotes a Euclidean distance between the MTC device m_i and m_j. Moreover, we assume that, the $K_\vartheta(.)$ associated with the data collected by m_i and m_j as w_i and w_j respectively. Based on the characteristics of correlation structure, various kinds of covariance models are proposed in (Berger et al. 2007) such as Power Exponential, Rational Quadratic, Matern and Spherical. Specifically, in this paper, we use Power

Exponential to define the correlation function corresponding with the distance between the MTC devices given by;

$$K_{\vartheta}(d_{i,j}) = \exp\left\{-\left(\frac{d_{i,j}}{\vartheta_1}\right)^{\vartheta_2}\right\} \tag{3}$$

where $\vartheta_1 > 0$ and $\vartheta_2 \in (0,1]$ denotes the limitation of controlling parameters of correlation and smoothness of a given random field. In this paper, we take the value of $\vartheta_2 = 2$ and then the correlation coefficient for device m_i and m_j expressed as

$$K_{\vartheta}(d_{i,j}) = \rho_{i,j} = \exp\left\{-\left(\frac{d_{i,j}^2}{c}\right)\right\} \tag{4}$$

where $c = \vartheta_1^2$ denotes exponent which control the degree of the correlation between the devices. Thus, we can compute the correlation matrix for N devices expressed as

$$K_{corr} = \begin{pmatrix} \rho_{1,1} & \rho_{1,2} & \cdots & \rho_{1,N} \\ \rho_{2,1} & \rho_{2,2} & \cdots & \rho_{2,N} \\ \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & \rho_{i,j} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{N,1} & \rho_{N,2} & \cdots & \rho_{N,N} \end{pmatrix} \tag{5}$$

The above matrix gives overall correlation existed between the devices and when the value $\rho_{i,j} = 0$ two devices are far away from each other not spatially correlated and $\rho_{i,j} = 1$ two devices are very close each other which high spatially correlated.

MTC devices Grouping Technique

In order to utilize the limited computation resources in smartphone we group the MTC devices according to the spatial location, since the device in one group may contain the similar data and thus we characterized that, the two devices are correlated. Therefore, we can reduce the computational cost of the system by processing the correlated devices together in either local or remotely

The grouping technique of MTC device consists of two stages; the first stage is to find the distance or similarities between devices and then grouping using the clustering algorithm. In this study, we use two clustering algorithms to describe the details of grouping technique includes k-means and hierarchical algorithm.

K-Means MTC devices grouping

The k-means algorithm commonly used to partition data set automatically into K disjoint groups (Paek, J and Ko J 2017). It continues by initialized K cluster centers and then iteratively to rectifying them. Given a MTC devices $M = \{m_1, m_2, ..., m_N\}$ randomly distributed at XY plane, the objective is to group into clusters which are closed to initialized centroid. We assume number of clusters or groups is randomly chosen as K and the centroids chosen among the devices and then the k-means similarity measured according to Euclidean distance defined as:

$$d_c(C_i - \mu_g) = \|C_i - \mu_g\|^2 \tag{6}$$

where C_i denotes the location coordinate of device m_i and μ_g represents the coordinate of initialized cluster centroid. In every iteration, each device assigned to a group with having minimum Euclidean distance. Then the centroid is updated using currently associated devices, which expressed as

$$\mu_g = \frac{1}{|S_g|}\sum_{j \in S_g} C_j \tag{7}$$

where S_g denotes the number of devices of current group or cluster.

