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ARTICLE

Energy-Efficient Data Dissemination Approach Using Multiple-Criteria Decision Modeling for Internet of Things Environments

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ABSTRACT: The modern internet infrastructure has enabled numerous applications by providing a seamless connectivity experience across each mode of connectivity. Infrastructure-based connectivity and device-to-device (D2D) are well-known connectivity modes for internet-based applications. The selection of the underlying communication medium significantly affects energy consumption during data transfer. This study proposes an Energy-Efficient Data Dissemination Approach (EEDDA) that integrates encounter prediction with a multi-criteria decision-making (MCDM) framework to reduce infrastructure-based energy consumption in IoT mobility environments. Unlike traditional optimization approaches that focus on single-objective routing or static network models, the proposed framework dynamically selects between Device-to-Device (D2D) and Internet-based transmission based on delay tolerance, encounter probability, data size, and energy consumption metrics. Real mobility traces from the publicly available University of Southern California (USC) dataset were used for validation. Simulation results demonstrate that under high delay tolerance scenarios, the proposed approach achieves up to 70%–80% reduction in energy consumption compared to conventional Internet-based transmission while maintaining Quality of Service (QoS).

KEYWORDS: Internet of things; device-to-device communication; energy efficiency; multi-criteria decision modeling; delay tolerant network

1 Introduction

Smart devices are the digital core of our lifestyle enabling smooth, efficient ways to conduct everyday tasks. These devices have many essential features, including ease of use and environmental awareness, which lead consumers to consider them personal property rather than digital tools. In addition to the vast number of applications available for work, entertainment, and social networking, mobile devices provide many methods for connecting with the rest of the world, such as cellular networks, Wi-Fi, and ad-hoc mode, and these devices have become omnipresent, resulting in a lot of energy consumption [1]. These also involve several challenges including nodes in the networks consuming their resources [2]. The large number of such devices forms a dense network, refereed to as the Internet of Things (IoT), which comprises billions of devices and requires extensive energy consumption. Such a network also requires an efficient data dissemination mechanism that adheres to the joint quality of service (QoS) and energy consumption requirements of both network management and end-users. Such an IoT network is the backbone that enables a vast range of modern applications [3,4].

Energy usage depends on the energy used by nodes at both ends for transmitting and receiving, the amount of network equipment used, and the number of hops to the final destination. The energy consumption for data transmission via Device-to-Device (D2D) depends on the data volume, the sending and receiving sides [5]. Mobile and wireless networks are part of our lives. More and more people are using interactive networks to exchange a wide range of information. A Mobile Ad-hoc Network (MANET) is a decentralized, network-less infrastructure that dynamically connects wireless nodes [6]. Nodes communicate directly with nodes in their transmission range and interact with others through multi-hop communication. Such networks are rapidly gaining popularity due to their ease of integration. Due to the rapid economic growth influenced by industrialization and globalization, energy consumption has been steadily increasing [7]. Industry, transport, and buildings are the three main economic sectors that consume the most energy and account for the largest share of homes. In mobile ad-hoc wireless networks, energy consumption is a significant issue, as most mobile nodes operate on a limited battery power. The latest models for calculating energy use in mobile ad-hoc networks have shown that both transmission capacity contribute to various components of energy-related costs [8].

In a previous study, a random forest model was used to predict encounters among different users with cell phones [9]. The proposed work determines the exact location and time of the encounter with a specific node. The purpose of the previous study was to reduce the resources consumed by continuously searching for any available nearby node at which the encounter may occur. In a previous study, human mobility patterns were used to enable efficient, securing, and less resource-intensive data transmission. A random forest model stores the history of human mobility traces as trees for encounter prediction. For encounter prediction, the model first predicted the mobile user's future location and stored it in a decision tree within the random forest model. The encounter prediction was made based on data stored in the decision trees. The mathematical representation of the random forest model is also provided. The model showed how the trees grow as function of a random variable's value [10]. This study will present the Energy-Efficient Data Dissemination Approach (EEDDA) using multiple-criteria decision-making. The suggested approach will save energy more effectively by making multi-criteria decisions.

The University of Southern California (USC) traces are used for this research. A network infrastructure layout of a campus is depicted in Fig. 1, illustrating mobile devices as source that share data with a workstation as destination. The dense D2D network enables data sharing. The decision engine will help sustain Quality of Service (QoS) and save energy. The novelty of the work lies in the reduced resource consumption of proposed model. The key idea is to minimize infrastructure-based transmissions by making optimal use of device's mobility to enable follow-up among smart devices through short range D2D tethered communication in the Internet of Moving Things. Given the rich opportunities for mobile experiences, this study has been verified through a similarity analysis of real mobility traces, exist in human society. Hence, the research focuses on reducing energy consumption and sustaining the QoS.

The Random Forest encounter prediction model predicts future co-location events using historical mobility traces. The predicted encounter probability (EP) is then passed to the decision engine. The decision engine compares EP with the Delay Tolerance Indicator (DTI) and evaluates transfer-time constraints. If EP satisfies the DTI threshold and transfer time is within acceptable limits, D2D transmission is selected; otherwise, Internet transmission is used to preserve QoS. This layered integration between prediction and decision-making constitutes the core contribution of the EEDDA framework.

