AN EFFICIENT MOBILE DATA OFFLOADING SOLUTION FOR OPPORTUNISTIC NETWORKS

Thesis submitted in fulfilment for the requirement of the Degree of

DOCTOR OF PHILOSOPHY

by

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DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in the Ph.D. thesis entitled **"An Efficient Mobile Data Offloading Solution for Opportunistic Networks"**, submitted at **Jaypee University of Information Technology, Waknaghat, Solan (HP), India** is an authentic record of my work carried out under the supervision of **Dr. Shailendra Shukla and Dr. Amol Vasudeva**. I have not submitted this work elsewhere for any other degree or diploma. I am fully responsible for the contents of my Ph.D. thesis.

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SUPERVISOR’S CERTIFICATE

This is to certify that the work reported in the Ph.D. thesis entitled **“An Efficient Mobile Data Offloading Solution for Opportunistic Networks”**, submitted by **Prince Sharma** at **Jaypee University of Information of Information Technology Waknaghat, Solan - 173234, Himachal Pradesh, India** is a bonafide record of his original work carried out under my supervision. This work has not been submitted elsewhere for any other degree or diploma.

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Dedicated

To

My Family

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Prince Sharma

ABSTRACT

In the current trend of increased use of smartphones and dependence on the internet, viable mobile data offloading solutions are highly needed to deal with their data requirements. The internet is in fact accessible to everyone nowadays in the current decade, due to the comparatively lesser mobile data cost. It has proven itself to be a mandatory asset for a COVID-19 like pandemic situation. Its cost is expected to reduce further due to evolutionary network technologies. However, just like any electronically dependent architecture there are limitations to its capabilities too. In order to satisfy maximum set of users with less network traffic using minimum infrastructure costs, the use of offloading solutions has been encouraged. The most promising solution is the empowerment of opportunistic communications using either extra infrastructure or the use of existing structures. But, the cost involved in upgrading of existing infrastructure is very high. Thus, the use of mobile data offloading using the available users offers a better solution. It enables the Mobile Network Operator (MNO) to deal with the explosive cellular data needs by leasing their capabilities. The existing literature survey suggests optimizing the mobile data offloading solutions at different levels. The problem of selecting the optimal offloaders has been identified to be NP-hard and is termed as Target Set Selection (TSS) problem. We aim to derive an optimal solution for TSS identification using hybrid opinion dynamics. The effectiveness of trust is also investigated for optimizing the results for TSS as well as for incentive derivation. We end up with Nash equilibrium-based game theoretic approach for incentive distribution in the network. The major contribution can be summarized as realizing mobility parameters in TSS, determining the optimal users for mobile data offloading. It is achieved using opinion dynamics contribution and trust-based optimization for appropriate incentive distribution amongst users. The incentive needs to be distributed in such a manner, that maximum users get activated at the earliest. In this thesis, an extensive research has been carried out to study the mobile data offloading solutions for opportunistic networks. An opportunistic network using feasible device-to-device (D2D) has been proposed offering an energy efficient solution to deal with the problem of growing data traffic amongst users. The study has been carried out to offer secure mechanism for efficient data offloading in an opportunistic network with less time delay, less

energy consumption, higher fault tolerance and optimum incentive distribution. The incentive is justified by the concept of Nash equilibrium. The overall major idea is based on the concept of using Hebbian learning principle for determining optimal offloaders with reasonable incentive. The overall contribution can be summarized as an efficient mobile data offloading solution for opportunistic networks.

LIST OF ACRONYMS & ABBREVIATIONS

Acronyms & Abbreviations

2G	Second Generation
3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
AA	Approximation Algorithm
AFOCS	Adaptive Finding Overlapping Community Structure
AI	Artificial Intelligence
AP	Access Point
API	Application Programming Interface
BLE	Bluetooth Low Energy
COVID-19	Coronavirus disease-2019
D2D	Device-to-Device
DBOCD	Dynamic Bayesian Overlapping Community Detector
DOA	Dynamic Offloading Algorithm
DTN	Delay Tolerant Network
FMOCO	Four-stage multi-user offline computation
FTSS	Final Target Set Selection
GA	Greedy Algorithm
IoT	Internet of Things
IP	Internet Protocol

ISP	Internet Service Provider
LTE	Long Term Evolution
MANETs	Mobile ad-hoc Networks
MATLAB	Matrix Laboratory
MIT	Massachusetts Institute of Technology
MNO	Mobile Network Operator
NETWORKX	Network library in Python
NMI	Normalized Mutual Information
NP-hard	Non-deterministic polynomial-time hardness
NUS	National University of Singapore
OA	Optimal Algorithm
ONE	Opportunistic Networking Emulator simulator
ONE	Opportunistic Network Environment simulator
OSNs	Online Social Networks
QoS	Quality of Service
RSSI	Received Signal Strength Indication
SAIS	Similarity Attraction and Infrastructure Support
TSS	Target Set Selection
UIM	University of Illinois Movement
VCG	Vickrey-Clarke-Groves
VDTNs	Vehicular Delay Tolerant Networks
VIP	Very Important Person
WiFi	Wireless Fidelity
WTSS	Weighted Target Set Selection

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CHAPTER 1
INTRODUCTION AND MOTIVATION

1.1 Introduction

The use of smartphones, Internet of Things (IoT) enabled devices, and their dependence on the internet creates substantial mobile data traffic. The trends show the evolution of more intelligent mobile devices, the high impact of advancing cellular network technologies, IoT adoption, the ability to analyze the WiFi coverage, the identification of newer mobile applications, and network speed improvements [1]. With the rising population, it is expected to have 15 percent more internet users in the year 2023 in comparison to the year 2018 [2]. Although the average mobile speed is also likely to climb up to 58 Mbps compared to 22 Mbps in the same respective years, keeping the mobile infrastructure costs in check is a challenge. There is a continuous evolution of mobile networks. The upcoming years are expected to be critical for network operators and service providers. They need to plan the network deployments with suitable environments considering the vast need for mobile-enabled devices and future applications. At the same time, the data traffic is also expected to reach nearly 924 Exabyte by the year 2022 [3]. Mobile data offloading offers an effective solution to meet such needs of increasing data traffic. The use of multimedia applications in day-to-day activities leads to an exponential rise in data traffic. The communication revolution has contributed significantly towards all aspects related to the technological evolution of mankind in recent decades. It lays the foundation of emerging novel fields related to IoT, machine learning, data science, cloud computing, data pre-processing, smart agriculture, social network analysis, etc. The current trends render the application of more optimal data offloading strategies. The present research focus includes improvisations for upcoming 5G and 6G communication enabling several services with higher system capacity, massive device connectivity, high security, extremely high quality of service, low latency, and less energy consumption [4]. The contribution of mobile data offloading becomes more significant when users have similar interests. Its significance rises furthermore when the data requirements are more delay tolerant. Also, the implementation of offloading scheme needs to keep pace with the rate of increase in mobile data traffic.

The users can be classified according to their network heuristics, which forms social network analysis. But, such network analysis using graph-based models restricts the networks to be more static than being mobile. Hence, such models need to overcome the unrealistic assumption using time-dependent analysis considering their mobility aspect. At the same time, delay tolerance of networks should also be considered [4]. A detailed study to identify such research gaps has been carried in the following chapter.

This thesis has tried to realize a mobile network with limited delay tolerance [5] using dynamic behavior-based characteristics of users [6]. It helps us derive an efficient mobile data offloading scheme that enables a limited set of users as helpers or offloaders. Our scheme uses opinion-based trust derivations to propose optimal offloading in opportunistic networks. The opportunistic networks are the ones that build up a community using some mode for communication for some fixed instance [7]. We also derive an optimal incentive framework using the trust-based characterizations of the network users. Finally, we have tried to prove it on the basis of simulation results using the state-of-the-art dataset.

1.2 Genesis of problem and solution motivation

The era of digitization enabled with the use of digital devices like smartphones encourages higher dependence on the internet. The use of virtual environments in the COVID-19 like pandemic situations enhances this need further. For example, consider a scenario where a conference schedule or demonstration needs to be circulated among many people within a limited geography. Thus, the traditional methodology is that they may opt to go about the schedule using their own mobile data. Such an approach would incur a cost of individual data units' times the number of people. However, assuming the limited geography feature pertaining to delay-tolerant similar interest-based items, there may be a smarter way to do it. In an efficient implementation, if some volunteer in their community who is trustworthy enough to provide the same schedule just by sharing its alternative cache, the extra data traffic might be reduced. This might incur an extra cost of energy consumption. However, this might result in the reduction of significant energy costs involved at the end of Internet Service Provider (ISP). Moreover, the ISP can distribute this load towards alternative traffic routes satisfying other users. In reply to offering help using their resources, the ISP may offer an alternative incentive for such helpers in the form of data coupons or monetary benefits. This incentive must be distributed in such a manner so that the entire cost of the network traffic is minimized, and it should encourage the participants to offer their offloading capabilities also. The decision of incentive distribution should not be limited to specific users, avoiding the network being partial.

Lack of mobility consideration

Most of the literature considers unrealistic models for determining the heuristics to determine network associations. The greedy methods use static graphs for network analysis. The graph nodes may represent users, and edges may provide relationships in a social network [8]. However, the sub-graphs may overlap and might need prioritization in correspondence to multiple relationships about different attributes. The network heuristics to consider multiple communities is ignored in the majority of the literature work. The greedy approaches tend to be partial concerning limited attribute-based associations, whereas most attributes' significance gets ignored in such circumstances. The mobility aspect is difficult to model for more extensive networks.

Randomness in the network

The graphs-based analysis generally used in network associations ignores the randomness in the network. The graphs in realistic models are dynamic. The attributes are limited to the opinion of the user or the access point only. However, the collective impact of communities [5] together could impact the network stability. It is not only the behavior between the user and the access point, which needs addressing but the user-to-user behavior could also be addressed in terms of opinion dynamics amongst users. This behavior is also evolutionary, which renders randomness in the network. Thus the network could be analyzed using opinion metrics amongst users.

Security of data offloading solutions

All the users in an opportunistic network are not trustworthy. There is a probability of malicious nodes that may reveal false or incomplete information and may raise security concerns. Such users need to be addressed for being trustworthy or non-trustworthy in order to address secure data forwarding. Although it can be handled using appropriate network protocols, appropriate offloaders persist because some network users are unwilling to share their information with others. The bandwidth and cache leasing is also significant to design appropriate reimbursement schemes. Therefore, we need to reduce the overall cost for serving mobile data requests. It can be helped by leasing the resources using an appropriate and secure mechanism for the joint optimization of routing policies.

Partial incentive distribution

The users would feel anticipated to participate voluntarily for want of incentive. The literature includes few incentive schemes, which are mostly partial, with few of the users given the entire privilege to decide upon the incentive distribution. Such mechanisms may become partial to observe the optimal incentive schemes. Most of the schemes involve the foundation using bi-directional decision-making in between the data requirements and rewards, just like the salary-bonus scheme. The incentive should not be uniform for all the offloaders; instead, it should depend upon their extent of participation in the offloading truthfully. The modeling of the users' behavior is also difficult to address the technical issues and economic issues involved in incentive derivation. Some literature-based models address the prospective limited only to Mobile Network Operator (MNO) or the Access Point (AP) but fail to manage it for the users.

1.3 Problem statement

There is a need to determine all possible solutions for mobile data offloading in all kinds of opportunistic networks. The primary concern is to check the feasibility of such offloading alternatives over realistic environments. Such opportunistic communications should satisfy all or maximum of the users so that the overall traffic is minimized considering the mobility aspect of users [7]. At the same time, is it possible to meet the energy requirements with no or minimum delay tolerance? If yes, then how can this be optimized using only a limited set of users? Another problem related to optimization is the discovery of secure users in the network. How can we deal with the security tradeoff with optimal offloading? Limiting the size of the target set of such offloaders will surely improve the throughput of the network, but what should be the size limit of such sets? The question here is how to detect the malicious users in the network? If such non-malicious users are identified, what should be the amount of incentive offered for such users? Should the incentive be uniform for all users? Or do they need to be rewarded according to their extent of contribution towards offloading in a network?

1.4 Objectives

The following list of objectives has been enlisted on the basis of the above problem statement. We have oriented our thesis work towards the achievement of following goals in this research work.

1.4.1 To optimize the target set using opinion dynamics. This could be done by observing the opportunistic communications among the ISPs and users.

1.4.2 To determine the energy efficiency and buffer management in the target set. The optimization needs to consider the opinion dynamics of users. This can be achieved by exchanging summary vector messages.

1.4.3 To determine the solution of the TSS problem using hybrid coordination of access points and the network users. It could be achieved by determining common interest-based classification and neighborhood determination.

1.4.4 To determine trusted TSS and its appropriate incentive. The optimization should be securely based on trust derivations of trustworthy and untrustworthy users. Therefore, the incentive determination approach should consider the aspect of offloading based on secure trust-based derivation.

1.5 Implemented methodology

A detailed survey of offloading algorithms [6] has been carried out to identify the impact of offloading, followed by identifying research gaps within. The state-of-the-art datasets were selected for realistic network modeling. The datasets were pre-processed according to the parameters which determine the effectiveness of data offloading solutions. Finally, on the basis of research gaps, we have determined the above-mentioned objectives.

The overlapping sets of communities [9] are defined with their deterministic boundaries, and a hybrid of the greedy and heuristics-based metrics are explored to achieve initial target sets. Such moderation helps to check the impact of using a hybrid approach for data offloading. The modeling was tested over MATLAB, and the results were compared with greedy, heuristic, and community-based methods. Finally, a collaborative process of the users and Access Points have been evaluated for its performance over the different state-of-the-art datasets and compared with the literature-based algorithms.

The optimization for target set selection can further be improvised using opinion-based dynamics. The opinion vector may be used to derive weights for feedback in different communities. This can help to select optimal helper nodes [10]. We have compared the results over MATLAB and compared our proposed schema with greedy and heuristic approaches. Such implementation offers better buffer occupancy and less number of nodes identified in target sets. Furthermore, this automatically reduces the traffic load over the network, offering optimal offloading.