Algorithm 1: K-Means MTC Device Grouping Technique

Input: Number of group; K
Location coordinates of device; $C_1, C_2, ..., C_N$
Output: Number of devices in each group; S_g
Random initialization for k-means group centroids; $\mu_1, \mu_2, ..., \mu_K$
$S_g = \varnothing$
repeat
for $i = 1 : N$ **do**
for $g = 1 : K$ **do**
compute $d_c(C_i, \mu_g) = \left\| C_i - \mu_g \right\|^2$
$U_g = \left\{ i : d\left(C_i, \mu_g\right) \leq d\left(C_i, \mu_l\right), l \neq g, i \right\}$
end for
$S_g = S_g \bigcup U_g$
end for
for $g = 1 : K$ **do**
$\mu_g = \frac{1}{\left| S_g \right|} \sum_{j \in S_g} C_j$
end for
until I iterations

Antenna Array

Hierarchical MTC Device Grouping

A part from the K-means which known as a nonhierarchical clustering algorithm, we use a hierarchical clustering algorithm called weighted average linkage (WAL) which generate number of groups by margining a small group (Sokal R.R 1958). WAL is a bottom-up hierarchical clustering algorithm in which at each iteration two nearby group (cluster) for instance G_1 and G_2 will merge to form a new group, let say G_3. Then, the actual distance between new group and another group G_g will obtained as

$$d_{3,i} = \frac{1}{2}\left(d_{1,i} + d_{2,i}\right) \tag{8}$$

At the beginning, each device forms an individual group and then we use the above operations to merge each group until we obtained the target number of group. The **algorithm 2** shows the details. After forming the groups based on the spatial correlation between MTC devices, we can obtain the correlation matrix of each group by using expression 5.

Algorithm 2: WAL MTC Device Grouping Technique

Given Number of group K and the set of devices $M=\{m_1,m_2,...,m_N\}$,
begin with each device to form a group
for $i=1:N$ **do**
  for $j=1:N$ **do**
Compute pair-wise distance between the MTC device using expression (6)
end for
end for
while Number of the groups bigger than K **do**
Find and merge a groups with maximum distance
Compute pair-wise distance between the MTC device and update a group using expression (8)
end while

Computation Model and Problem Formulation

When the data from MTC devices processed locally or remotely, the energy consumption evaluated by the overall workload of CPU capability, and clock frequency (CPU cycle per second). In general, the CPU capability measured by the number of CPU cycles allow computational resources to be reserved for required application or task, represented by β and depicted with the size of the input data size or task required to be processed which denoted as λ. After receiving data from MTC devices a smartphone grouping according to spatial correlation, and then decides whether a group should be processed locally at smartphone or offloaded to the MECS. As we assume the data sensed by the MTC device follows the multivariate Gaussian distribution, then we adopt the idea of information entropy to measures the size data between the MTC devices (Cover T.M. 2012). Then, we utilize the differential entropy instead of entropy because we assume the data collected by MTC devices are quantized with a similar quantization size as $\Lambda=\{\Lambda_1,\Lambda_2,...,\Lambda_N\}$. Hence, the entropy of the multivariate Gaussian model given by

$$h(W)=\frac{1}{2}\log\left[(2\pi e)^N|K_N|\right] \tag{9}$$

where $|K_N|$ denotes the correlation matrix for N MTC devices. Then, we use entropy framework to model the size of the data contains in each group. Therefore, the entropy $H(\Lambda_g)$ of the set of data $W^{\Lambda_g}=\{w_1^{\Lambda_1},w_2^{\Lambda_2},...,w_1^{\Lambda_{N_g}}\}$ of each group expressed as

$$H(\Lambda_g)=\frac{1}{2}\log\left[\left(\frac{2\pi e}{\Lambda_g}\right)^{N_g}\left|K_{N_g}\right|\right] \tag{10}$$

where N_g denotes the number of MTC devices contains in each group and Λ_g represent the average size of the data collected by each MTC devices in a group g. Based on the expression above we obtain the size of the input data for each group.