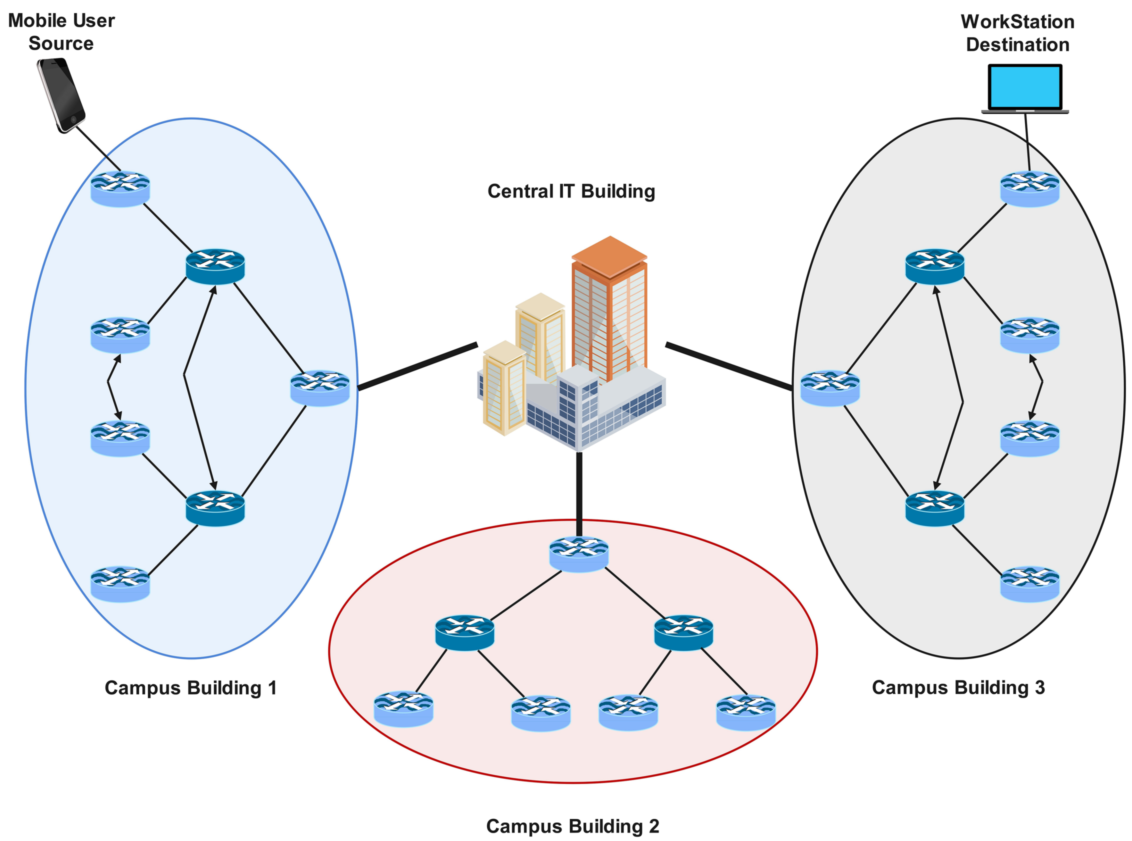

Figure 1: A campus network infrastructure information.

The core contribution of this study is as follows:

- We proposed an energy-efficient data dissemination scheme for densely populated campus comprising several mobile users following a particular mobility pattern in their daily routines.
- To incorporate mobility traces, we use the USC mobility data traces, which record the mobility history of each associated node.
- We incorporate multi-criteria decision modeling as a core decision engine to predict a mobile device's mobility encounter.
- We compared the energy consumption performance of device-to-device (D2D) and internet based data dissemination.

The remainder of this paper is organized as follows. The existing works and techniques for energy-efficient data dissemination are discussed in Section 2. The model energy-efficient data dissemination model is explained, along with its mathematical representation, in Section 3. The experiments, results, and comparisons with standard techniques are discussed in detail in Section 4 of Energy consumption model. Finally, Section 5 concludes the study.

2 Related Work

The conventional world has become a digital one, where almost anything can be accessed anywhere. The digital society, however, is responsible for high energy consumption. Several business sectors have benefited from emerging technology and technological developments over the last few years. The trend is toward developing more inventions to meet our daily demands. Yet another aspect to consider is their safe and effective use. Advances in technology, such as 3G, 4G, and 5G, offer advantages but also lead to high energy consumption [11]. The energy conservation theory has been introduced to cope with this situation. One of the main issues is reducing network infrastructure energy consumption through approaches, such as an energy-efficient data dissemination. In [12], the performance of various DTN routing protocols was evaluated while incorporating the mobility traces. The study shows that mobility traces provide robust information on user mobility pattern, enhance data delivery probability, and reduce the number of data packet replicas and average latency. The study illustrates performance enhancement for the BubbleRap, dLife Comm, and dLife protocol, with and without mobility traces.