We use the optimization opportunities of D2D networks for efficient energy savings and use the buffer management policies to offer mobile data offloading. The methodology uses optimization with buffer and latency aspects of the network. The use of Summary Vectors for local and neighbor exchanges can successfully reduce the overall energy consumption of the users and their neighbors using the k-means clustering and their betweenness centrality.

Next, we address the security aspect of users in terms of malicious or non-malicious nodes in the network. First of all, we introduce the trust-based metrics for users' classification. All sets of feasible users have been divided based on graph weight metrics and a possible set of time-dependent analysis. The implementation is tested using dynamic modeling over NETWORKX library-based analysis done with Python programming language. The secure performance is evaluated for its contribution over state-of-the-art datasets. The perspective of the access point, as well as the users, has been taken into consideration.

At last, we aim at deriving the optimal incentive based on metrics obtained from the perspective of trust. The game theory-based feasible aspects of incentive derivations are evaluated to optimize and reduce incentive concerning their heuristic-based offloading potential. The results are checked for Nash equilibrium-based incentive distribution for positive, neutral, or negative trust-based outputs. The proposed algorithm is compared with the salary-bonus schema, and optimal results have been derived. We have taken a special consideration where few nodes are not the decision-makers; however, the performance of an overall network is observed for optimization and incentive distribution. An implementation is also proposed to increase the participation of users for offloading purposes.

1.6 Contributions

The thesis explores several improvements towards optimal target set selection problems and appropriate incentive schemes for efficient mobile data offloading. It proposes several optimization algorithms in between the users and Internet Service Provider (ISP) access points for applications over limited environments such as conferences, societies, and disaster management systems. The most important task is to achieve an optimal target set for efficient offloading. In this thesis, we have explored all the metrics related to data offloading schemes in opportunistic networks [11], similar interest-based users. In the end, we propose the categorization of users based on contribution to propose optimal incentives accordingly. We have figured out the workflow methodology in Figure 1.1.

The contribution of our research is published using comparative analysis as follows:

- Initially, we propose to check the impact of opinion dynamics for smaller sets. We have observed that users' individual and group-based opinions within the network may deliver more optimal target sets. Finally, we have checked the performance of our opinion dynamics-based algorithms over realistic datasets using MATLAB. This work has been published as:
    - P. Sharma, and S. Shukla, "Optimal Target Set Selection via Opinion Dynamics", *2018 Fifth International Conference on Parallel, Distributed and Grid Computing (PDGC 2018),* IEEE, 2018.
- A specific scenario of using D2D based communications in the opportunistic environment allows users to offer energy-efficient solutions using proper buffer management techniques. The opinion dynamics contribution towards optimal users' identification is checked in this work. Such proposed implementation is published as:

- P. Sharma, "Energy Efficient Target Set Selection and Buffer Management for D2D Mobile Data Offloading", *International Journal of Data and Network Science*, Growing Science, 2020.

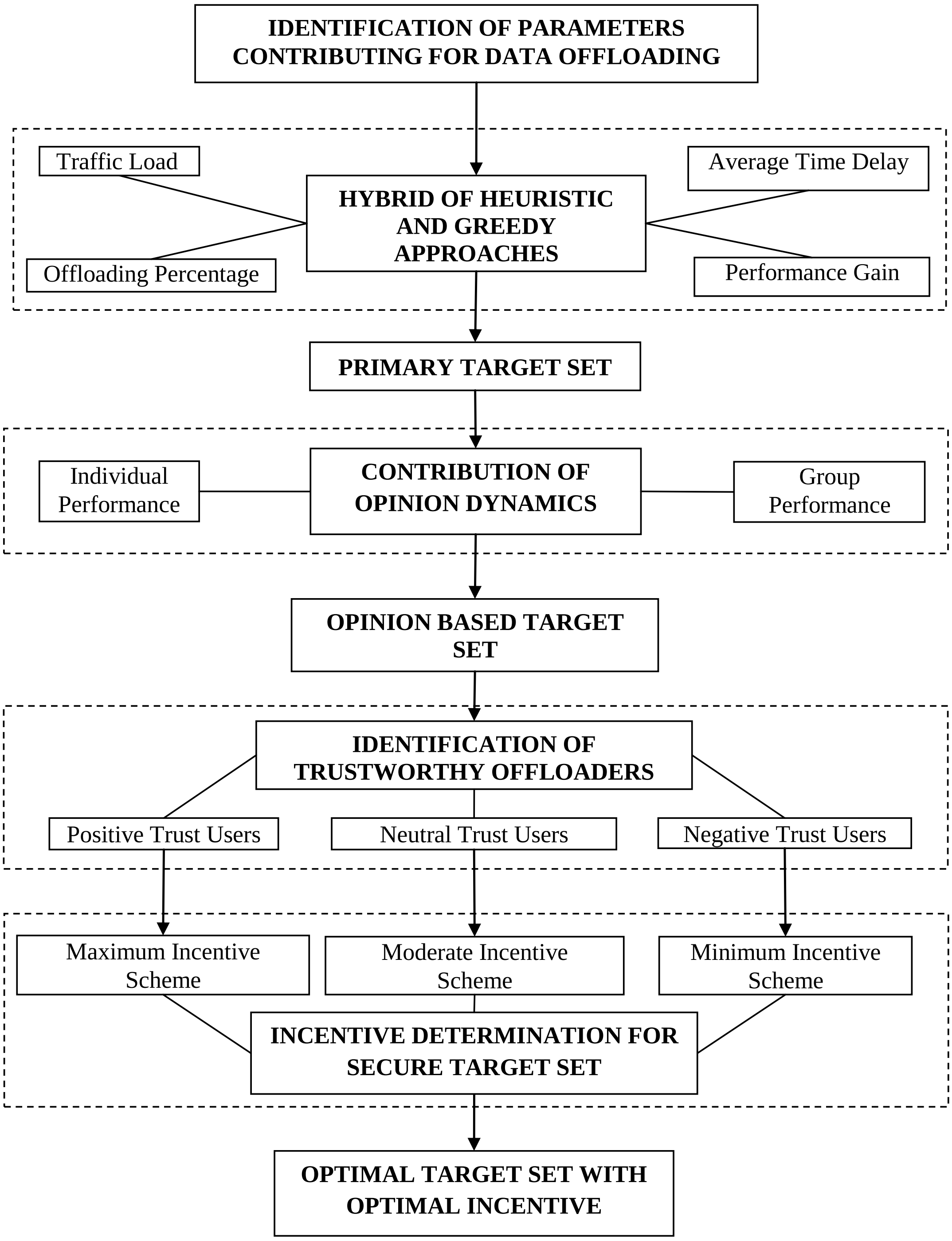

Figure1.1: Workflow diagram

- We have focused on the problem of optimization of TSS identification. We have compared the performance of our proposed FTSS algorithm with the literature-based algorithms of greedy and heuristic approaches. The results have been analyzed for two significant datasets from MIT and NUS. This work has been accepted for publication as:
    - P. Sharma, S. Shukla , and A. Vasudeva, "Data Offloading via Optimal Target Set Selection in Opportunistic Networks", *Mobile Networks and Applications,* Springer, 2021.
- To address the security tradeoffs for our offloading methodology also needs a particular concern. This is validated using two state-of-the-art datasets using trust derivations based on local and global opinions of the users. It has been proposed to be implemented for smart agricultural techniques and is accepted as follows:
    - P. Sharma, S. Shukla, and A. Vasudeva, "Trust-based Opportunistic Network Offloaders for Smart Agriculture", *International Journal of Agricultural and Environmental Information Systems*, IGI Global, 2021.
- There needs to be a reason for the network offloaders to enhance their volunteer participation in offloading. An incentive offering does this task and has been anticipated in the literature too. But, the incentive schemes need to be impartial, addressing the concern of their extent of participation in offloading. We have used the trust-based metrics and verified the implementation using the game theory-based Nash equilibrium to derive incentive schemes for the offloaders. We compare our proposed inventive scheme with the literature-based salary-bonus scheme, and results have been published as follows:
    - P. Sharma, S. Shukla, and A. Vasudeva, "Trust-based Incentive for Mobile Offloaders in Opportunistic Networks", *2020 International conference on Smart Electronics and Communication 2020: (ICOSEC 2020)*. IEEE, 2020.

1.7 Chapters' layout

The organization of the thesis is divided into seven chapters. The layout of the chapters and thesis organization is shown in Figure 1.2 and is described as follows:

Chapter 1 provides the basics of identifying offloading approaches related to mobile data, incentive mechanisms of offloaders, the problem genesis, the objectives, a review of modeling and strategy followed, the research contribution made by this work, and lastly, describes the chapters' layout.

Chapter 2 covers the entire literature survey related to mobile data offloading, which we have gone through. Initially, it highlights the need for offloading solutions. Then, it covers the types of offloading solutions related to wired or wireless networks. Finally, it includes the network models with their pros and cons along with their future scopes.

Chapter 3 discusses the newly proposed energy-efficient algorithmic solution towards optimal target set identification. It uses the collaborative perspective of access points and network users. It involves identifying target set based on the users' interests followed by the optimizations using opinion dynamics of the users to derive optimization towards an optimal offloading solution. It includes the comparative results of the proposed algorithm against the greedy approach and heuristic mechanism over the Cambridge dataset.

Chapter 4 considers the special scenario of using energy-efficient solutions for the opportunistic network. This is backed up by the use of D2D usage for an energy-efficient solution for target set selection. This chapter identifies the impact of energy usage differences with the help of proper buffer management techniques being helped by the summary vectors sharing amongst the neighborhood of users.

Chapter 5 focuses on target set selection and the features determining the effectiveness of data offloading schemes. It lays the foundation of our fundamental problem identification and the collaborative solution applied by a hybrid of the greedy-heuristic-based approach. Finally, the simulation results are discussed by comparing the algorithms in the literature with our FTSS algorithm.

Chapter 6 focuses on the security tradeoffs required for offloading. It discusses the impact of trust-based metrics on network connectivity. This chapter identifies the reliable, optimal offloaders for trust-based mobile data offloading in opportunistic networks. It also signifies the need for the dynamic behavior of users, classifying them into positive, negative, or neutral trust-based offloaders. It identifies the existence of malicious users in the practical realization of a network. It includes the comparative analysis over a conference dataset from the Haggle project. This chapter also aims to identify an appropriate suitable incentive strategy to support data offloading in opportunistic networks. It also uses the classification model of trust-based analysis to finalize optimal incentive schemes for incentive derivations. Finally, it discusses the Nash equilibrium requirement for exploring the game theory-based multi-dimensional aspects in incentive derivation.

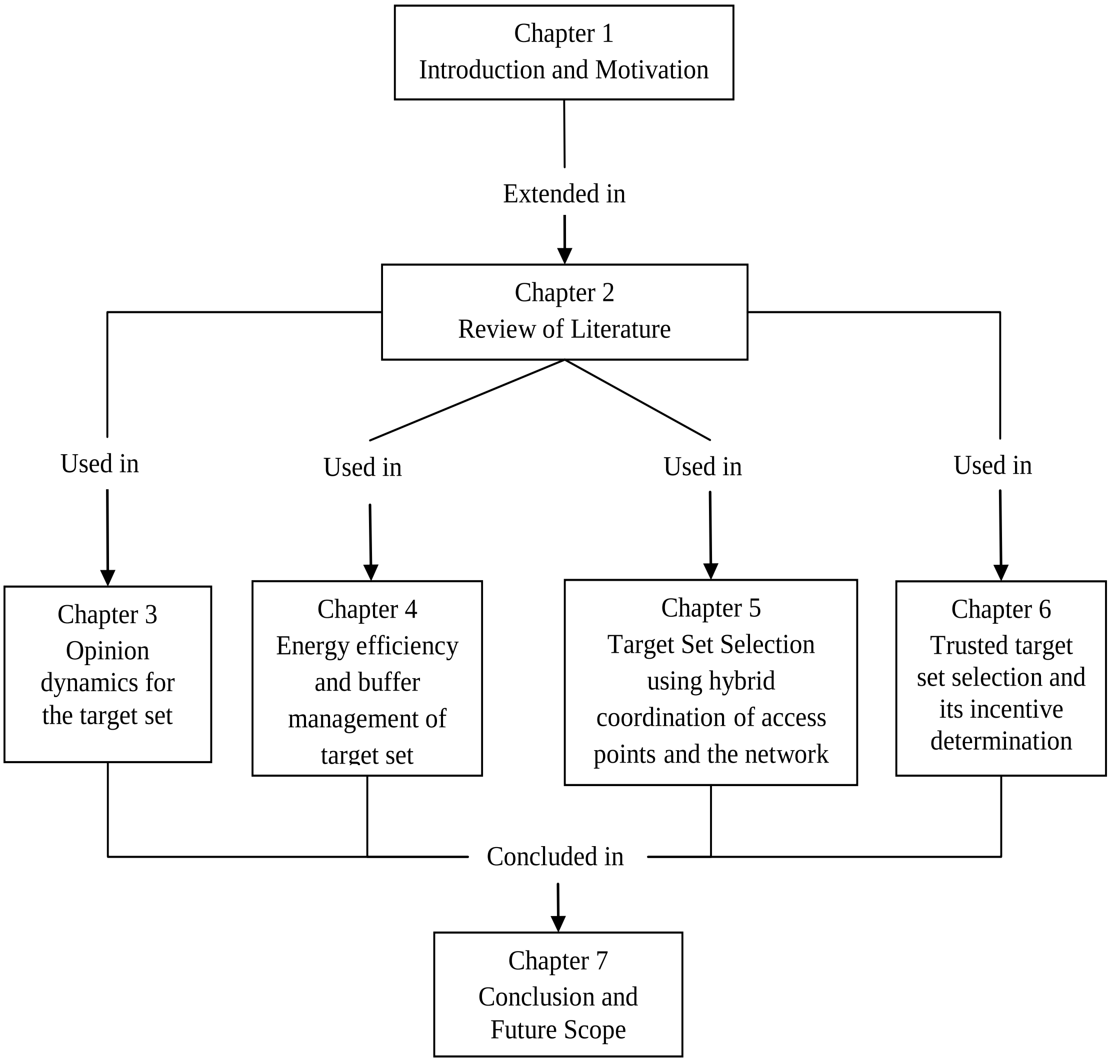

Figure1.2: Chapter's layout

Chapter 7 discusses the collaborative conclusion of our thesis after comparing the proposed trust-based algorithms for optimal target set selection and appropriate incentive schemes in the thesis. This chapter includes the thesis summary, concluding remarks and also describes direction for the probable future work with suggestions of our offloading methodology.