Local Execution

For the local computing (smartphone), the energy consumption and processing time for the group i denoted as E_i^l and T_i^l respectively as it represented in (Dinh et al. 2017). Then, the processing time is expressed as

$$T_i^l=\frac{\beta^l\lambda(i)}{f_i^l} \tag{11}$$

where f_i^l denotes clock frequency of the local at smartphone, $\lambda(i)$ denotes the size of input data of group i that obtained using expression (10) and β^l represents computation capability at a smartphone. The energy consumption for group i expressed as

$$E_i^l = k(f_i^l)^\varsigma T_i^l \qquad (12)$$

where $k(f_i^l)^\varsigma$ denoted as power coefficient at smartphone and k is constant which depends on the architecture of the switched chip capacitance. In addition, the parameter ς denoted as constant frequency exponent with the value $\varsigma \geq 2$ (commonly the value is approximate to 3) (Gerards et al. 2015). In our study we use $\varsigma = 3$. Since the computation resource at the local is limited, some groups will be offloaded to the MEC server. Then, we let $f_{\max}$ as available computation resource at a smartphone (local) that means $f_i^l \geq f_{\max}$ the group i is offloaded.

MECS Execution Analysis

In MECS or remotely execution, the processing time consists of uplink and downlink transmission delay and the execution delay of the data. We ignore the downlink transmission delay because the size of output results is much less compared to the input data (Zhang et al. 2013). The expression of uplink transmission delay is defined as

$$T_i^{tr} = \frac{\lambda(i)}{R} \qquad (13)$$

where R denoted as transmission rate of the channel which expressed as

$$R = B\log(1+\gamma P^{tr}) \qquad (14)$$

where B represent a channel bandwidth allocated for smartphone and P^{tr} denotes the smartphone transmission power and γ denotes channel gains which normalized by white Gaussian noise power. Then the energy consumption for transmission expressed as

$$E_i^{tr} = P^{tr} T_i^{tr} \qquad (15)$$

In addition, the processing time at MEC expressed as

$$T_i^s = \frac{\beta^s \lambda(i)}{f^s} \qquad (16)$$

where f^s and β^s denotes the clock frequency and the CPU capability of the MEC server and $\lambda(i)$ denotes the size of the input data of a group i. Therefore, the offloading time for smartphone, T_i^o is given by

$$T_i^o = T_i^{tr} + T_i^s \qquad (17)$$

Offloading decision process

The priority-based data offloading decision provided to stabilize the energy consumption for all the possible area where the data from MTC devices can be processed. The proposed offloading decision identified by two key parameters namely as required computation ability (CPU cycles per second), f_i and size of the data obtained after grouping λ from expression (10). Then, the offloading function formulated as

$$\eta(i) = \frac{\lambda(i)}{f_i} \qquad (18)$$

where $\eta(i)$ denotes the offloading decision evaluated on the smartphone, when the value of $\eta(i)$ is higher, then the smartphone does not have enough computation ability to process the data or the size of the data is big compared to the computation ability, then the data is offloaded to MECS.

Problem formulation

With referring to the expressions above, we define the optimization problem of smartphone as total energy consumption for processing MTC devices after grouping based decision policy z_i which is formulated as

$$\min_{z_i} \sum_{i=1}^{K}\left(\left(1-z_i\right)E_i^l + z_i E_i^{tr}\right) \text{ such that}$$

$$C1: \sum_{i=1}^{K}(1-z_i)T_i^l \leq T_{\max}$$

$$C2: \sum_{i=1}^{K} z_i T_i^o \leq T_{\max}$$

$$C3: \sum_{i \in K} f_i^l z_i \le f_{max}$$

$$C4: \eta(i) \le \frac{\lambda(i)}{f_i}, i = 1, 2, ..., K$$

$$C5: z_i \in \{0,1\}, i = 1, 2, ..., K$$

where constraints $C1$ and $C2$ denotes the completion time for computing in each group and $C3$ denotes limited computing frequency at local which can decide whether the group offloaded or not, $C4$ represents offloading decision of data from group and $C5$ denotes a computation decision variable, which achieved by determine the minimum energy consumption of the group for either locally or remotely. T_{max} is control time for all the group to be processed and must not exceed the total processing time.

The above optimization problem is an integer-programming problem, which can be solved using several heuristic approaches such as dynamic programming, generic programming, brute force or exhaustive search method and variable relaxation approach (linear and semidefinite programming relaxation). To find the efficient optimal solution to our problem we use the exhaustive search method.