Energy efficiency is of great importance to the research community, as it extends analysis to wireless networks in general and helps to cope with the continued growth of energy-demanding applications in scenarios with limited energy resources [13]. In particular, green radio solutions are being studied for potential wireless systems [14,15], and the base station side implements a discontinuous transmission mode (DTX) to reduce LTE communications use. In the LTE-A standard, the discontinuous reception/transmission (DRX/DTX) mechanism is also defined to allow devices to sleep when data to or from the base station is not being or transmitted. For MTCs over cellular infrastructures, this function is certainly of particular interest. Liang et al. [16] investigated, in particular, the DRX/DTX optimization to improve devices' sleep cycles and ensure service standards; however, no one has worked on multiple-criteria decision approaches.

The study proposed the optimal use of existing telecommunications infrastructure and infrastructure-less mobile social networking in proximity to transmit traffic with delay-tolerant features [17,18]. A network model is proposed to model the energy consumption problem and identify a more efficient energy solution. Experimental results show that D2D reduces energy consumption through multi-criteria decision-making. For this research, an experimental setup is used to obtain the results for the multiple-criteria decision energy model.

Zeng et al. [19] proposed a Generative Spatio-Temporal Graph Network (G-STGN) to predict mobility patterns in a vehicular environment. The proposed scheme effectively performs in motorway and urban environments and attains a significant learning performance in comparison to the five state-of-the-art base-line algorithms. In [20], a novel Spray-Learn-Wait routing protocol is proposed that utilizes clustering-based movement prediction, aided by reinforcement learning, to improve data dissemination in an opportunistic network. The proposed schemes outperform the Epidemic, FirstContact, and Prophet schemes in terms of mean delivery probability, mean message delivery latency, mean overhead ratio, and mean dropped and removed messages. Table 1 presents a comparison between existing schemes and our proposed scheme.

Table 1: Summary of the existing schemes.

Ref. No.	DTN Network	Mobility Traces	Encounter Prediction
[6]	Yes	Yes	No
[9]	No	Yes	Yes
[13]	No	No	No
[17]	Yes	No	No
[18]	Yes	No	No
[19]	No	No	Yes
[20]	Yes	Yes	Yes
Our	Yes	Yes	MCDM

In this study, the EEDDA uses multiple-criteria decision energy models. The model implements a multi-criteria decision, and based on the encounter prediction results, the node decides whether to transfer the data over the internet or D2D. Unlike prior work that focuses on DRX/DTX optimization, routing heuristics, or single-objective energy minimization, this research introduces a decision-layer abstraction that combines machine learning-based encounter prediction (Random Forest model) with a multi-criteria decision engine. Traditional optimization schemes such as shortest-path or minimum-cost flow models typically optimize a single metric (e.g., delay or energy) and assume relatively static network topology. However, IoT mobility environments are highly dynamic and require context-aware adaptive decision-making. The proposed MCDM framework simultaneously evaluates encounter probability, delay tolerance severity, transfer time, data size, and energy consumption, enabling a more flexible and adaptive energy-aware transmission strategy.

3 Proposed Methodology

This section provides a comprehensive explanation of the system model for an energy-efficient data dissemination approach.

The EEDDA uses multiple criteria to make a decision based on encounter probability results, the user's delay time, data transfer time, the sender and receiver's encounter times, and data size. Then the EEDDA will decide whether the data may be transferred through over the internet or D2D. The current system first uses the user's mobile phone (node) data traces collected at the building location via the App-based system to reduce energy consumption [21], serving as an encounter device. It will involve predicting encounter traces and IP address stability, then analyzing both. After that, the encounter device forwards them to the decision engine. Then, with the help of the decision engine, data will travel over the internet while maintaining QoS, or travel D2D, thereby reducing energy consumption. In the last phase, the Energy-Efficient Data Dissemination Approach (EEDDA), using multi-criteria decision-making, reduces energy consumption across the network.

In Fig. 2, the overall operation of the energy-efficient data dissemination approach examines the delay-tolerance indicator for the user who initiates communication by sending data. Next, the proposed multiple-criteria decision approach will check the encounter probability between the sender and receiver, then compare the encounter probabilities of both users, i.e., sender and receiver, with the delay tolerance index to ensure that both users, i.e., the sender and receiver, encounter within the given period. Finally, the approach will check the users' encounter time, i.e., sender and receiver. If the conditions are specified after confirmation, the model would decide whether to use D2D or the internet.

The USC mobility traces used in this study are publicly available anonymized datasets collected from Wi-Fi access logs on the University of Southern California campus. The dataset includes anonymized user identifiers, timestamps, and location transitions. These traces are used solely for encounter prediction modeling and energy-aware decision evaluation.

The use of Multi-Criteria Decision Making (MCDM) is particularly suitable for delay-tolerant IoT scenarios because network conditions, user mobility, and data urgency vary over time. Unlike classical optimization techniques that compute a static optimal solution, MCDM enables dynamic evaluation across multiple conflicting criteria in real time. This makes it more appropriate for environments where encounter opportunities are probabilistic and infrastructure energy costs are variable. Therefore, MCDM provides a robust framework for adaptive energy-efficient communication selection. It is also important to note that any node in the network is able to run the MCDM algorithm due to the lower computational complexity requirement.