CHAPTER 2
REVIEW OF LITERATURE

2.1 Introduction

The use of the internet is increasing rapidly with each passing year and is expected to rise further exponentially. More and more users are increasing their dependence on mobile devices such as smartphones, tablets, and IoT devices. The internet-based services offered using such devices add further reasons to the rise in data traffic. The pandemic situation surrenders a significant portion of the population over such online services. There is also an evolutionary revolution in the infrastructure requirements to enable internet-based services. We observe this trend of rapidly shifting from 2G to 3G, 3G to 4G, and 4G to 5G. For example, the global traffic report from Cisco predicts 66 percent of the global population to have internet access. Their analysis comprises more than thrice the population of IP-connected devices by the year 2023. Thus the contributions towards addressing the issues of mobile data expect a significant contribution from the research community. Specifically, the need for how mobile data traffic could be reduced is essential. There are several solutions proposed in the literature which contribute towards a reduction in data traffic. However, without degrading the quality of service of mobile users, the increasing mobile data continues to burden the mobile network operators. It is accompanied by the use of efficient mobile data offloading solutions. This chapter presents a literature survey related to mobile data offloading, which covers the recent work done in the previous two decades from the year 2005 to 2019.

2.2 Classification of data offloading technologies

In the literature, we may observe several classification criteria for data offloading technologies in mobile networks. Although there is a feasibility of various such levels of classification, a majority of them are implemented heterogeneously. Thus the data offloading methods could not be said to be categorized into fixed types. The mobile data offloading solutions can be categorized based on infrastructure requirements as infrastructure-based or infrastructure-less offloaders. They can be categorized based on delay tolerances amongst the users as delay tolerant or delay non-tolerant offloading phenomenon. These offloading solutions can be classified on the basis of involved participants as Access-Point-based or Users-based solutions. In literature, generally, wired and wireless offloading classification has been used.

2.3 Related work

In [4], the authors propose the mathematical framework of Delay Tolerant Network (DTN) based mobile traffic offloading. The model showcases the significance of several data items in a realistic mobile environment. The authors acknowledge the data not to be of a similar type or content size. They have also emphasized designing efficient offloading schemes considering different demands and interests of mobile data. According to their research work, the DTNs have been limited in practice due to storage and battery capacities with opportunistic communication contacts. The real-trace-driven simulations support the research analysis. The results show improved system performance in the human environment as well as in vehicular environments. The authors have proposed a Greedy Algorithm (GA), Approximation Algorithm (AA), and Optimal Algorithm (OA) for similar rates of contact, similar interests, and similar buffer requirements. The results include the analysis of offloading amounts concerning different life spans and buffer sizes.

The authors in [5] have considered the physical attributes of mobile phones, APs, and base stations in collaboration with mobile social networks. Their work takes advantage of APs support in hybrid networks. This helps in the detection of space-crossing communities in such networks. The researchers have proposed a data forwarding scheme. Their algorithm uses the infrastructure and common choices and is called Similarity Attraction and Infrastructure Support (SAIS) to detect such communities. The results have been compared with the routing algorithms Simbet algorithm. Nguyen routing algorithm and Bubble Rap algorithm have also been compared with SAIS. The analysis has been observed on the basis of attributes like delivery ratio, overhead ratio, and average latency. The analysis is done over MIT and UIM datasets. The main idea is to use the collaboration of the AP with physical proximity for data forwarding and community detection. Until their contribution, the overlapping community detection is generally ignored in the literature related to the architecture of mobile phones and APs. The authors also use the AFOCS algorithm for determining the physical proximity communities to identify the dynamic behavior of graphs. The study of measuring the communication overhead in real scenarios has been left to be studied as the future scope under the real scenario of frequent community updates in large social networks.

The research work in [6] demonstrates the need for offloading for mobile computing. The energy savings have been analyzed using the Lyapunov optimization. The model uses dynamic offloading to yield a Dynamic Offloading Algorithm (DOA) for energy optimization. The adaptive dynamic offloading algorithm determines the software components. This helps the components to execute the functionality in wireless networks remotely. Their approach uses several different classifications for identifying a component that could either be offloaded or not offloaded.

In [7], the researchers focus on the need to identify the upper bound of user properties. This helps identify the users who should be delegated for content dissemination and speed up the dissemination process. There is a proposal of a reinforcement learning approach based actor-critic method. Their approach needs the agent to observe the system states, takes suitable action, and receives the reward. Such a methodology enables the determination of an appropriate control strategy for the offloading task automatically, which is independent of pre-existing knowledge about the behavior of users.

The researchers have proposed a target set selection problem in [8] and compared the greedy heuristics and random algorithms for determining optimal offloaders. The model has been evaluated over datasets from the real world. It has also been evaluated for synthetic datasets for comparison with the literature-based algorithms. The major parameter of consideration is to use the social network and their analysis for deriving the algorithms. The research work ignores the concept of overlapping communities, and the dataset is also static in behavior.

The work in [9] shows the use of Bayesian network-based overlapping community detection. They have analyzed Dynamic Bayesian Overlapping Community Detector (DBOCD) over real dynamic and synthetic datasets. The significant contribution of the work is space crossing community selection, where the user observed a similar pattern based on graph-based parameters.

The work in [10] focuses on the integration of device-to-device (D2D) communications with current cellular technology. The authors show that D2D has significant potential to improve network and client performance. However, the results also show that the D2D gain depends on establishing proper offloading criteria and having more source and destination pairs. The work also discusses the feasible failure to match the QoS requirements with lengthy packet delays and energy drainage of the clients. The need to identify D2D network best links is also compared with LTE for link lengths, bit rates corresponding to fair scheduling. Their work also ensures a larger extent of high bit-rate connections at heavy traffic loads. The authors have also considered the need for a dynamic model for offloading the data traffic. Such opportunistic networks have also been worked out by the authors in [11, 12] using reinforcement learning.

In [13], the authors emphasize the applications of social networks for solving target set selection problems. The researchers aim to discuss the minimum target set and maximum active set approximations. However, the implementation is derived based on theoretical derivations. The results are derived using theorems supported by graphical analysis.

The authors in [14] emphasize the usage of cloud-based resources to offload computational tasks. They have proposed a four-stage multi-user offline computation algorithm (FMOCO) to balance mobile devices' performance and energy computations. The algorithm is based on the search-adjust approach attributed to the unlimited availability of resources. The results are analyzed for the impact of the number of cloud-based virtual machines, number of users, network bandwidth, the available battery power of mobile devices, and the computation power.

In [15], the researchers have discussed the use of Access-Point-based infrastructure offloading for offloading. The work focuses on the fixed deadline data items depending upon the capacity constraints of the WiFi access points. The authors have encouraged the usage of alternative mobile access networks for offloading. The offloading strategies are selected based on delivery guarantee requirements. The authors identify the need for collaboration of users for enabling offloading, for which they need to share resources like battery and storage space. The overall implementation is also relied upon over the incentive mechanism to motivate the users for successful participation. The security and privacy concerns of the users are the less focused issues for mobile-to-mobile transmissions. The need for infrastructure has also been emphasized for practical offloading environments.

The researchers in [16] address the issue of deadline-sensitive data items considering the capacity constraints of access points. Their work proposes a greedy algorithm for offline data offloading as well as for online data offloading. The performance is compared with random selection and sequential allocation algorithms. The problem has been identified to be a 0-1 Knapsack-based optimization problem with optimal constraints. The solution is derived on the basis of probability theory for evaluation analysis. However, the results have been verified using simulations over synthetic setups.

The authors in [17] have identified the use of class schedules and class roasters from a university learning portal to determine the contact patterns to infer the mobility of users. However, the traces are analyzed in reference to few mobile applications. The insights of the model are derived on the basis of Haggle project-based studies by Intel and Cambridge. The implementation is evaluated for delay tolerant networks. The model is based on a natural approach to data collection. The authors have relied on measurement-based studies for DTNs, virus propagation, and dynamic distributed database.

The research work done in [18] focuses on the contribution of human mobility patterns over opportunistic offloading. They have compared eight datasets on the basis of several properties and have classified them as Access Point-based and direct contact-based datasets. The results show several opportunistic network scenarios. The major contribution is the justification of power-law based on values up to one day. Another important finding is to rely upon opportunities more than the geographical location findings in opportunistic networks. Finally, the research directions for future opportunistic communications have been figured out using extensible simulations.

The study done in [19] shows the implications of mobile phone data usage to derive friendship networks amongst users. The researchers compare the survey data reports with observational data of mobile phones. Their work showcases the usage of behavioral patterns and concludes that the observational data alone can infer a high percentage of friendships. Furthermore, the authors have identified the significance of social network analysis for friendship analysis using specially programmed devices.

The work done in [20] proposes a multiple attribute-based decision-making algorithm to rank the available networks for access. The algorithm enables the users to provide an inter-system mobility policy for the users. The authors have emphasized the impact of usage of heterogeneous networks and the users' quality of service requirements. The proposed algorithm works with the mobile network operator MNO domain. The solution presents a scheme that adapts network performance dynamically on the basis of user preferences for data offloading.

The authors propose decentralized algorithms for cellular traffic offloading in D2D networks [21]. Their work focuses on an interference-based communication model using caching schemes. The major contribution of their work is to maximize the offloaded content and to share messages between devices considering the local aspects rather than the global information. The model proposes to use the directed graphs for sender-receiver pairs based on caching approaches.

The authors in [22] investigate the viral marketing strategies based on the greedy approaches and propose a model for social network analysis. Their work proposes an optimal heuristic-based approximation algorithm using the characteristics of degree centrality and distance centrality. The theoretical analysis shows the influence over marketing strategies, thereby showing the impact over subset determination. The results are compared among random, heuristic, greedy, and central algorithms. The major contribution of analysis is identifying active and inactive users and their transformation from one stage to another. The influence of users is also identified as an NP-hard maximization problem.

The work done in [23] showcases the challenges related to needs, benefits, and technological solutions for mobile data offloading. The authors identify the increasing data traffic requirements. The researchers emphasize the rising use of smartphones and the high cost of the telecommunication spectrum. The authors have predicted the future bandwidth requirements. The use of femtocells and WiFi has been identified as the major mobile data offloading solutions and the need for scaling and optimization in data offloading strategies. The huge success of WiFi has been attributed to the vast unlicensed spectrum, higher data rates and user experiences, distributed ownership costs, and high QoS and security. The authors conclude that mobile data offloading is beneficial for the operators as well as the subscribers.

The researchers in [24] have explored the limits of WiFi capacities. Their study is derived based on experiments and trace-driven simulations, which show the efficiency of on-the-spot and delayed offloading. However, the simulation ignores the effect of change of network load and the network bandwidth. Although their implementations are device-specific about the experiment, it renders a good insight into the extent of offloading. The results predict that the majority of offload offerings using delayed offloading and improved energy efficiency. The simulations have been carried out for limited and extended-time delays with the temporal offloading phenomenon.

The researchers in [25] have exploited the newly released phenomenon of WiFi-certified passpoint programs. It explores the WiFi capabilities to deliver added-value services and offload mobile traffic. The researchers find out the capacity and energy-saving gains which can be achieved by using the passpoint hotspots for offloading cellular data traffic. The simulation is exploited over a real-time network. The authors show mobile data consumption and characteristics in terms of capacity gains and energy gains. It lays the foundation of hotspot identifications for better mobile data applications.

The authors in [26] propose a routing mechanism to offload mobile data using delay tolerant networks. Their significant contribution is the assured delivery, integration of heterogeneous networks, unicast routing, and evaluation of varying infrastructure capabilities. The network has been emulated over ONE simulator, and the results have been compared with DTN routing protocols. The simulation illustrates that majority of traffic could be offloaded using DTN schemes. Nevertheless, the work is limited to single-copy DTN routing, which could be improvised with multi-copy routing using the required feedback mechanism. The energy usage impact has also been overlooked in the simulation, which needs to be addressed to optimize data offloading. Also, the actual overload conditions need to be addressed to have a more probable impact on DTNs.

The work done in [27] showcases the proposal of an optimal solution towards target set selection in social networks. The authors have used the properties of graphs over social networks. The major contribution is mathematical analysis for approximation towards the NP-hard problem. The treewidth-based algorithmic approach delivers optimal results using tree decompositions. The properties of cliques are also used for computing the lower bounds of the TSS problem. Their contribution lays the foundation of the mathematical background of the TSS problem for optimal data offloading solutions. The proposed algorithm has a running time complexity of $n^{O(w)}$, where n identifies the number of users and w represents the treewidth within the graph. The work focuses on the careful application of the TSS problem, with most of the feasible optimizations being implemented over-analysis of social networks.

The authors in [28] propose a solution, using contact durations in opportunistic vehicular networks to offer optimal mobile data offloading—their model suits the heterogeneous networks comprising cellular and opportunistic networks. However, the implementation is limited to only those users who request the mobile data. The solution is suited for non-realtime data offloading for VDTNs. The major emphasis is on the storage policy of mobile data by the users and the model based on the heterogeneous environment using trace-driven simulations for contact-aware vehicular networks. The main contribution of the approach is the use of the average contact rate of a helper to all the other users for better analysis and design. In addition, the data segmentation for large video content-based data could be further investigated for better applicability of the model.