Analyzation of the optimization problem

To analyse the performance of our proposed grouping technique, we present the exhaustive search method (ESM) to find the optimal solution, which is obtained from a finite number of iterations. According to the optimization problem, we use a binary number as a decision variable that provides the complexity of $o(2^K)$. In every iteration, we compute all the possible decisions and then we use constraints to find the optimal solution that provides the minimum energy cost. The summary of ESM is illustrated on **Algorithm 3**.

Algorithm 3: Exhaustive Search Method for Energy Minimization on Smartphone

Input: K, $E^l, E^{tr}, T^l, T^o, f^l$
for $i = 0 : (2^K - 1)$ **do**
$z = getDecision(i, K)$
for $j = 1 : length(z)$ **do**
if $z(j) == 0$ **do**
Local computation(smartphone)
else
Offloading at remote server (MEC)
end if
end for
Get the value of total energy cost
Validate the constrains
end for
Find the optimal solution of total energy cost
Output: E_{opt}, T_{opt}

Numerical results and analysis

In this part, we analyze the performance of the proposed grouping techniques based on the total energy cost consumed on a smartphone device on processing the data collected from MTC devices. We consider the sets of MTC devices are randomly scattered at $200m \times 200m$ region such as $[30, 40, 50, 60, 70, 80, 90, 100]$ and the smartphone device allocated at the center of the region. With referred in (Miettinen A. P. and Nurminen J. K. 2010), we assume the smartphone is N900 device having the maximum CPU frequency of $600MHz$ and CPU processing speed of $650 MegaCycle / bytes$. Furthermore, the computing power of N900 is $0.9W$ and the value of k is obtained as

$$\frac{0.9}{\left(600 \times 10^6\right)^3} = 4.1667 \times 10^{-27} J / cyc$$

The value of transmitted power of N900 is $1.012W$ with the range of frequency from $400MHz$ to $800MHz$ and channel bandwidth between the smartphone and base station is $185kHz$ with the channel gain of $18dB$. We assume base station is equipped with mobile edge computing server having CPU frequency of $6000 MHz$ and the processing speed of $960 MegaCycle / bytes$.

We evaluate the performance by comparing the total energy cost when the data processed in the three scenarios; if all the data processed at smartphone (locally only), at MECS (remotely only), and based on optimal solution obtained after analyzing the optimization problem. First, we discuss the results of k-means grouping technique based on energy consumption and the completion time of the when the number of MTC devices are random grouped into 4, and 7 with a degree of correlation of 0.05 and last we compare with WAL grouping technique.

Performance of K-Means Grouping Technique

In this technique, the MTC devices are grouped based on the number of the group or cluster chosen in randomly manner. The Figure. 2(a) and Figure. 2(b) shows the total energy cost versus the number of MTC devices based on different number groups. From both figures, the proposed exhaustive search method performs better compared with all the data collected from MTC devices processed either locally or offloading to the remote server. With the limited resources at the local, some groups will be offloaded to the remote MEC server that results on the alternating on the performance between the local and remote processing.