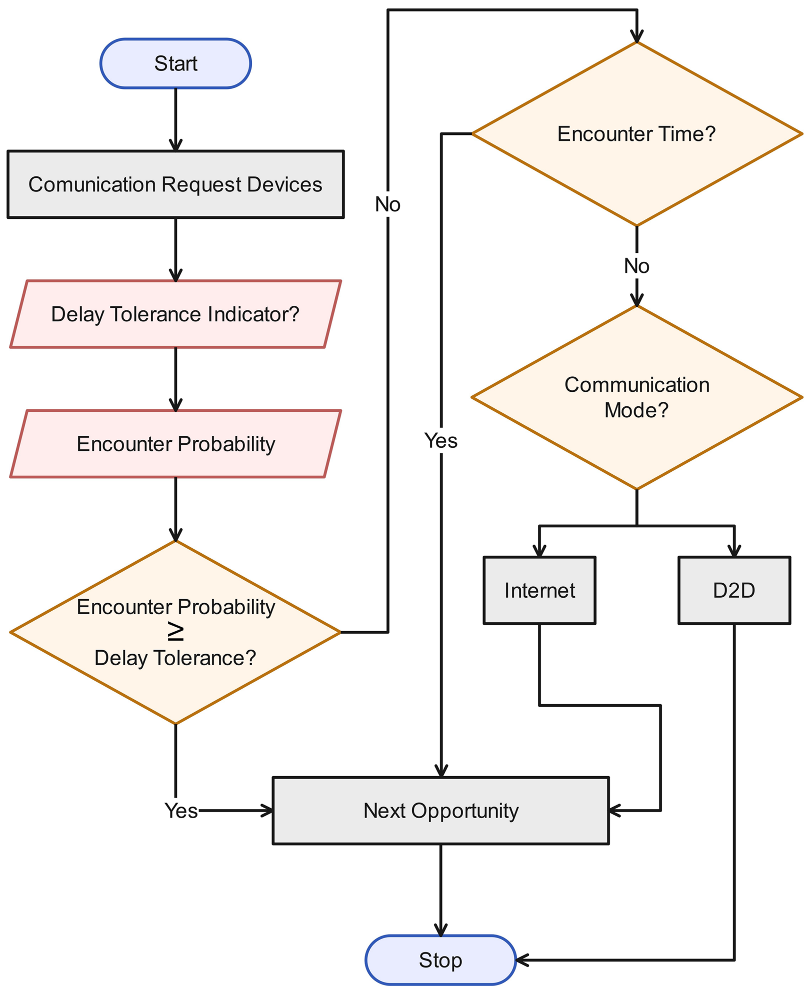

Figure 2: The overall working of the energy-efficient data dissemination approach.

3.1 Energy Consumption Model

To evaluate a more sustainable energy solution, a network model is used to represent the energy consumption problem. Let the network be represented as a directed graph $G = (N, L)$, where N is the set of nodes and L is the set of directed edges. The flow of objects between any two nodes i and j is represented by an edge (i, j), where $i, j \in N$. Each edge (i, j) has an associated potential and an energy consumption function $C_{i,j}$. Let $S \in N$ denote the sender node, and $x \in N$ represent a transmitting node. The available bandwidth depends on the network link capacity and is defined as U_{ij} for each link (i, j). Considering the demand and supply at each node, the values are represented as: $B_i < 0 \quad \text{(source node)}, B_i = 0 \quad \text{(relay node)}, B_i > 0 \quad \text{(destination node)}$.

For prototyping, we assumed a general, simplified energy consumption model for wireless or wired energy dissipation, in which the transmitter dissipates power to power the radio or line electronics. The power amplifier consumes energy to transmit traffic, and the receiver dissipates energy to receive and process radio or line electronics, as shown in Fig. 3.

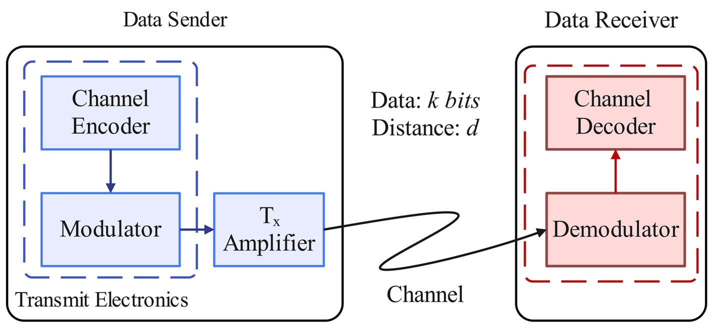

Figure 3: A general energy consumption model.