The authors in [29] investigate an essential aspect of distinguishing the communities of users and reviews the state of the artwork related to identifying the overlapping community detection algorithms. Their significant contribution is the comparison of fourteen such algorithms, which helps to assess over-detection and under-detection. The research investigates the central problem of nearly disjoint clusters in social networks obtained from a real-world dataset. The primary focus is on the measures like Normalized Mutual Information (NMI) and Omega Index. The review considers mainly the non-weighted networks. However, the weight bears important information depending upon its applications. Their work investigates the two major research issues: when should we apply the overlapping methods and how significant overlapping is for a particular application.

The work done by the researchers in [30] also focus over overlapping community detection problem. They have showcased the use of the AFOCS algorithm for the successful detection of overlapping community structure in a dynamic structure and the possible help in the mobile applications about mobile ad-hoc networks. They have successfully contributed towards faster and adaptive updates of network structure. The approach applies to limit the mobile ad-hoc networks. The results have been demonstrated using mobile applications for MANETs and OSNs, showing the effectiveness of their proposed algorithm for detecting network overlapping communities.

An effective methodology of using a limited set of users within a limited frame has been demonstrated in [31]. The experimental setup successfully determines the use of Bluetooth-enabled devices to identify socially significant daily users. In addition, the dataset has been used very effectively in several literature studies.

The authors have surveyed the literature related to the challenges faced by WiFi networks in data traffic offloading in [32]. They have also proposed few recommendations to address such research problems. The authors have emphasized the need for a successful offloading mechanism using temporal and spatial improvements. The analysis shows that the combined effort of users and service providers could help in offloading properly. However, mobile data offloading solutions are challenged by the availability of ad-hoc options, the limitations of devices, their energy requirements, and authentication.

The researchers in [33] have identified the applicability aspects of several publish-subscribe models for determining the common parameters and their design tradeoffs. Time, space, and synchronization-based decoupling have been identified as the distinguishing dimensions of event services between publishers and subscribers. The findings emphasize the preference of static schemes for primary objectives than discrete values. The issues are identified as the events, the media types, and the QoS of schemes.

The authors in [34] propose a caching-based incentive determination scheme for data offloading optimization using cooperative mechanisms. The architecture is centralized using the mobile users to cache and forward mechanism to pass on the contents from the mobile network operators (MNOs). The algorithm focuses upon the use of D2D associations among mobile users using a heuristic approach. The proposed caching scheme achieves better performance in terms of the utility of MNOs and mobile users. The incentive offer is based on the Vickrey-Clarke-Groves (VCG) scheme, which takes care of the users' individual rationality and truthfulness properties. The authors propose an effective algorithm with polynomial time complexity for winner selection and cache allocation strategy.

In [35], the authors have used the properties of directed acyclic graphs for optimizing the general graph problems. The work focuses on the concept of weighted target set selection (WTSS) problem analysis for identifying the spread of influence propagation. The contribution is summarized as a polynomial algorithm for WTSS, the derivation of the polytope of WTSS on cycles. The authors have targeted the implementation using CPLEX 12.6 with Python API for testing. The central idea is transforming a graphical problem into a tree, using transformation of 0-1 knapsack into WTSS problem. The authors present an insight of transformation of graph-based problem to special cases using trees or bipartite trees for influence maximization.

Barbera et al. in [36] have proposed the use of series opportunistic delegation for data offloading. The authors have used characterization of social scenarios. The data has been classified using week data distribution and categorize the significant contributors in the network as VIP users for offloading. The authors have compared the proposed VIP selection strategies using their social contribution and their optimal offline solutions. The strategies are implemented over limited real-world network traces and synthetic traces. The work focuses on data offloading using the betweenness centrality, degree centrality, closeness centrality, and pagerank attributes of network members. The algorithms are optimized using random blind promotion and greedy promotion schemes. The varying numbers of contributors are compared for their extent of coverage using these schemes. However, such implementation is supported only for completely connected networks, which is impractical in real-time networks.

The authors in [37] have studied the NP-complete target selection problem for social network analysis. The major contribution is analyzing the impact of diameter, cluster edge deletion, vertex cover, and feedback system. Their work considers the impact of deletion of edges transforming the graphs into cliques. Another aspect of similarities in trees has also been checked, including the property of identifying the minimum number of edges required to make the graph acyclic. The results confirmed that the TSS problem remains hard for the diameter parameter and motivates the researchers to identify the impact of the complexity of TSS. The authors emphasize the need for TSS the combining the identification of several parameters for a suitable solution.

In [38], the authors have identified the impact of social network-based attributes like access delay, spreading impact, mobility impact, homophily, and locality for successful content dissemination. A traffic offloading framework has been proposed using the social network service (SNS). The SNS is offered using opportunistic sharing in mobile social networks (MSNs). The implementation is a combination of online SNSs and offline MSNs using the access patterns of users. The research work focuses upon opportunistic offloading and traffic offloading in MSNs and information spreading in SNSs. The results have been compared for different extents of users' satisfaction considering the MIT, INFOCOM, Beijing, and SUVnet datasets. The analysis shows that the proposed TOSS algorithm reduces cellular traffic to a huge extent. At the same time, TOSS guarantees the access delay requirements of the users also.

The authors in [39] propose an algorithm for opportunistic offloading using movement predictions using the inter-device communication of mobile devices. The work is implemented using the attributes of static coverage and free-space coverage. The researchers have also used group-based coverage metrics separately. The algorithm for TSS uses the position and speed of nodes to determine the required information for opting for different offload strategies. However, the implementation is limited to static network analysis, and the dynamic update of coverage metrics is restricted using a random selection of users.

In [40], the authors have co-related the assignment problem with the Hungarian algorithm solution. The work proposes a dynamic Hungarian algorithm to propose a solution for solving the assignment problem in changing edge weights. The authors have proved the correctness and efficiency of the algorithm using simulation results. Their algorithm has the computation complexity of $O(kn^2)$, with k representing the number of changed rows or columns in the matrix derived from cost analysis and n representing the most significant portion of the bipartite graph. Finally, the authors propose applying their algorithm for applying in the solutions requiring repeated solutions with dynamic evolvements.

The authors in [41] have proposed a social network-based solution for D2D connected networks for data delivery. The idea is to embed the social network-based properties to establish links. A game-theoretic approach helps the approach with feasible weights enabling fewer communication costs and high satisfaction. Such an approach tries to balance the domains in terms of physical and social associations. The authors have also used the time-varying aspects to demonstrate a low-complexity better response with the inertia algorithm (L-BRIA). It has been used to establish Nash equilibrium convergence. However, the implementation is dependent upon a content delivery application. Their significant contribution is towards a less complexity-based algorithm.

The authors in [42] emphasize the usage of D2D networks for high rate wireless transmission in local cellular networks—their work targets to overcome information asymmetry about battery levels. In addition, the authors have also used evaluations on rewards and quality of service standards. The authors have compared the approaches of using auction and contracts for determining incentive mechanisms. They have successfully showcased the pros and cons of both strategies with their suitable implementations in D2D networks. The categorization of users as for help users and cellular users offers better suitability for architectural requirements of the network modeling. The results show a rise in the operator's utility with varying extent of budget and proportion of help contributors. The auction mechanism is dependent on the feedback of users and the acceptance of the contract.

The authors in [43] propose a reinforcement learning approach for cost and energy-effective data offloading simultaneously. However, the implementation is based on the WiFi offloading problem from the mobile users' perspective only. The heuristics of multiple mobile users' is left for further implementation. The authors have demonstrated that the reinforcement learning-based algorithm performs better when the mobility pattern is unknown. The results show that the probability of completing the transfer is more than delay-aware offloading. Furthermore, the energy and costs involved are reduced using reinforcement learning implementation based on dynamic programming.

The work done in [44] showcases the impact of social attributes to derive relationships and influence in the networks. The authors prove the hypothesis based on statistical tests using timing-based actions in online mode. They have successfully showcased that reshuffling the timestamps of actions does not significantly change the amount of correlation amongst users. The derivations are based on attributes like homophily, confounding, and influence for measuring social correlations. The researchers have been able to identify social influence-based correlations amongst the users. Apart from influence identification, their work also quantifies the social influence to illustrate its impact on social ties.

In [45], the authors propose a Stackelberg game-based proposal to motivate users to participate in mobile data offloading. Their approach tends to cover the gap between the service providers and the users with similar requests in limited areas. The proposal acknowledges the delay-tolerant and delay-intolerant networks based on Nash equilibrium using the Stackelberg game. The authors can determine the impact of social edges, delay effects, and the benefits of improved models. They have also worked for utility maximization of users using mobile caching users (MCU).

The researchers in [46] can determine the secrecy rate based on the accuracy of trust degree. The work proposes to use direct or cooperative transmission modes in the presence of potential eavesdroppers. The authors have developed a confidential framework using mutual trust amongst the users. The work proposes an efficient and secured transmission strategy using the trust degree attribute of the users. The results show that the secrecy rate is comparatively higher using their proposed scheme.

In [47], the researchers have proposed a caching-based content-centric approach for determining the incentive offerings for vehicular delay tolerant networks. The authors have proposed a suitable system architecture using a caching system for vehicular cellular networks. The proposal of a robust and distributed incentive mechanism enables the users to be classified as true or false nodes on the basis of their contribution towards reputation. The assumption of the pseudo-watchdog mechanism requires special components to monitor the behavior of vehicles. The behavior attributes for good and bad observations have been incorporated to evaluate the extent of contribution.

The work done in [48] uses the attributes of similarity and betweenness for analyzing the social network within a disconnected delay-tolerant network. It also considers the impact of mobility among the users in the MIT dataset and compares it with epidemic and PRoPHET routing mechanisms. However, the implementation ignores the combined group impact of the communities together. The results show an optimal number of messages delivered with a moderate number of hops and lesser end-to-end delay. The authors have used the property of node's egocentric betweenness centrality and its social similarity to determine the Simbet routing metric.

The theoretical and mathematical modeling for heterogeneous networks has been studied in [49] on a trust basis. The authors associate the topological properties of the users with having a significant contribution towards understanding their influence spreading capabilities. The results show that k-core decomposition method-based nodes have a higher impact on network trust. The proposed algorithm can extract more refined subgraphs for network analysis using the properties of cliques. The results have been compared with epidemic routing mechanisms to show optimality in-network classifications.

The impact of opinion amongst users has been studied in [50] for solving optimization problems. The authors have successfully shown that the human opinion formations and the study of their actions could be used to solve complex mathematical problems. They have emphasized the impact of social structures to be used for small world and random graphs. The major advantage of implementation is the single tunable parameter used in the algorithm to moderate the behavior of users. The use of discrete opinion values also illustrates the use of positive and negative trust amongst users.

The authors in [51] use the property of trust amongst users for cooperative communications among D2D users. The hybrid trust model, multi-dimensional trust evaluation, classification of users, and optimal partner selection mechanisms are the significant contributions of their work. The researchers carefully study the significant aspect of users to be classified in terms of all feasible behaviors. However, the result is limited to D2D networks without optimal incentive consideration. The trusts have been sub-classified as cognition trust, decision trust, and behavior trust implemented over Cambridge and Infocom datasets. The significant contribution of their work is the consideration of the selfishness of users in D2D networks, making it more realistic in observation.

The authors in [52] have studied the economics-related aspects of WiFi-based offloading. Their work showcases the impact of WiFi usage for data offloading and the multiple aspects of pricing-based revenue. The authors have used the parameters of traffic demands and willingness to pay, WiFi connection probability, and base station association for result analysis of delayed and non-delayed offloading solutions. The results have been illustrated with special device-based datasets for reflecting the optimal economic gains in implementation. In addition, the authors have shown results with flat as well as fixed pricing models for optimal traffic volumes.

The authors in [53] propose an incentive mechanism for optimal cellular traffic offloading. The significant contribution is towards the balance between the extent of traffic offloading and users' satisfaction in offloading in delay tolerant and WiFi connected networks. In addition to delay tolerance, the researchers have been able to determine the offloading potential of users for designing incentive mechanisms. The framework uses a Win-Coupon strategy to minimize the incentive cost of the cellular network operators. Furthermore, the properties of truthfulness and individual rationality have been used to derive an optimal solution to reduce the incentives. The main focus of the researchers is over low computation complexity-based algorithms for incentive determination.