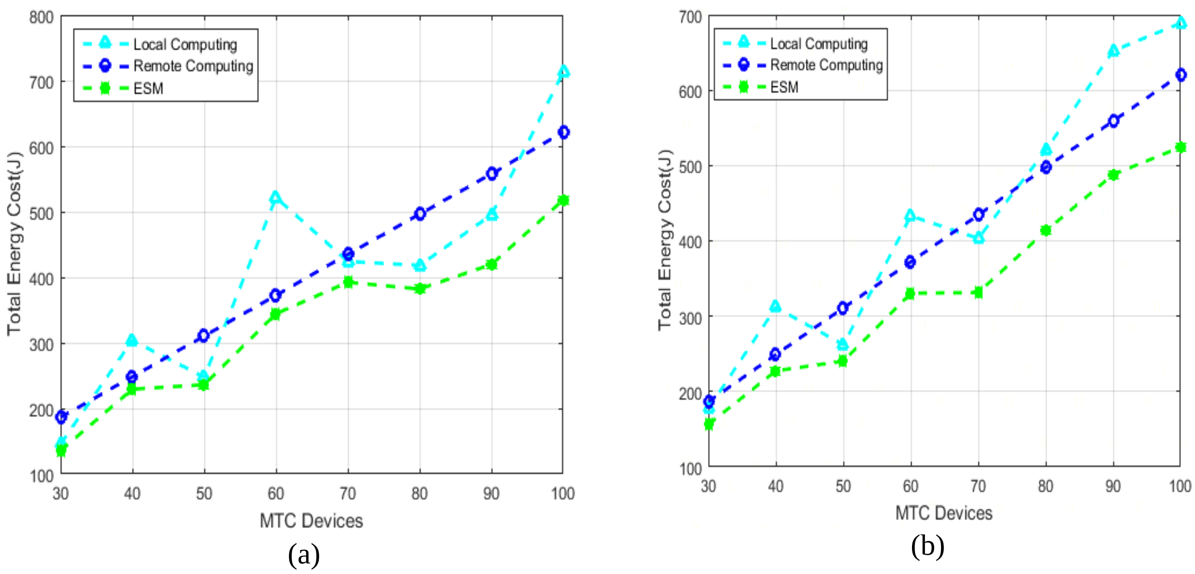
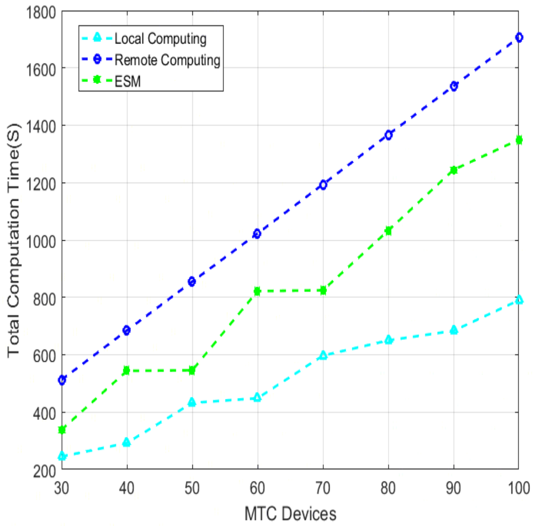


Figure 2: Energy cost for smartphone device when MTC devices grouped into different size (a) K=4, and(b) K = 7

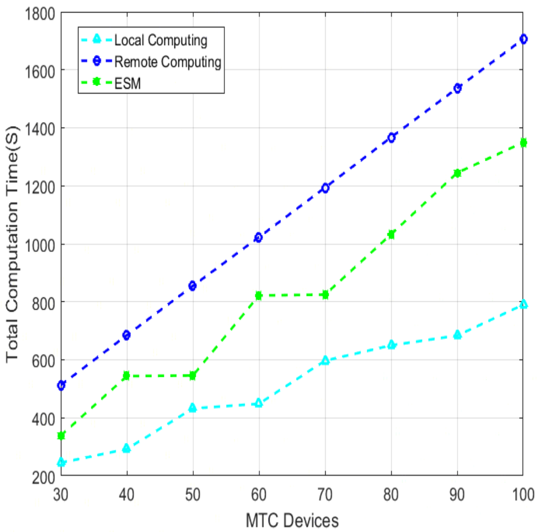
At the higher total energy cost at smartphone the remote computing more favorable to process the data collected from MTC devices.

From Figure. 3(a) and Figure. 3(b), represent the total computation time versus the number of MTC devices for three scenarios of a different number of groups. The results illustrated that local computing has a better performance compared to remote computing in all the scenarios because the smartphone is allocated nearby to the MTC devices compared to MECS. Furthermore, under the optimization constrains the Exhaustive search method it has a better performance compared to remote computing.

In Figure 4(a) and Figure 4(b)shows the variation between total energy cost and the computation time. Indeed, when completion time increases the number of groups to be offloaded decreases, thus decreases the total energy cost, which depends on the number of groups offloaded. As the number of MTC devices increases the performance of at MECS becomes close to the optimal exhaustive search method because a greater number of groups are offloaded.