For example, in radio transmission, by appropriately setting the power amplifier, power control can compensate for signal propagation loss. For example, if the transmission distance is less than the threshold d_0, the free space propagation model is used with the attenuation parameter $\epsilon\ f_x$. Otherwise, the multipath (mp) propagation model is used with the attenuation parameter ϵ_{mp}:

$$E_{T_x}(k,d) = E_{T_{x-elec}}(k) + E_{T_{x-amp}}(k,d) \tag{1}$$

For the case of radio transmission:

$$E_{TT}(k,d) = \begin{cases} k \cdot E_{\text{elec}} + k \cdot \varepsilon_{fs} \cdot d^2, & d < d_0 \\ k \cdot E_{\text{elec}} + k \cdot \varepsilon_{mp} \cdot d^4, & d \geq d_0 \end{cases} \tag{2}$$

The energy consumed by the transmitter E_{elec} depends on variables such as digital coding, modulation, and signal filtering. The amplifier's power, the distance to the receiver, and the acceptable bit error rate depend on it. It is possible to measure the energy consumption of the data obtained by:

$$E_{R_x}(k) = E_{R_{x-elec}}(k) = k.E_{elec} \tag{3}$$

Based on the above general energy consumption model for communications, two significant and changeable factors will change the overall energy consumption. It is compared with the energy consumed by the electronic components and the signal-processing mechanisms in the transmitter, receiver, and relay amplifiers, as reflected in the amount of data k and the transmission distance. Is the transmission distance d traversed through the networks reduced? The shorter the transmission distance, the lower the electricity consumption. The minimum- cost flow issue across various data volumes is clarified, and lower energy consumption is observed when moving data between locations and nodes. To model the approximate wireless sensor networks (WSNs), a first-order radio energy model is deployed. Such an energy model mimic the several components of WSNs, such as electronic circuitry, distance effect, amplifier energy, and size of data being transferred over a short range. This model also resembles the machine-to-machine (M2M) communication.

3.2 Delay and Multiple-Criteria Decision Model Effect on Energy Consumption

A multiple-criteria decision model is used to select the preferred communication mode between two nodes. The multiple-criteria decision model considers communication traces to select the communication mode. The model chooses the mode for a specific time interval between the user, and after that specific time, the model will again decide the mode of selection between two devices. Each data point has a different sensitivity. Suppose the time interval in which data must be transmitted is increased. In that case, more users can be physically located in the same location so that the multiple-criteria decision model will select a device. To generating these plots, the USC dataset is used to store user traces in the form of ID, start time, end time, person, and location. The multiple-criteria decision model uses the traces of the users to select the optimal model of communication between them using their time and location during a specific time interval. The users are located in 6 possible locations and traces for seven days from Monday to Sunday. The traffic demand between the users is selected using a random sample of data from different users.

To calculate the impact of the delay, the EEDDA uses a multiple-criteria decision model that calculates the optimal way of transferring the data based on the prediction based on a specific time slot and location. Each data point has a different severity level, and some data needs to be transmitted immediately while others can be transmitted in several days. They showed how the delay affects the choice of network to data transfer and its impact on energy consumption. The multiple-criteria decision models will only allow one permissible connection between two nodes, as given in Eq. (4). Two nodes can transmit data either using D2D or through the internet. The EEDDA model ensures that only one connection between two nodes selects the optimal approach for transferring data via D2D or internet communication. The model use users traces to decide the mode of communication between users. The multi-criteria decision model will eliminate the selection of users' requests and also determine and also determine connection activation. A user can be either a D2D user or an internet user at any given time frame. Traceability information is needed for the multi-criteria decision model to select the mode of communication between two users at any given time interval. The decisions on the possible way of selection are made based on previous traces. If two users are not meeting in a given time frame, the model will prefer to send data over the internet. If they are expected to meet in a given time frame, the system will transfer the data between these users using the D2D approach to minimize energy consumption.

3.3 Energy Consumption Model for Device-to-Device and Internet

When sending data over the internet, it is submitted to the core network and forwarded according to the TCP/IP protocol, and, on the other hand, it is downloaded from the core network. Energy usage depends on the energy used by the transmitting and receiving sides of the nodes for downloading and uploading at both ends. The number of network devices used between routers/hops is used until the final destination. The delay value depends on the bandwidth used and the storage space available to carry data in Eq. (4); I_{nodes} is the power consumed by nodes for uploading and downloading.

$$I_{nodes} = max\left\{\frac{m}{b_1}, \frac{n}{b_0}\left(\nabla E_m + \nabla E_n\right)\right\} \tag{4}$$

where b_1 and b_0 are the bandwidth upload and download of the node that sends and receives. In our case, each node's upload and download bandwidth is 0.1 and 1 Mbits/s for uploading and downloading data to the internet. During data transmission, the difference in power consumption by a node is E_m.

$$C_{bit} = \frac{P_1}{b} \tag{5}$$

where n represents the number of bits being exchanged, b is the highest bandwidth used, and $P - 1$ is the maximum power extracted by a device. The incremental energy cost of one-bit transfer to model the energy usage of network equipment will also be considered.

$$I_{inc} = n \times C_{bit} \tag{6}$$

Also, the overall incremental transmission energy cost should be considered as the amount of node energy consumption and the total node energy consumption. Where k is the number of network devices used during the connection, in the EEDDA, suppose there are three switches, two core routers, and two edge routers in both places. Energy consumption can be estimated from Eq. (7), as each node's total energy and energy usage.