Table 2.1: Comparison of contributions for data offloading related literature

Literature work	TSS based	Incentive	Dynamic network	Trust	Overlapping community	Oriented Application
Li Y. et al. [4]	No	No	No	No	No	DTNs
Li Z. et al. [5]	No	No	Yes	No	Yes	Social networks
Huang D. et al. [6]	No	No	Yes	No	No	Mobile computing
Valerio L. et al. [7]	No	No	Yes	No	No	Opportunistic networks
Han B. et al. [8]	Yes	Yes	Yes	No	No	Social networks
Ghorbani M. et al. [9]	No	No	Yes	No	Yes	Dynamic networks
Andreev S. et al. [10]	No	No	Yes	Yes	No	D2D networks
Han B. et al. [11]	Yes	Yes	Yes	No	No	Opportunistic networks
Valerio L. et al. [12]	No	No	Yes	No	No	Opportunistic networks
Ackerman et al. [13]	Yes	No	Yes	No	No	Graphical network
Liu W. et al. [14]	No	No	Yes	No	No	Offloading networks
Rebechhi F. et al.	Yes	Yes	Yes	Yes	No	Cellular networks

Literature work	TSS based	Incentive	Dynamic network	Trust	Overlapping community	Oriented Application
[15]						
Gao G. et al. [16]	No	No	Yes	No	No	Opportunistic networks
Srinivasan V. et al. [17]	No	No	Yes	No	No	Dynamic networks
Hui et al. [18]	No	No	No	No	No	Opportunistic networks
Eagle N. et al. [19]	No	No	Yes	No	No	Social networks
Oremadole J. et al. [20]	Yes	No	Yes	No	Yes	Heterogeneous network
Jiang J. et al. [21]	No	No	No	No	No	D2D networks
Kempe D. et al. [22]	Yes	No	Yes	No	No	Social networks
Gupta V. et al. [23]	No	No	No	No	No	Offloading networks
Lee K. et al. [24]	No	No	No	No	No	Offloading networks
Hoteit S. et al. [25]	No	No	No	No	Yes	Offloading networks
Mayer C. et al. [26]	Yes	No	No	No	No	DTN
Ben-Zwi O. et al. [27]	Yes	No	No	No	No	Social networks
Zhu X. et al. [28]	No	No	Yes	No	No	Opportunistic networks

Literature work	TSS based	Incentive	Dynamic network	Trust	Overlapping community	Oriented Application
Xie J. et al. [29]	No	No	Yes	No	Yes	Networks
Nguyen N.P. . et al. [30]	No	No	Yes	No	Yes	Dynamic networks
Eagle N. et al. [31]	No	No	Yes	No	No	Social networks
Aijaz A. et al. [32]	No	No	Yes	No	No	Offloading networks
Eugster P.T. et al. [33]	No	No	Yes	No	No	Distributed networks
Zhang Q. et al. [34]	No	Yes	No	No	Yes	Wireless networks
Raghavan S. et al. [35]	Yes	Yes	Yes	No	No	Social networks
Barbera M.V. et al. [36]	Yes	Yes	No	No	Yes	Social networks
Nichterlein A. et al. [37]	Yes	No	Yes	No	No	Social networks
Wang X. et al. [38]	No	No	No	No	No	Opportunistic networks
Baier P. et al. [39]	Yes	No	No	No	No	Opportunistic networks
Korsah G. A. et al. [40]	No	No	Yes	No	No	Hungarian algorithm

Literature work	**TSS based**	**Incentive**	**Dynamic network**	**Trust**	**Overlapping community**	**Oriented Application**
Chen Y. et al. [41]	No	Yes	Yes	No	No	D2D networks
Zhang C. et al. [42]	No	No	Yes	No	No	Offloading networks
Anagnostopoulos et al. [43]	No	No	No	No	No	Social networks
Zhang et al. [44]	No	Yes	Yes	No	No	Social networks
Ryu Y. J. et al. [45]	No	No	No	Yes	No	Secured networks
Magaia N. et al. [46]	No	Yes	Yes	Yes	No	Vehicular networks
Daly and Haahr [47]	Yes	No	No	Yes	No	Social networks
Malliaros et al. [48]	No	No	No	Yes	No	Secured network
Kaur R. et al. [49]	No	No	Yes	No	No	Social networks
Yan J. et al. [50]	No	No	Yes	Yes	Yes	D2D networks
Lee J. et al. [51]	No	Yes	No	No	No	Offloading networks
Zhuo. et al. [52]	Yes	Yes	Yes	No	No	Offloading networks
La Q. D. et al. [53]	No	No	Yes	Yes	No	D2D networks
Asadi A. et al. [54]	No	No	Yes	No	No	D2D networks
Li Y. et al.	No	Yes	No	No	No	Tolerant

Literature work	TSS based	Incentive	Dynamic network	Trust	Overlapping community	Oriented Application
[55]						networks
Han B. et al. [56]	Yes	No	Yes	No	Yes	Social networks
Awada A. et al. [57]	Yes	Yes	No	No	No	Cellular radio networks
Cai R.J. et al. [58]	No	No	Yes	Yes	No	MANETs
Chaterji S. et al. [59]	No	Yes	Yes	No	No	Networks
Elijah O. et al. [60]	No	No	No	Yes	No	IoT network
Gao L. et al. [61]	No	Yes	No	No	Yes	Cellular networks
Dawy Z. et al [62]	No	Yes	Yes	No	No	Cellular networks
Heble S. et al. [63]	No	No	No	No	No	IoT network
Janani V.S. and Manikandan [64]	No	No	Yes	Yes	Yes	Ad-hoc networks
Alsharif N. and Shen X. [65]	Yes	No	Yes	No	No	Vehicular networks
Martello S. et al. [66]	No	No	Yes	No	No	Network applications
Movahedi Z. et al. [67]	Yes	Yes	Yes	Yes	No	Ad hoc networks

Literature work	TSS based	Incentive	Dynamic network	Trust	Overlapping community	Oriented Application
Liwang M. et al. [68]	No	Yes	No	No	No	Vehicular networks
Yu S. et al. [69]	No	Yes	No	No	No	Networks
Montori F. et al. [70]	No	Yes	No	Yes	No	IoT network
Yang C. et al. [71]	No	Yes	No	No	No	Heterogeneous networks
Zhou H. et al. [72]	No	No	No	No	No	Opportunistic networks
Gember A. et al. [73]	No	No	Yes	Yes	No	Offloading networks
Wang R. et al. [74]	No	No	Yes	Yes	No	D2D networks
Vazquez F. [75]	No	No	Yes	No	No	Networks

Table 2.2: Research focuses about mobile data offloading in the past 15 years

Years	2005-2009	2010-2014	2015-2019
Target Set consideration	[22], [27], [47]	[8], [13], [26], [36], [37], [39], [52], [56], [57]	[15], [20], [35], [65], [67]
Trust consideration		[10], [47]	[15], [45], [46], [48], [50], [53] , [70]
Dynamic decision consideration	[16], [17], [19], [31], [40]	[6], [7], [8], [10], [11], [13], [29], [30], [32], [37], [49], [52]	[53], [46], [44], [50], [41], [28], [14], [42], [9], [15], [35], [20], [5],
Incentive consideration		[8], [11], [36], [51], [52]	[15], [34], [35], [41], [44], [46] , [70]
Overlapping consideration		[29], [30], [36]	[5], [9], [20], [25], [50], [34]

In the Table 2.1 we compare the literature related to the need of data offloading solutions, their focus of consideration and areas of application. On the basis of time scale analysis of the above literature survey, we observe pattern as listed in Table 2.2. Prior to the year 2009, the researchers were mainly focused over target set selection problem orientation and dynamic properties of data offloading solutions. It was probably due to comparatively newer approach of solution problem of data offloading. Towards the present decade, the focus expanded with the research focus over dynamic networks. In the recent years, the major area of concentration is over trust parameter involved in data offloading infrastructures. The network overlapping phenomenon is also considered equally significant in the present trend of research work related to mobile data offloading. In addition, the incentive distribution for optimal offloaders has also been an area of focus in the recent decade. In a nutshell, we may conclude the focus of research to be concentrated more over network overlapping, trust determination, and incentive distribution. In the upcoming chapters, we will be elaborating over these aspects of network offloading parameters and their feasible optimization solutions. Along with these new aspects of research orientations, we also proceed with parallel contribution towards target set selection consideration and the network dynamics.

The networks have been using various networking technologies for communication also. A small survey of each of these is also described now followed with a comparative analysis towards the end of this section.

Femtocells

The femtocells are small, less expensive, low-power consuming base stations which are deployed by the users to utilize their wired backhaul connections enabled by the licensed spectrum. Their implementation is limited to small cell networks in comparison to macro cells where larger networks are addressed. The femtocells have evolved form of cellular repeaters and picocells, but are more autonomous and self-adaptive [76]. However, the spectrum allocation and co-channel deployments are the major concerns associated with the research associated with them. The typical femtocell AP base stations transmit about less than one fifth of the power in comparison to a typical WiFi AP.

Femtocells have better indoor data rates due to the offering of more bandwidth. It is attributed towards lower path loss between the devices of users and the femtocell than a typical macrocell. Its implementation offers good coverage for subscribers [77]. It not only increases the network coverage, but also the number of cells and hence the capacity of the network. Femtocells are the prior choice as an operator, because they provide a cost effective way of significantly increasing the data rates of the wireless networks at the user's premises. They use the backhaul of existing broadband connections of users. Consequently, there is no additional cost of deployment or energy. The power requirements of femtocells are also very low due to its less range of impact. They are best suited as a solution for small coverage areas and low capacities.

As far as the entire network is considered taking into account the ISPs and the users, the overall cost is increased. The location and configuration model of femtocells requires an extensive research in the area of self-configuration and self-optimization, which should be different to that of the macrocell environment. The coverage area of femtocell network is limited, so it can be preferred to limited geographical surroundings only. Femtocells are limited to the cell sizes ranging upto less than 30 meters, whereas picocells, microcells and macrocell have ranges up to 100 meters, 500 meters and greater than 1 kilometers, respectively [78, 79].

Bluetooth

The bluetooth technology uses a specific bandwidth spectrum in unlicensed frequency band of 2.4 GHz. It is an open standard for short range radio-frequency communication. With the evolution of time, there are several versions of bluetooth, with Bluetooth 1.0 as the earliest and the latest one being the Bluetooth 5.0. Recently, the use of Bluetooth in IoT has revolutionized the IoT industry. The development of Bluetooth Low Energy (BLE) is the outcome of research associated with power-constrained devices using wireless sensors and controls [80]. However, presently it is suited for smaller data communications only.

The research and development related to bluetooth technology implementation is very active. It is attributed to the adoption of updated standards each year. Bluetooth 5.0 has a range about 200 meters which is nearly double the range of classic or Bluetooth

4.0. The latency of the latest Bluetooth standard 5.0 is reduced to less than 3ms as compared to the classic Bluetooth latency of 100ms. The energy consumption has also been significantly reduced due to the indigenous designing which uses modulated signals and the advanced frequency spectrums. In comparison to its previous version of Bluetooth 4.0, the latest one can consume power nearing half. It offers a great advantage for IoT devices due to such significant performance improvements in terms of data speeds, ranges, and broadcasting abilities.

The bluetooth technology suffers the major challenge in terms of network scalability. There are a sheer number of devices and users along with the frequency of interactions involved between them. The heterogeneity of bluetooth enabled devices, and the platforms make interoperability another challenge for IoT networks enabled using bluetooth technologies. The security and privacy concerns of bluetooth technologies are serious concerns due to huge volumes of data emerging from the physical world enabled by IoT devices. The mobility of devices results in great stress over the access and service requirements of bluetooth networks.

WiFi

The WiFi technology is an IEEE 802.11 standard, which offers a full TCP/IP stack for internet connection, which was supposed to compliment the wired standard of IEEE 802.3 originally [81, 82]. It operates at the frequency band of 2.4 GHz traditionally. However, it is capable of operating at 5.0 GHz offering more channel space and a clearer signal. But power consumption has always been an issue with it [83]. There has been continuous research going on to improve its energy efficiency.

The price of WiFi chipsets is considerably dropping making it a more economical solution included in more devices for future IoT devices too. The faster data transfer rates make them the best among the available choices for ad hoc networking. The evolving WLAN industry is increasing rapidly due to lower-priced WiFi stations and their rapid standardization. The dual-band protocols enable development of other available options with WiFi technologies.

The throughput and data rates are slow in reference to the present requirements. The protocols need to be updated with the pace of upgrade of networking standards too.

The power consumption rate of WiFi-enabled devices is more in comparison to bluetooth and femtocells standards.

The combination network of femtocells, bluetooth and WiFi technologies yield heterogeneous networks. Thus, its properties are limited to the extent of in-built technologies used in it.

2.4 Comparative analysis of femtocells, bluetooth and WiFi technologies

There are several technical differences between femtocells and WiFi. In [84], the authors have listed out a few of such differences. The access methodology differs in terms of security for both of them. The femtocells follow similar security protocols as that of the ISP, whereas WiFi networks have their specific protocols like WEP or Universal Access Method (UAM). Femtocells have been used preferably for indoor use, whereas WiFi is preferred in an outdoor environment. There is a significant difference between the costs involved for implementing networks using WiFi or femtocells. To maintain optimal QoS, WiFi use the methods of service differentiation, admission control & bandwidth reservation, rate adaptation methods. However, femtocells require hardware changes to provide QoS of equivalent level. The frequency bands used by femtocells may face the challenges of co-channel interference when implemented with the co-channel frequency deployment model. Otherwise, the use of separate channels may result in the reduction of overall system capacity. These aspects can be ignored in WiFi implementation because they use different frequency bands, which are not dependent upon any cellular service. The authors in [79], suggest preferring WiFi over femtocells in an indoor environment due to its wider transmission bandwidth. The experimental setup results show that WiFi offers lower latency and lower active mode power in comparison to femtocells. Although there is a drawback of using WiFi as its power consumption is slightly more than femtocells, when the network is idle. The femtocells face the challenges of higher latency because they require state transitions based on radio resource controls. In [76] the researchers compare the two technologies on ideal conditions as well as practical field scenarios. Although WiFi networks offer better data rates, but the difference in the data rates is reduced significantly considering the obstacles and distances under consideration. Thus the researchers have successfully confirmed that the deficiencies of femtocells are significantly reduced in similar environmental conditions in comparison to the WiFi-enabled networks. However, the potential weakness of femtocells is its complicated process of internet access, which adds time and affects performance. For HTTP-based web browsing, WiFi gave more optimal results than femtocells. However, it is more susceptible to network congestion than a femtocell-based access network. The real-time transfer protocol-based testing results show that the femtocells are better than WiFi. In such networks, the femtocells operate correctly with a little or no packet loss for larger files, under extreme load conditions. The results in [wififemtocells3thesis] also illustrate that although the femtocells offer less data rates than WiFi, but this difference is reduced significantly in the case of nearly-ideal propagations. When multiple users are served by the same APs, both networks' perceived performances per user have nearly similar result values. Few user terminals connected to femtocells consume more power than when connected through WiFi systems.