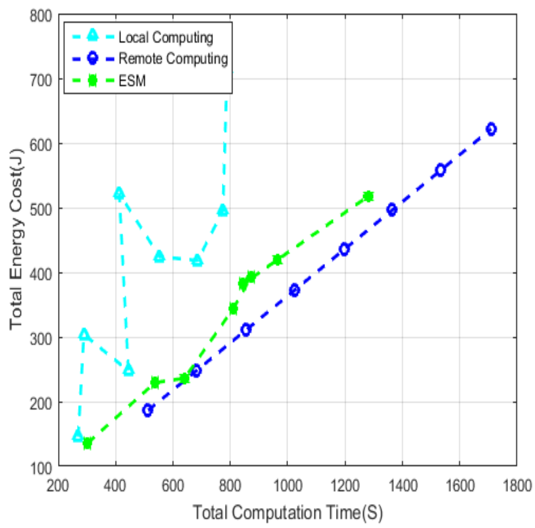


(a)

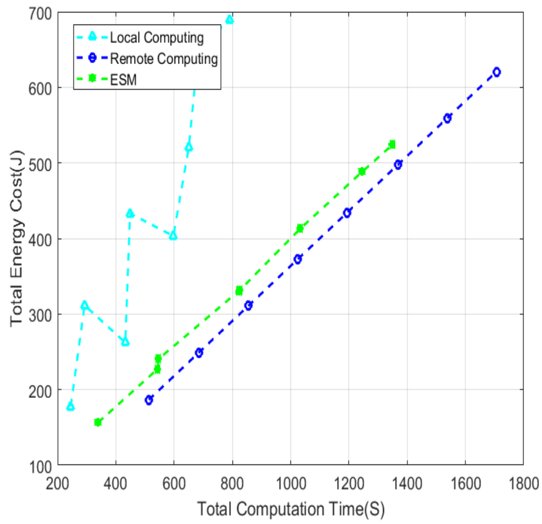


(b)

Figure 3: Completion time for the data processed when MTC devices grouped into different size (a) K=4 and (b) K = 7



(a)



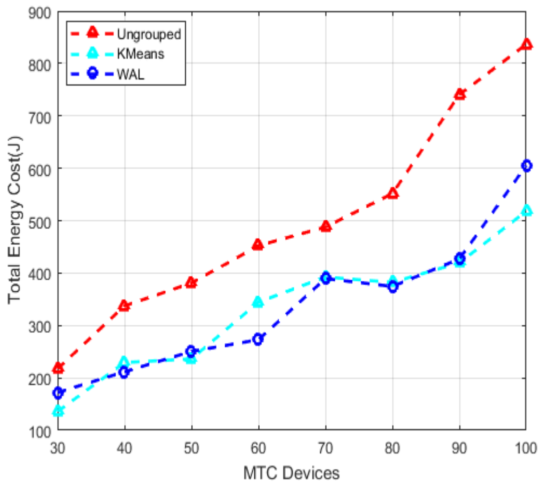
(b)

Figure 4: Variation between the Smartphone total energy cost and completion time when MTC devices grouped into different size (a) K=4 and (b) K = 7

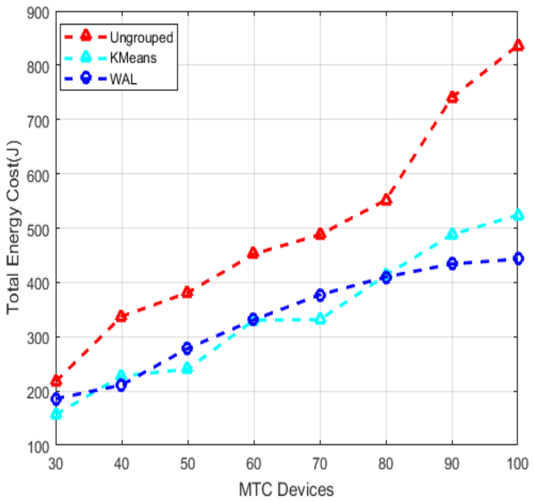
Comparison of grouping techniques

We compare two grouping technique with the ungrouped scenario in this subsection. The Figure 5(a) and Figure 5(b) shows the optimal total energy cost consumed by a smartphone with respect to number of MTC devices obtained using the exhaustive search method. The results indicate that the two proposed grouping techniques performs better compared with ungrouped technique.