$$EE_c = I_{nodes} + \sum_{j=1}^{k} I_{inc1} \tag{7}$$

D2D communication technologies have recently been developed, and nearby smart devices can directly interface with each other to form a communication network. Instead of being transmitted through the devices, data traffic can be offloaded to D2D network infrastructures, such as base stations. For example, some users download substances from BSs by approving internet communications, while others might recover substances from their associates. D2D messages, along these lines, significantly reduce limit requests in BSs and also reduce BS energy consumption, calculating D2D energy data sent independently to N users, according to Eq. (8):

$$DD = R_f \times \left(U_p + \nabla_L T_{PX}\right) \times \left(\frac{S_{mbps}}{A_I}\right) \tag{8}$$

U_p = Minimum active power unit 130 W, R_f = number of radio frequencies 6, ∇_L = linear transmission dependence factor 4.7, S_{mbps} = Data size 20 Mbps, T_{PX} = Transmission power, A_I = Air interface 4.

Data size is another parameter that plays a crucial role in energy consumption during data transmission. The total energy consumption for a given number of bits equals the energy consumed by sending and receiving nodes, plus the energy used by all switching and routing equipment that route data between the two nodes. The total energy consumption can be calculated using Eq. (4), which gives us the energy consumption between two nodes. The parameters m and n specify the number of bits that need to be transmitted between two nodes. The incremental energy cost is given by using Eq. (6), while Eq. (5) provides the maximum energy consumed for a given bandwidth. The total energy for the communication between two nodes on the internet is calculated using Eq. (7). The energy consumption using D2D is calculated through Eq. (8).

3.4 Multiple-Criteria Decision Model among Traditional and Device-to-Device Network

The use of Multi-Criteria Decision Making (MCDM) is particularly suitable for delay-tolerant IoT scenarios because network conditions, user mobility, and data urgency vary over time. Unlike classical optimization techniques that compute a static optimal solution, MCDM enables dynamic evaluation across multiple conflicting criteria in real time. This makes it more appropriate for environments where encounter opportunities are probabilistic and infrastructure energy costs are variable. Therefore, MCDM provides a robust framework for adaptive energy-efficient communication selection.

Algorithm 1 shows the multiple-criteria decision model. Inputs of the multiple-criteria decision model are some variables which are declared at the start of the model which includes, Users denoted by u_1 to u_n, time encounter by user $EP(u)$, the maximum time to transfer denoted by T, Delay Tolerance Indicator (DTI) in days denoted by $DTI(d)$ and location of users denoted by $Loc(u)$. The output of our proposed multip-criteria decision model is the selection of the optimal data transmission mode, i.e., D2D or over the internet, between users. The output of the proposed model will be based solely on the values of defined variables at the model's first instance.

Algorithm 1: Multiple decision model

Require: Users = $\{u_1, u_2, \ldots, u_n\}$; Encounter Time (*ET*); Encounter Probability (*EP*); Maximum Transfer Time (TT_{max}); Delay Tolerance Indicator (*DTI*); Location ($loc(u)$)
Ensure: Optimal Network Selection
1: **while** true **do**
2: $u_1 \leftarrow DTI(d)$ {Check DTI for sender user}
3: $(u_1, u_r) \leftarrow EP$ {Check encounter probability between sender and receiver}
4: **if** $EP(d) \leq DTI$ **then**
5: Available$(u_1, u_r) \leftarrow t$ {Encounter possible within DTI}
6: **end if**
7: **for all** $U(u_1, u_2, \ldots, u_n) \in loc$ **do**
8: **if** $t \leq TT_{max}$ **then**
9: mode ← Data-Disseminate (s, d) using D2D
10: **else**
11: mode ← Data-Disseminate (s, d) using Internet
12: **end if**
13: **return** mode
14: **end for**
15: **end while**

Operations of the proposed multiple-criteria decision model are explained step by step below:

- First, the model will examine the delay-tolerance indicator for the user who wants to initiate the communication by sending data. Line 2 in Algorithm 1 illustrates the mathematical form of this statement.
- Next, the proposed multiple-criteria decisions will check the encounter probability between sender and receiver, as per line 3 of the algorithm.
- Line 4 of Algorithm 1 illustrates the comparison of encounter probability of both the users with delay tolerance index to ensure that both the users, i.e., sender and receiver, will encounter a given period. The encounter probability results extracted using the Random Forest Model.
- Line 5 in the multiple-criteria decision algorithm above will check the encounter time of both the users, i.e., sender and receiver.
- If the conditions specified above are met for all the users after confirming in line 6 and 7 of the Algorithm 1, the model would decide the mode of communication either by D2D or over the internet based on the following conditions.

4 Simulation Environment and Results

The model is simulated in a Python environment by establishing the entire model, comprising D2D and internet-based communication, incorporating the mobility traces. The simulation settings are presented in Table 2.

4.1 Simulation Results

The numerical studies compare energy consumption between D2D and the Internet. Effect of a multiple-criteria decision model on energy consumption as a function of data size, number of users, and delay.

Table 2: Simulation settings.