In [84], the authors have identified several factors which affect signal propagation in indoors to differentiate between WiFi and Bluetooth. These technologies have been compared on the grounds of technical characteristics of received signal strengths, probability density, population's median, and outlier samples. The result analysis shows that the evaluation of the mean of group samples is easier for real-time systems. The mobile devices show a significant difference in network performance. It can be compensated by relating the measurements of devices to multiple devices. The authors have also evaluated the impact of blueooth and WiFi for manufacturing discrepancies on signal reception. The response rate (RR) of both of them was found to be similar, which establishes the observation that the manufacturing tolerances have less impact on response rate. The authors have also concluded that the RR is not directly related to the distance for bluetooth. However, it is helpful in WiFi. The results also show that the designer can assume all receiving devices to exhibit similar behavior in the development of an indoor localization system when derived from the same model. Considering the propagation path properties of WiFi and bluetooth, the authors have been able to conclude that the ratio-based approach suits the identification of the positioning algorithm. The results show that the signal strength of both these technologies varies less between the sensors of similar type. Instead, multipath propagation is more impactful on signal strength, whereas radio signals have different propagation characteristics in different directions. The authors in [85] present the comparison of security mechanisms, which are implemented in bluetooth, WiFi, and WiMAX technologies in limited geographies of personal area, local area and wide area regions for each respectively. It focuses on confidentiality, integrity, and accountability. The implementation of the Wired Equivalent Privacy (WEP) algorithm is checked for its implementation with RC4 stream-cipher. Some design flaws have also been identified in its implementation. The researchers conclude WEP to be highly insecure and should be avoided in case of availability of any other security mechanisms like robust security network association (RSNA) or pre-RSNA. However, its implementation requires new hardware because of the replacement of RC4 with Advanced Encryption Standard (AES). The advancement in the bluetooth versions shows a huge difference in bandwidths and the extent of security. According to the researchers, bluetooth network is more vulnerable to physical layer Denial of Service (DoS) attacks. With every upgrade of bluetooth version, there is a significant difference between itself and the earlier version. In [83], the results show that BLE can produce 30 percent better energy efficiency than WiFi. BLE is the improvised implementation of bluetooth. There is no significant change observed in their parameter changes. However, it needs special consideration for the scenario when there is concurrent sensing as well as transmission using BLE. There is a feasible disturbance in the connections, when there are multiple devices using bluetooth simultaneously. Although there is a significant difference in power consumption of BLE and WiFi, however, the rate of data transfer suffers in its implementation. BLE is more secure than the traditional bluetooth [86]. The use of bluetooth is preferred more over WiFi, specifically for IoT devices. Its reason is that bluetooth is more energy efficient. However, there is a lot of research done for energy improvisation of WiFi also. The results in [86] show that WiFi inbuilt IoT devices consume less power than the BLE implementation of bluetooth. It is attributed to the coupling of the WiFi module with the processor as against BLE, in terms of power consumption. The authors in [81, 82] have also compared the occurrence-based and Weibull-based fingerprint databases for analyzing the impact of standalone and co-existence environments for WiFi positioning results. The results show that stronger received signal strength indication (RSSI) values account for more stable RSSI observations. It also shows that the use of the Adaptive Frequency Hopping (AFH) method decreases the bluetooth interference to WiFi scanning. In the case of coexisting environments of bluetooth and WiFi, it may result in less accurate positioning of WiFi, if the bluetooth devices are closer. The use of miss-scanned samples should be avoided for networking consideration too.

2.5 Open problems and future research directions

According to the survey of literature done in the previous sections, we can conclude that there is an immense need to properly identify the basic parameters to categorize the users in the network. It will help to model realistic scenarios of implementation and utilize a collaborative approach of the users and the access points of ISPs. The impact of dynamically changing attributes of the users in the network should be considered for efficient offloading. The literature survey shows the need to save energy as the significant contribution of offloading. It also successfully demonstrates the need for static and dynamic network identification about time spans. Due to the rising trend of smartphones' usage and virtual environment-based industry requirements, smart sensor deployment or existing infrastructures need the current trend of the present decade and the predicted future according to the projected mobile data growth. The global pandemic-like situations further enhance the need for efficient data offloading mechanisms. The infrastructure should address the concerns related to interoperability. The mobility of users and the fault tolerance of such evolving dynamic environments should also be addressed. Apart from such considerations, the parallel addressing of security concerns also requires equal attention. Above all, the context-aware decisions of rapidly evolving networks are also adapted to suitable fixed environments.

2.6 Simulation environment and tools

In the literature studied, we have identified several network analysis tools and environments. The majority of the work is implemented using several network simulation tools and libraries like MATLAB, SCILAB, GEPHI, Opportunistic Network Environment simulator (ONE), Python using the Networkx library, Network Simulator 2, Network Simulator 3, MPI-NeTSim, and OMNeT++. However, the functioning of libraries was limiting the varied analysis and restricting the users from observing networks with limited functionalities. So we finally ended up using python scripts for dataset processing and network modeling and analysis. However, we observed several limitations amongst themselves and finally concluded to observe network analysis using Python. NETWORKX is a special package suitable for creating, manipulating, and analyzing the structure, dynamics, and functions involved in complex network environments. The significant advantages of the NetworkX Python package are:

1. Its ability to work with larger, non-standard datasets.
2. With its standard interface of programming, it is more suited for graphical analysis and implementation.
3. It has an interface for existing numerical algorithms and codes written in other languages.
4. Python, itself as a language, is powerful in programming allowing flexible representations of networks for network algorithms.

Based on the above discussion, we formulate our thesis problem statements and have tried to figure out problem statements and propose appropriate solutions that were collaboratively concluded in the last Chapter 7 of our thesis.

CHAPTER 3
OPINION DYNAMICS FOR THE TARGET SET

3.1 Introduction

The explosive growth of data traffic due to dependence on cellular networks in recent decades has been an area of challenges being faced by internet service providers. Although there is advancement in networking technologies, there is a significant gap in the demand and supply due to the rising population and simultaneous dependence on internet-based technologies. According to the recent Cisco report [2], it is expected to have 5.3 billion internet users by 2023, which is expected to be 66% of the expected global population. The report also forecasts that the number of devices using IP networks will be thrice the population. The primary reason for this hike in data traffic is the use of smartphones and smart IoT-based devices. In addition to the use of devices, the applications are also data-driven, increasing this traffic further. Such a massive increase in internet communications may lead to data overloading problems for cellular networks. Thus, such solutions that can cater to the needs of such high demands of optimizing networking data gain appropriate significance. Several solutions in the literature directly or indirectly focus on offering solutions for such data traffic problems.

This data traffic can be controlled by deploying extra infrastructures, which is a costly implementation. In addition, it will be a time-taking scenario that may fail to keep pace with the upcoming demand with the rising population. Thus a mere up-gradation of existential networks is not a preferable solution. Another method could be the use of existing resources efficiently. Also, it is noteworthy that mobile devices generate a significant portion of this traffic. Thus, the research area that offers such solutions to cater to such high demands of optimizing networking data gains appropriate significance. One such solution implemented by cellular networks is mobile data offloading [11]. Mobile data offloading is the currently implemented evolutionary trending solution for heavy traffic load requirements, using the offload potential of existing users. It can be done by using WiFi as an alternative for reducing global data traffic problems. Thus the data traffic can be reduced by using complementary network services like femtocells, Bluetooth, or WiFi, by using opportunistic communication. Such a methodology may help the access point to use the existing resources of users. In order to motivate the users to offer their resources, several frameworks have been proposed. These frameworks help the ISPs in the intelligent selection of such users in the network. Opportunistic communications use user-to-user sharing. Such communication is more advocated to select an appropriate subset of users or devices, significantly reducing the overall traffic cost. Such a problem is categorized as the Subset Selection problem in the marketing world. It tends to determine the priority for other possible devices and to facilitate communication between them. The problem of determining a limited set of users from a larger set, in such a way that the impact is maximized in terms of activation of more number of users, is known as target set selection. Such users share their resources helping the access points to deliver the data packets successfully. The criterion of selecting such helpers has been focused on literature concerning access points only. However, such optimization needs to be bidirectional, where the contribution needs to be from the access points towards the users and vice versa.

However, the existing models are static, which is an unrealistic scenario. Hence, it is less significant to observe the static network characteristics. The greedy, heuristic or community-based solutions can be observed based on the prior information of the static users. Thus, a human behavior-based approach proposed for opinion dynamics evaluation [49] could be implemented to identify the optimal target set. Incorporating the trust degree of eavesdroppers for cooperative communication in [45] supports such feasible modeling. Similar approach is supported for successful routing in delay-tolerant MANETs in [47]. In this chapter, we emphasize optimizing the target set, using the opinion dynamics as the first step towards a better offloading mechanism. We propose to optimize the target set using the interest matrix of users and the opinion vector matrix. Such solution offers to reduce the traffic load across a sub-network. It aims to minimize the otherwise data traffic addressed by the access point. This proposed implementation is supported by our publication in [87].

3.2 Motivation and related work

The research area focusing on finding out optimum offloaders has been significant due to the data traffic offloading opportunity for ISP by sharing its load. Data offloading can be categorized into wired and wireless offloading. In addition, it can be delay tolerant or intolerant. However, few authors have proposed the device-to-device socially aware option for offering offloading services in cellular networks.

The authors showcase mobile social networks' significance [8] in studying the target set selection problem for bootstrapping mobile data offloading. The authors have used the delay-tolerant functionality of non-real-time applications to deliver data to a limited set of selected users. The authors have shown that target users can successfully propagate the information based on their subscription and social participation. However, the approach uses the static properties of network subscribers to derive their greedy, heuristic, and random algorithms. The authors have also proved the information diffusion function's submodularity to implement the greedy algorithm over it. The authors in [110] have identified the social characteristics of tie strengths to establish the neighborhood of users. These strengths are used to assign the physical and social weights in the D2D networks. The authors have used a real-world Facebook dataset to establish their results based on social tie strengths. The authors have successfully established better responses with network efficiency to justify their Nash Equilibrium with stability inertia. The physical locations of network users have been to identify the physical characteristics of users. A network model using the dynamic potential game has been proposed. It helps in strategy adaptation and offering payoff learning strategy. Such visualization helps the network to implement Q-learning and offer a distributed algorithm. However, the model presumes that the users do not change their locations, which categorizes the network to be static. In addition, the authors have assumed the availability of total frequency reuse by the D2D users. Such assumption is impractical due to the changes in bandwidth capabilities. In [89], the authors have focused on the wireless relay networks and have classified them into D2Ds and DTNs. In addition, the impact of non-cooperation amongst users is also observed. The authors have emphasized the changes in the resource capacities, content knowledge, and geo-temporal information to check for the selfishness of users. However, the aspect of energy consumption and the data delivery ratio have been ignored while evaluating the truthfulness of nodes. The authors have considered the aspect of trustworthiness of nodes for confidential communication in [45]. The users have degree of trust amongst themselves which has been used by the authors to enable efficient communication in wireless networks. However, the viewpoint of the access point has been ignored in this implementation. The authors have proposed to offer direct transmission as well as cooperative transmission to the users.

The data offloading limited to application usage is also showcased in [90] by the authors to enable software-defined networking. Although such an approach reduces the energy and implementation cost, it becomes less suited for practical networking across large networks, assuming the latency benefits to be fixed. The effect of change in availability and capacity needs to accompany the diversity of data offloading. Although the security concerns of applications can be addressed by the use of enterprise-based offloading, at the same time, it enhances the latency. An effort to model the graphical network has been made in [91] for malicious node detection. The authors have identified a correlation between the social relationships and forwarding behavior of the users to determine the malicious behavior of nodes. However, the social attributes of static users have been used in this work to determine the trust associations, thereby ignoring the temporal changes due to the mobility of users. The author has classified the agent-based opinion formation models into Voter models and Threshold models in [91]. He has explored the new patterns using the co-evolution of network and opinion. The work focuses on identifying the relative speed of the opinion spreading and network adaptation processes using correct temporal evolution and transition models. The authors in [92] show that extreme information results in segregation and has a limited impact on the population. The research also identifies that the initial condition is significant in determining the population clusters depending upon the opinion choices. In addition to this work, there are proposals of the majority rule model and Sznajd model in [93]. The authors propose a novel model based on population dynamics to confirm its compatibility with opinion dynamics. They have used opinions in a community to be dictated by the factors of inflow and outflow. The applicability of human opinion dynamics to solve complex mathematical problems has been explored in [94]. The authors have proposed an algorithm named Continuous Opinion Dynamics Optimizer (CODO) and compared it with a variant of swarm optimization (SWO) algorithm in the exact topology-based implementation. The results suggest utilizing a balance of integrative and disintegrative forces for problem-solving. Thus the use of target sets for mobile data offloading in opportunistic networks is a quite significant area of research with further implication results. From the literature, it is evident that social characteristics contribute significantly towards the selection of optimal target set users. However, at the same time, the energy and latency aspects of users need appropriate attention considering the mobility point of view.

3.3 Proposed target set implementation

The problem of target set identification involves optimal classification of nodes as more preferred set of helpers who can assist the access points of ISPs to offload the data using them. The problem of target set selection is an NP-hard problem, for which there is no feasibility of a definite problem. However, approximate solutions are feasible for the same. The system model can be viewed either concerning the AP or the network users. However, the target set needs to have a bidirectional model for practical relevance. It needs to consider the aspects of mobility of users along with their consideration of different interest items. Initially, we assume that the nodes agree to share their identity to enable data offloading. Such a network model may find an optimal efficiency considering various network features and determining their co-relationship with offloading.

We consider the optimization problem in terms of graph *G = (V, E)*, where *V* represents the users in the network in the proximity of the AP, whereas *E* determines the corresponding associations amongst them. The model classifies the users based on the adjacency matrix of interests. For *n* number of nodes within the range of AP, we aim to determine as a subset of *V* such the overall network traffic of AP is minimized. The system model presumes that all *n* users demand a data item of *K* bytes at any instance. If *n* is the number of users willingly participating in data offloading, then our aim is to determine $m \in n$, such that the overall traffic of $m \times K$, is minimized. When only k-bytes are shared across m users, the following issue of minimization is the discovery of an ideal solution for target set because of decreased network traffic. It is mathematically given as $f(x) = \sum_{q=1}^{m}(k_q)$. Here k_q represents the traffic accumulation across node q. In order to consider network dynamics, we consider the dataset with heuristic associations across regular time intervals. Such modeling ensures the replication of a static network into a dynamic one. The significant contribution of our implementation is the utility derivation of each user based on opinion dynamics. In addition, our model helps in the identification of optimal target set users for mobile data offloading.