Furthermore, as the number of group increases the WAL has low average energy cost especially as the number of MTC devices increases. Due to the random allocation of MTC devices on the region in every iteration affect the performance of the two grouping techniques are alternate on few numbers of MTC devices.



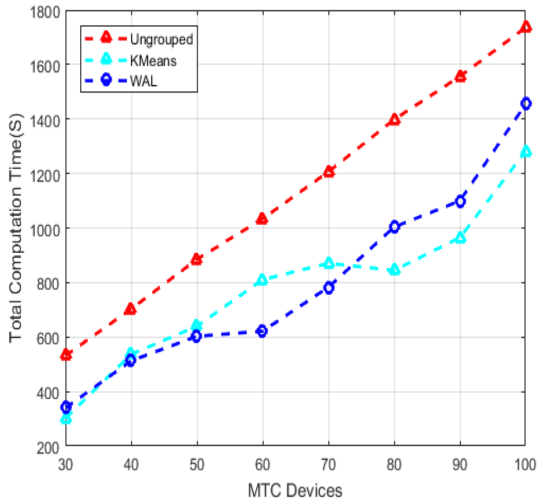
(a)



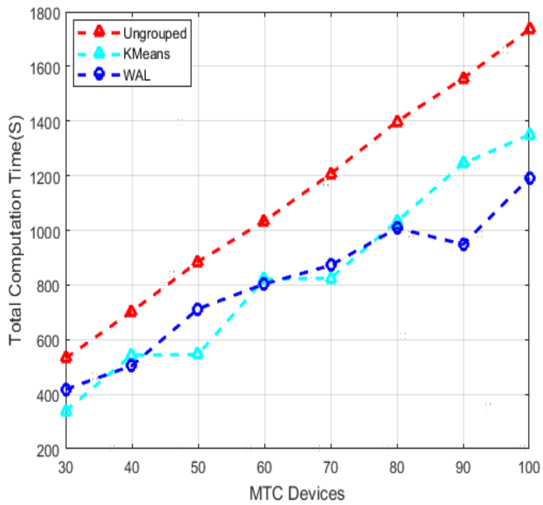
(b)

Figure 5: Comparison for total energy cost when MTC devices grouped into different size (a) K=4 and (b) K = 7

In Figure 6(a) and Figure 6(b) depicts the relationship between the total completion time obtained by solving the optimization problem. It observed that in all the plots the overall completion time of grouping techniques is much low compared to ungrouped. It is because of the size of data processed is much more significant due to reducing data redundancy. Besides, the grouping techniques at small number MTC devices their performance almost similar and as number MTC devices increase the average performance of WAL improved.



(a)



(b)

Figure 6: Comparison for completion time when MTC devices grouped into different size (a) K=4 and (b) K = 7

CONCLUSION

In this paper, we presented grouping techniques to reduce the data redundancy originated from correlated sources of MTC devices. Our objective was to minimize the total energy cost on the smartphone device, which containing both the smartphone energy cost and transmission energy due to the data offloading. We consider the two grouping techniques, the hierarchical (WAL) and nonhierarchical (K-Means) to group MTC devices based on the spatial correlation. Our numerical results illustrated that the proposed ESM approach provide optimal performance and achieves better performance compared with local computing or remotely computing.

Our current context is based on the single user and single mobile edge-computing model whereby the existing correlation among the MTC devices is stationary. In the future we will extends to the multi-user multi-MECS scenario and investigate, more complicated networks model for grouping techniques

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