Parameters	Values
Environment	Python
Data Size (TB)	0.5–64
Number of Users	0–200
Delays (Days)	1–5
Number of locations	1–5
Node Buffer (MB)	2
Simulation Time (secs)	3000

4.1.1 The Effect of Data Size on Energy Consumption

To calculate the effect of varying data size on energy consumption, considering the EEDDA case study, where communication is done between two nodes. While assuming the number of nodes in Eq. (7) remains fixed, the effects of directly changing the data size on energy consumption can be seen. The data size is changed from 0.5 to 64 Tb, and the energy consumption for both the internet and D2D is calculated. Fig. 4 shows a comparison of energy consumption according to data with varying sizes. The experiment was performed for the same group of people. More energy is consumed when data is sent to the internet. This is because big data size requires more time and energy for uploading on the internet and then for transmission to the destination. In this, the sender and receiver's data is calculated with various data sizes, and the energy for both aspects, transfer through D2D and the Internet. Fig. 4 depicts that, as the data size increases, energy consumption in the internet is extremely higher than in D2D communications.

4.1.2 Effect of Number of Users on Energy Consumption

To evaluate the effects of an increasing number of users in terms of energy consumption, utilizing the growing number of nodes while keeping the data size fixed in both Internet and D2D communications. The effect of the increasing number of nodes is discussed in both cases. The number of nodes is increased from 10 to 200 in a campus scenario where users want to transfer data of varying sizes between them. Each user's energy is calculated and added to calculate the overall power of the users. The number of nodes and other parameters remains fixed for fair evaluations. As the number of users increased, the amount of energy consumption among them grew in an exponential form. The change in energy consumption in the case of D2D communication is lower as compared to the internet. The results of this case study are shown in Fig. 5. Normally, as the number of users increases, energy consumption for data transmission in the network is high, but it is still lower than that for internet data transfer.

Fig. 5 shows that 200 nodes transfer the data through D2D; then, how much energy will be used, and if the same 200 nodes send the data through the internet, how much energy will be used. These nodes randomly select the data size. Now, it can be seen that when ten users send data through D2D, 139 J of energy is used; when ten nodes send data through the internet, 684 J is used. It clearly shows that the internet consumes more than 1/3 of the energy that D2D does; even with 200 users, D2D consumes 6096 J, while the internet consumes 203 J simultaneously. This shows that D2D is more efficient.

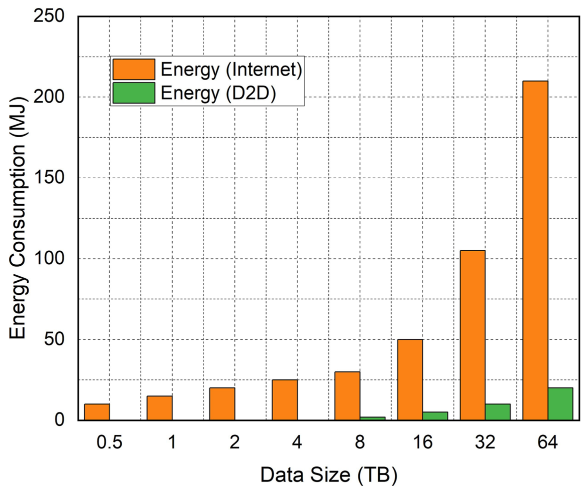

Figure 4: The comparative analysis of energy consumption based on data size.

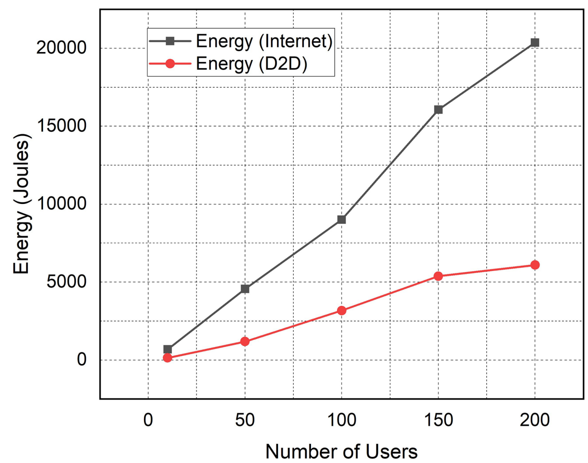

Figure 5: The comparative analysis of energy consumption based on no of users.

The results shown in Fig. 6 are from Algorithm 1; the multiple-criteria decision model determines the optimal communication mode for different user demands. For generating the result, the USC traces of the users are used. The user's data demands are fixed and consist solely of the user's traces. The results are generated under the assumption of 200 users. The data transmission delay is considered for days 1, 2, 3, 4, and 5. This comparison plot shows that as the delay increases, more data will transfer through D2D. A set of 200 nodes communicating the data to each other in random data sizes, based on multiple-criteria decisions to decide whether the data may transfer through D2D or the internet. On the 1st day, the ten users appear to be in the same physical location, transfer data via D2D communication, and consume 139 J of energy. The other 190 users are transferring the data over the internet, consuming 9990 J of energy. On the 2nd day, the 48 users can appear at the same location and transfer data via D2D, consuming 1183 J of energy. Other users are transferring over the internet, consuming 8049 J of energy. On the 5th day, 185 users can appear at the exact location and transfer data via D2D, consuming 6096 J of energy. The other 15 users are transferring the data over the internet, consuming 342 J of energy.