The complete process of identifying the successful target set users is collectively handled by the APs along with the network nodes interested in similar data items. The implementation is divided into two algorithms, namely Algorithm 3.1 executed at the AP level, and Algorithm 3.2 coordinated at each node level. The AP derives the set of users based on common interest categories. The nodes help in further optimization of the set of users based on their neighborhood opinion values. We propose to derive an $I \times N$, and derive the sub-community of maximum interest. However, all such users are not equally significant. The opinion vector $O_x(t)$ is initialized for all nodes using some uniform distribution as is done in [49]. In order to derive the significance of a user in a more extensive network, the correlation between socio-centric betweenness [43] and egocentric betweenness value [47] is used. Thus each user evaluates the opinion value for its neighbors based on Network Ranking (NR) of the users and utility function of similarity and betweenness. The NR_x for the user x is given by the total number of associations that a particular user x practically has to the maximum number of feasible associations. The similarity utility is derived using the extent of association similarities of users. The adjacency matrix is used to determine the betweenness utility value Bet_x using the reciprocal of $A_x^2 \times (1 - A_x)$. The utility function is evaluated using the following equation:

$$SimBetUtil_x(t) = \alpha \times \frac{Sim_x(d)}{Sim_x(t) + Sim_y(t)} + \beta \times \frac{Bet_x}{Bet_x + Bet_y} \qquad 3.1$$

In addition to the social characteristics of users, the change in the opinion vector $\Delta(O_x)$ is evaluated using the following equation:

$$\Delta(O_x) = \frac{\sum_{i=1}^{m} [O_y(t) - O_x(t)] \times W_{xy}(t)}{\sum_{j=1}^{m} W_{xy}(t)} \qquad 3.2$$

$W_{xy}(t)$ represents the network influence of the node x with respect to node y in the network and is given as $W_{xy}(t) = NR_x(t) \times SimBetUtil_x(t)$. The value of $NR_x(t)$ is between 0 and 1, as this is dependent on the maximum vertex degree.

Algorithm 3.1 Algorithm to determine interest-based target set by an access point.
INPUT: N, I, A.
OUTPUT: $Set1$.
PROCEDURE
1: Initialization : $Set1 = \emptyset$
2: Identify $Max(I)$, using $Max(I) = Maximum[\sum_{x=1,y=1}^{x=n,y=i}(N \times I)]$
3: $\boldsymbol{for}$ $Max(I)$ **and** $x = 1$ to n $\boldsymbol{do}$
4: $\quad$ $\boldsymbol{if}$ $N \times I = 1$
5: $\quad\quad$ update $Set1 \leftarrow x$
6: ***end for***
7: ***return*** $Set1$

Algorithm 3.1 identifies the initial target set users using the interest-based matrix. The user communities may be determined on the basis of their interests. The optimal set users obtained after implementing Algorithm 3.1 are checked for their neighborhood associations in terms of local neighborhood opinions using Algorithm 3.2. The concept of opinion dynamics is used for the derivation of optimal set of helpers known as target set users.

Algorithm 3.2 Algorithm for determining the opinion-based target set $Opt_M N$.
INPUT: $Set1$,
OUTPUT: $Opt_M N$
PROCEDURE
1: Initialize $Set2 \leftarrow \emptyset$
2: ***for*** all nodes $k = 1$ *to* m in $Set1$ **do**
3: $\quad$ evaluate NR_k
4: $\quad$ ***for*** $j = k + 1$ to m such that $j \neq k$ **do**
5: $\quad\quad$ evaluate $SimBetUtil_j$ and W_{kj}
6: $\quad\quad$ evaluate ΔO_j
7: $\quad$ ***end for***
8: $\quad$ ***if*** $|\Delta O_j| \leq \Delta O_j/(m-1)$
9: $\quad\quad$ update $Set2 \leftarrow k$
10: $\quad$ ***end if***
11: ***end for***
12: update $Opt_M N \leftarrow Set2$
13: ***return*** $Opt_M N$

3.4 Complexity analysis of the algorithm

The overall complexity for the worst case implementation of our system model-based algorithms depends on the size of network-m and the maximum number of neighbors-j, which a user can have. Also the value of $j \ll m$, using statistics of uniform distribution. In terms of number of operations, the overall complexity of our implementation is of the order $O(m \times j) \cong O(m)$, because $j \ll m$. For the time complexity of our implementation, the first algorithm is implemented at the AP level, whereas the second algorithm focuses on local opinion of each user at its neighborhood level. Thus, the job now distributed amongst users and gets distributed. Hence the overall time complexity is also reduced in comparison to message exchange overload. The space complexity is also reduced due to the buffer usage of local helpers in the network.

3.5 Experimental results and performance analysis

The Cambridge dataset used in [18] is processed using different time frames to observer mobility amongst users. The network is visualized in a graph, consisting of users as vertices and the imotes as the access points. The time constraints are used to showcase the significance of dynamic properties of the network. We aim to optimize the target set based on confidence levels determined by the use of opinion dynamics. The confidence level for a user is evaluated using the ratio of nodes involved in offloading to the total number of users in the network. It helps to determine the dependency of users over the AP or vice versa. The extent of nodes connected using the target sets is used to determine the mobile data offloaded using the helpers. The dataset is processed to determine the graphical structure as the primary pre-processing step for network simulation. The graphical formulation offers a significant advantage for implementing NETWORKX library functions to illustrate the network view and data processing. We implement our simulation using Python 3.3 over Ubuntu for further processing.

Figure 3.1 shows the success ratio of implementation of target sets used for data offloading. The success ratio of users is identified based on our proposed implementation with the standard greedy approach used for the target set. It is differentiated based on the weights of target sets identified by the greedy approach compared to the opinion dynamics-based derivation. We process the dataset of varying sizes, increasing the number of users from 100 to 1000, and observe the ratio of target set users identified for data offloading. The opinion value of most of the target set users does not change for long and contributes successfully towards probable optimization. However, the change is not continuous throughout, yet it becomes significant for discrete changes in the target set sizes.

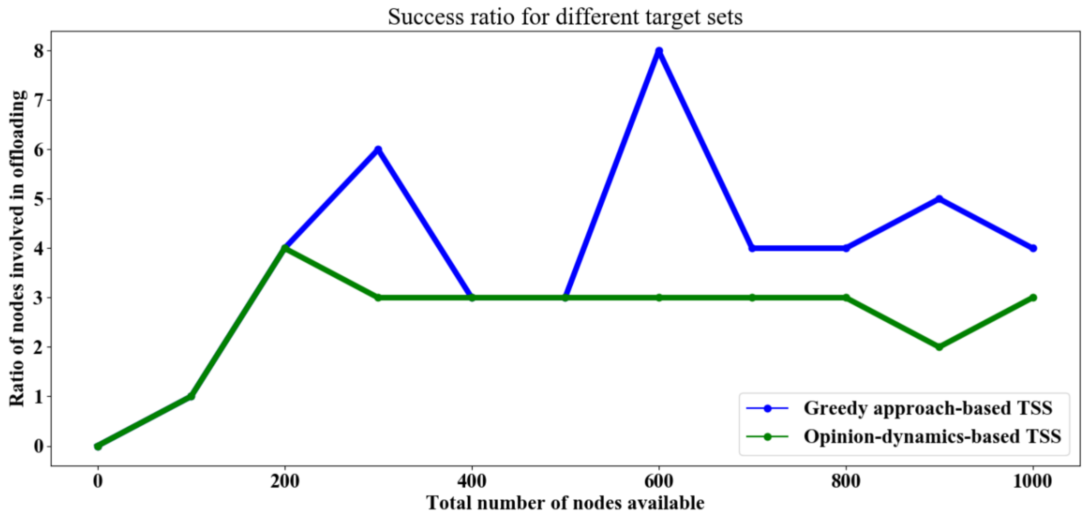

Figure 3.1: Success ratio of target sets

Figure 3.2 shows the message transfer load encountered during data offloading using the target set users determined by our proposed approach compared to literature methodologies of degree-based greedy and heuristic implementations.

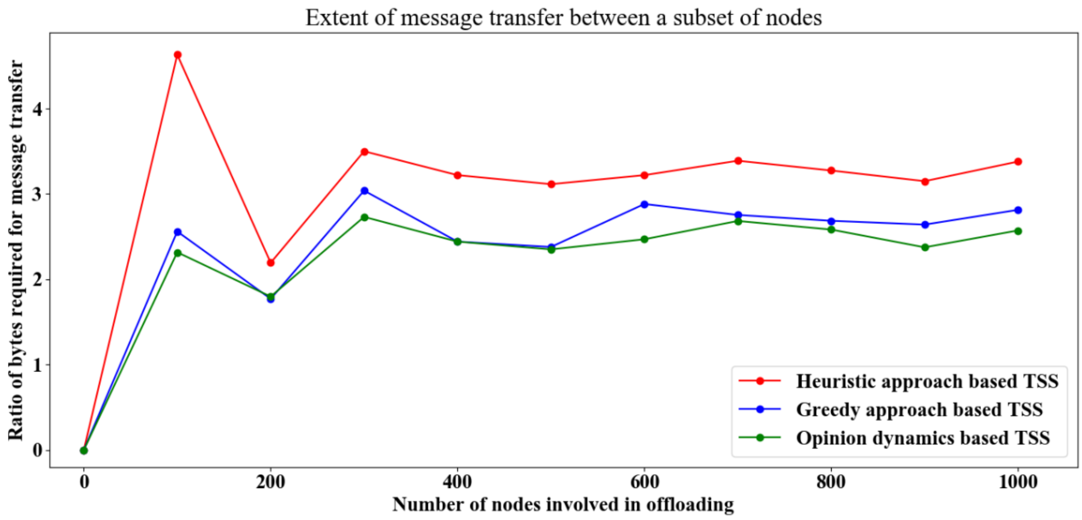

Figure 3.2: Extent of message transfer comparison

The extent of message transfer accounts for the cache used by the users, to distribute the data in the neighborhood users. We use the property that total number of bytes involved in message transfer is directly proportional to the number of subset users in the target sets. Figure 3.3 also shows the similar results in terms of percentage of data sent using the optimal target set users identified using our proposed methodology.

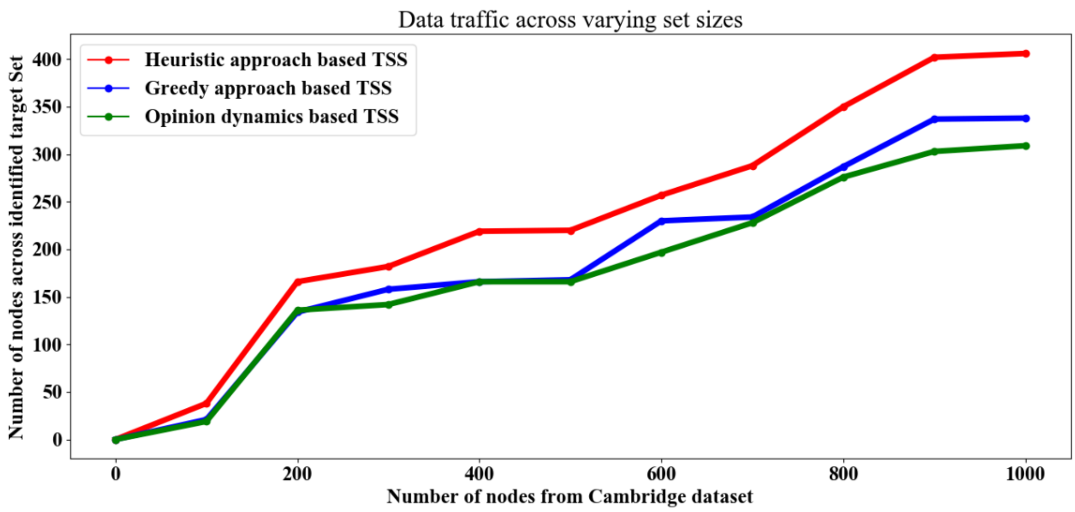

Figure 3.3: Data traffic for varying data set sizes

After offloading, the total network traffic accounts for the percentage of data sent using the nodes instead of the AP. The slight peak in the Figure 3.2 is due to the higher frequency of similar nodes, active in the dataset initially.

3.6 Conclusion and future scope

We have validated our finding that distributing the network load using collaborative decisions of AP and the users helps determine optimal offloaders. Hence the interest-based classification done by the AP initially followed by the opinion values of individual users helps in data forwarding using fewer target set users. A significant portion of additional overhead can be compensated using more optimal offloaders to satisfy a significant portion of a network. However, the concept of overlapping users needs to be addressed where different users might be interested in multiple interest items. It would be interesting to observe the results of our proposed implementation in such scenarios. The forwarding metrics may prove more beneficial for ISPs if global topology information is unavailable when the real-world networks exhibit machine learning-based characteristics.

CHAPTER 4

ENERGY EFFICIENCY AND BUFFER MANAGEMENT OF TARGET SET

4.1 Introduction

Owing to the continuously rising needs of mobile data and increasing internet traffic, there is an enormous need to deal with alternative solutions to address such issues. However, several solutions have been proposed to deal with the high demands of data and traffic reduction networks. These alternatives can overcome the issues of limited bandwidths and network conjunctions. The construction of additional BSs is an intuitive answer to these challenges. The network capacity can be increased by increasing the cell sizes of the BS or by their up-gradation to new generation networks like WiMAX or LTE to be used for data transmission of more extensive content. Likewise, using technologies based on broadband networks could also be used to accommodate substantial data demands. At the same time, this also leads to higher energy usage and a higher cost of settlement. Hence, such solutions do not suit the present demand in pursuit of the present scenario of internet services. Nowadays, the main necessity is to maintain pace with the increased demand for data traffic and the available grid supply. The use of WiFi like alternatives which offload the data traffic from the natural cellular networks shows significant results in reducing the traffic of ISPs. It is also helped by the use of immediate and deferred offloading alternatives. Although not instantaneous, deferred offloading delivers significant improvements as long-time benefits in specific instances while dealing with massive data. Certain drawbacks are also related to the WiFi offloading and cellular offloading, but they can be overcome by using D2D-based delay tolerant networks or partially connected networks. Hence, the store-carry-forward approach offers a significant contribution towards opportunistic networks for mobile data offloading. The use of D2D networks is helped by optimal resource utilization, thereby reducing the overall monetary costs involved. Although D2D networks face low data transfer rates using the unlicensed spectrum, it may help to reduce data traffic across ISPs. The mobile devices can be connected using WiFi direct or Bluetooth in a D2D manner to disseminate similar data items between users.