It shows that as the delay increases, the likelihood of D2D data transfer increases. If the data is not urgent, the delay option is better for transferring the data and saving energy without compromising QoS. The user modes are determined based on their traces, so to maintain QoS, our EEDDA-based model ensures data delivery over the internet. Based on this plot, the delay option is efficient, as it can transfer data via D2D while saving energy. The results concluded that the multiple-criteria decision model is an optimal approach when the severity of the data is low and can be transmitted over multiple days. More data will be sent via D2D modes, thereby optimizing energy consumption between users.

4.2 Energy Comparison Based on the Availability of Users at Each Location

The EEDDA model optimizes power consumption using a multi-criteria decision model to account for user availability at a specific location. For the case study, five locations are considered, each with 200 users who want to communicate with each other. After utilizing the multiple-criteria decision model for each location, assume different percentages of users are physically available at each location, such as location-1 having 45% of the total users; the total users available at location-1 are 90. Location 2 accounts for 55% of the total users; the total number of users available at Location 2 is 100. Location-3 has 70% of the total users; the total users available at location-3 are 140. Location-4 has 85% of the total users; the total number of users available at location-4 is 170; location-5 has 45% of the total users, total users available at location-5 are 190. Fig. 7 illustrates the energy consumption of the internet vs. D2D-based data transmission at different location.

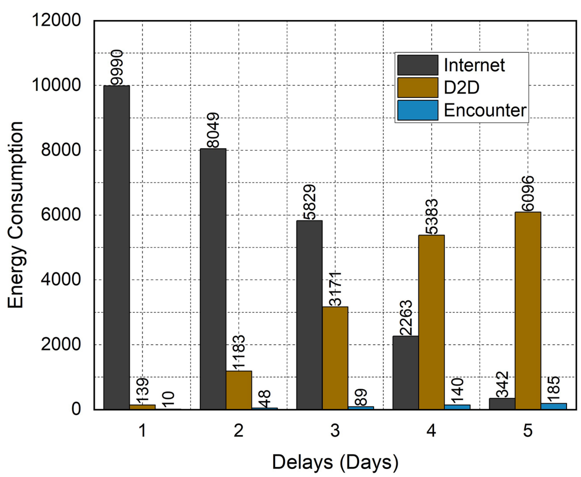

Figure 6: Energy consumption vs. delay.

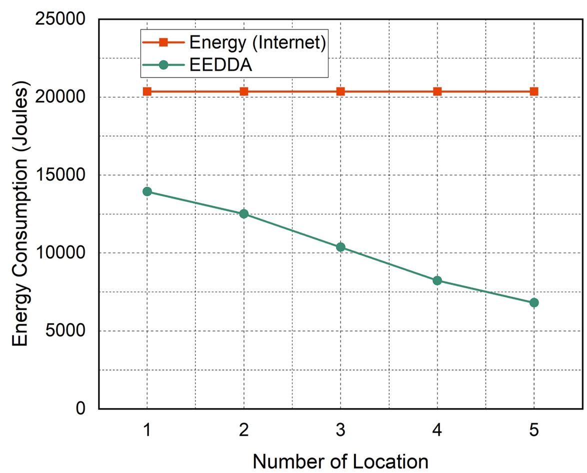

Figure 7: Energy consumption vs. location.

The proposed study evaluates the selection of conventional Internet and D2D communication for DTN-based data dissemination. The outcomes of the proposed study provide an insight to the benefits of shifting the data transmission over D2D for DTN-bases application, that highly conserve energy as well as maintain the QoS requirements. Additionally, this study highlights the significant benefits of incorporating mobility traces to reduce energy consumption, even under varying data sizes, locations, and numbers of users.

5 Conclusion

A new approach to multi-criteria decision-making for reducing energy use and maintaining service standards was proposed in this study. Our proposed EEDDA approach assess user availability and stability and determines network selection. Our EEDDA decides on a network (D2D or Internet) for data transfer based on user availability (location and time). The work best utilizes the existing telecommunications infrastructure, and infrastructure-less mobile social networking in proximity to transmit traffic with delay-tolerant features. The key idea is to reduce infrastructure-based transmissions by leveraging devices' mobility to prevent stalking among intelligent devices through short-range D2D tethered communications within the Internet of moving things. A case study and a mathematical model are presented to minimize energy consumption. The results show that the proposed model is more energy-efficient. The results are verified for both device-to-device and the internet connections. The case study mentioned in this study offers clear evidence that substantial energy savings can be achieved while ensuring data transmission. Additionally, the optimization model used in this study, such as MCDM, is readily applicable to other datasets with minor modifications, making it ideal for extending the proposed work to other environments and datasets.

In the future, we intend to explore several DTN routing protocols, such as Epidemic, Spray and Wait, probabilistic forwarding (PROPHET), MaxProp, and GeoSpray, to evaluate the performance of data dissemination approaches. Furthermore, we are motivated to extend this work across multiple datasets to improve the generalizability of future studies, as relying on a single dataset can limit evaluation.

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Availability of Data and Materials: Data openly available in a public repository, named as USC/Mobility dataset [21].

Ethics Approval: Not applicable.

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