This chapter proposes using a hybrid approach using D2D and mobile nodes. The primary advantage of our recommended solution for mobile data offloading is that it leverages the existing context and social activities of the mobile node practically without incurring any monetary costs. D2D communication becomes significant because it may reduce energy usage levels significantly. Such modeling becomes significant when a smaller subset of users may be interested in the same data objects. For example, a group of students belonging to the same class who are friends may be interested in the same set of photos or videos shared by their classmates. The literature suggests using offloading using either immediate offloading or deferred offloading based on the availability of resources. However, most of the D2D techniques need to be enabled by using an application service in the background. Such a model may help to discover the available mobile devices in the neighborhood. Such implementation is necessary because the mobile connections are stochastic. At the same time, D2D connections need appropriate buffer management schemes so that the communication is not at the cost of memory limitations. The publication in [95] supports the results and analysis of this chapter.

4.2 Motivation and related work

The data offloading techniques proposed in the literature can be broadly categorized in terms of delay-tolerant or delay-intolerant approaches. The delay tolerant networks have successfully offered opportunistic communications by data forwarding and data dissemination techniques. However, there is minimal emphasis on methods and calculations to address overloading in data offloading solutions in the latest decade. The authors in [96] review several heterogeneous network design types and determine their feasibility with macro-networks for a proper interface. It supports adding heterogeneous elements into the existing cellular networks using the proposed multi-tier framework based on random spatial models. The user experience and network capacity are enhanced using small cells like picocells or femtocells in a multi-tier network. The authors in [97] have studied the feasibility of dynamic content over a mobile social network. The major contribution of their approach is the optimal determination of network bandwidth for early content distribution. In addition to the network optimality, the authors' determination of maximum network scalability is also considered. The authors have proposed a system model, consisting of a single wireless service provider and some mobile users. The system determines the age of data for its distribution, based on the rate allocation vector and the method of communication between users. The results ensure that the data updates can be distributed over a mobile social network in a scalable manner using the proposed content sharing protocols. The work done in [98] emphasizes determining the tradeoff between determining the traffic being offloaded and users' satisfaction. The authors have determined an appropriate incentive mechanism for 3G traffic offloading. The methodology uses a reverse auction-based bidding mechanism to determine the offloading potential and delay tolerance of the users. The seller-buyer association uses the operator as the buyer, and users as the sellers are used to model the network auction. The authors encourage the use of DTNs in networks, ignoring infrastructure dependence. The research works show the extent of offloading, average offloading delay, and percentage of winning bidders observed for high, middle, and low delay tolerant networks. The major contribution of their work is to determine the dynamic characteristics of users' delay tolerance using their proposed incentive mechanism. In [66], the authors establish the usage of D2D communications for increasing energy efficiency and QoS of wireless networks. The D2D communication can successfully underlay to a cellular network, as shown in the implementation. The results show the need for D2D receivers to be equipped with antennas to avoid interference from the base stations. The use of non-binary network nodes to determine the minimum capacity of cooperative networks improves the frame error rate (FER) performance in high signal-to-noise (SNR) regions. The significance of D2D communications has been investigated in [100]. The architecture of D2D is similar to Mobile ad-hoc networks (MANET) and Cognitive radio networks (CRNs). The authors have listed the advantages and disadvantages of inband D2Ds and outband D2Ds. The inband D2D uses licensed spectrum categorized into underlay and overlay categories, where the same radio resources are shared, or dedicated cellular resources are used, respectively. The outband D2D uses an unlicensed spectrum and eliminates the interference issues between D2D and cellular networks.

In [98], the authors propose to find out the metrics of using D2D networks for offloading by considering the aspects of power-law distribution. The authors have also proposed an interest estimation model, which considers the aspects of social influence and Bayesian inference to investigate whether some particular user neighbors are attracted to a particular data item. The results have been verified over the Cambridge dataset. A distributed efficient D2D offloading algorithm has been proposed, which can be applied over mobile devices. The proposed approach results are compared with the earliest deadline first policy and shortest remaining processing time first policy using the concept of an expected user's expected available duration. The absence of incentives for mobile users to share their material is a significant disadvantage to D2D communication because sharing unavoidably takes up limited resources and potentially endangers user privacy. This aspect has been addressed in [101] using the roadside units, and D2Ds in [102]. The researchers have studied the incentive problem related to D2D-based data offloading. Their significant contribution is the modeling of incentive in offloading as an auction game and the proposal of a randomized auction mechanism for data offloading in cellular networks using D2D communications. Their work is dependent upon the decomposition of optimal fractional solutions into weighted integral solutions. The authors have proposed the approximation algorithm using the Lagrangian approach with sub-gradient and heuristic derivations. The auction is also justified for Vickrey-Clarke-Groves distribution.

The entire work done by researchers in the above literature suggests that D2D communication offers better offloading potential than the compared approach as well as there is a feasible contribution towards incentive determination as well. However, the major drawback in the literature survey suggests emphasizing the contribution towards the target set users for heterogeneous networks concerning energy consumption and memory constraints of devices. In the previous chapter, we have incorporated the phenomenon of opinion dynamics, which establishes a more stable network. It is expected to fit into the dynamic environment enabled by D2D communication too. In addition, as reviewed in the above literature, there is minimal work done on the simultaneous belonging of a device into multiple communities in a realistic environment. In this chapter, we have used the social characteristics of users in a real-time environment using the D2D networks. This may help establish opportunistic communications amongst users while considering devices' energy and memory constraints in a D2D network. This work is supported by the results of our publication in [95]. We acknowledge the energy and memory constraints of the network resources in a D2D network.

4.3 Proposed optimal target set algorithm

The primary concern is to model the observed behavior of a D2D-based opportunistic network. It needs to consider all the users within the network considering the energy dissipation aspects. The literature suffers the drawback of finding an appropriate model, which could consider the communication between heterogeneous networks. For the system model, we consider an ISP to have a set of APs with their cellular towers CT_1, CT_2,...,CT_n. Hence in graphical visualization, we have a particular node that is considered as the data broadcaster. Limited to the conceptual networking, we limit to observe the only n number of mobile users such that $U = U_1, U_2, \ldots, U_n$, where U is the users within the accessibility range of CT_n. For the simplicity of our network model, we consider that each user U_n is able to download or upload $d(t)$, data bytes at time t. Also $d(t)$ is defined as a composite function $d(t) = [b(d), \mu(t)]$, which represents that $b(d)$ is the message size held by node U_1 and $\mu(t)$ is the time taken to transfer the data item $d(t)$. Initially, the data items are arranged in the ascending order of data bytes. We also consider that the data item is indivisible, which either ensures a successful or an unsuccessful transfer in the network model. We consider that the data is successfully transferred before the time-to-live, TTL interval. The coverage of the cellular network is presumed to be distributed. The network bandwidth may be weak across the center of a larger area cell, due to higher density. We consider such scenario because the signal strength deteriorates as we start moving indoors. However, we have better bandwidths across street like cases. Although the addition of tiny cells may resolve an inadequate interior coverage, it takes a substantial time to deploy and become expensive. Therefore, we suggest that each device is able to communicate with D2D indoor or patchy situations. We presume that the mobile towers are infrequently used in rural areas and occasionally a partially linked network is established. We postulate that nodes can develop an ad hoc network in this circumstance. In our system model, we assume that the users form an undirected graph, with the list of neighbors to be shared with every node. The initial stage in any process of data downloading is the problem of selection, since it is important to start the dissemination appropriately. One technique for selecting the source is the community-based source selection problem. The NP-complete problem of the community-based source selection is based on a reduction from the dominant problem. Heuristic method is utilized to address the problem. Next to source selection, the following goal is to prune the message before the TTL, when data is inundated.

Our initial algorithm aims to identify a subset of users, which belong to same or different communities according to our above system model. This subset is able to offload the data successfully which is otherwise meant for an AP of a cellular network operator. Our objective is to separate each community based on similar subscription of services, into different degrees of identification and optimize the process for subset selection. This should address the dynamic property of the users in the D2D network. In contrast to the previous chapter, we optimize the initial target set users using the *k*-means clustering algorithm. It considers the parameters of location, list of neighbors and the betweenness influence *BI* of the users. In addition to node selection, the current chapter aims to detect the overlapping nodes also, which tend to belong to multiple communities. It is done using the Cut Vertex value, *CV*. The *BI* is evaluated by each user, using the following equation:

$$BI(n_i) = \sum_{j=1,k=j+1}^{j=N,k=N-1} \frac{g_{jk}\,(n_i)}{g_{jk}} \qquad 4.1$$

In the above equation, $g_{jk}\,(n_i)$ represents the number of paths which include node n_i, and g_{jk} gives the number of edges connecting node n_j and node n_k. The *CV* is evaluated using k-truss algorithm, as stated in [97]. It is derived using the graph theory concept of *k*-influence subgraphs. The k-means clustering is derived using the equation 4.2 as follows:

$$BI(n_i) = \sum_{j=1,k=j+1}^{j=N,k=N-1} \frac{g_{jk}\,(n_i)}{g_{jk}} \qquad 4.2$$

4.4 Proposed neighborhood overlap and message pruning algorithm

This algorithm provides a technique, which is useful for detecting overlapping nodes and computing summary vectors. Because the network is dynamic, the important element of this technique is to employ only local network information because global information incurs significant communication costs, processing, and energy depletion. The method uses self-centered betweenness as it identifies that a node belongs to many communities, resulting in overlapping nodes. The main advantage of egocentric interconnection is that every node requires just two hop-neighbors, rather than global network knowledge.

Algorithm 4.1 Algorithm for determining optimal target set user by the access point.

Input: Set of network users N, Location of users L, Neighbor set of users $Nbrlist$.

Output: Clusters C and T.

Step 1: Initialize: $C \leftarrow Null$ and $T \leftarrow Null$.

Step 2: For each user in the range, the access point accesses $Nbrlist(n_i)$

Step 3: For each user in the range, the AP evaluates $BI(n_i)$.

Step 4: The AP computes CV using $Nbrlist$ and $k - truss$ method.

Step 5: Create d - dimensional observations vector X using location L and $BI(n_i)$.

Step 6: Create cluster C applying k-means method over matrix X.

Step 7: Update $T \leftarrow C$, with maximum CV.

Step 7: Return T and C

The SV idea is built on a bloom filter, which reduces the overwhelming communication and duplicate signals. The latest message exchange with the remainder is monitored by each node assigned to a buffer so that duplicate communications are not accessible. The buffer saves and gathers messages from other mobile nodes. In order to manage every node efficiently the indices of all messages must be stored to a hash table and kept in a single identification known as a summary vector. Only the short vectors will be exchanged whenever a node reaches the vicinity of another node. Each summary vector modification is determined by the message requested from a neighbor. The nodes also save time for exchanging specific nodes to avoid a duplicate exchange of communication. The ego node calculation and redundant message tapping algorithm is defined in these stages.

Algorithm4.2 Overlapping node detection and summary vector based message pruning algorithm

Step 1: Each node i evaluates its egocentric betweenness σ_i.

Step 2: Node i exchanges σ_i with all of its neighbors in the $Nbrlist$ and computes the threshold value: $\varsigma(i) = \sum_{j=1}^{n} \sigma_j$, where $(j = 1,2,3,..,n)$ represents the jth neighbor of node i and σ_j represents the egocentric betweenness of neighbor j.

Step 3: Node i finds the overlapping node from its neighbor set on the basis of comparisons of $\varsigma(j)$ and $\varsigma(i)$. If $\varsigma(j) > \varsigma(i)$, then the node j is declared as overlapping node (OL) or the vice versa.

Step 4: The identified overlapping nodes (OL) from the previous step share SV_1 with each node i and compare them. If there exists common entries in between, then ignore the final target sets T, else share the data of uncommon entries.

Step 5: Return final target set T.

We now discuss the algorithm that the access point is to implement. Every node i in the first phase, discovers the ego-width in the $Nbrlist$, in order to assess the usefulness of the node for its vicinity. Egocentric betweenness is described as the likelihood of a node being between the two nodes. A higher σ_i value interprets that a node is more likely to be linked to other nodes. $A^2_{i,j}$, includes all paths with length 2 from the node i to the j, taking A as an adjacent node matrix. We must not assess smaller connections as unit length walks since they do not add to betweenness. The number of geodesic links of the length 2 between node i and node j is calculated in the end using $A^2[1 - A]_{i,j}$. Every node exchanges the ego betweenness value with its neighbors. It is represented as σ_i. Each node selects its preferred list of neighbors OL, which can affect the dispersion of data on the network more effectively. Finally, during the anti-entropy association, the SV value is updated periodically using CV and OL. The users exchange their SV values and compare them with buffered messages. If the similarity value is below 50 percent, then the user requests the missing data.

The initial step of the method uses $Nbrlist$ to calculate the centrality. For this phase, it is possible to decrease $O(n^2)$ space complexity for the matrix generation and $O(n^3)$ runtime complexity to $O(n^2)$ with a random method. The second phase of our proposed algorithm uses *k-truss* algorithm which has far less complexity.

4.5 Simulation results

The simulation results have been divided into two stages. Initially, we have demonstrated the performance of our proposed algorithm. It is followed by the comparative analysis with community-based approach [36]. We have evaluated the performance of our proposed implementation based on the parameters of energy utilization, tolerance delays and SNR values. The simulation considers a network area of $1 \times 1\ km^2$ area with 1000 users. k-means clustering algorithm is used for clustering of users. In addition to it, we also use *betweenness* and *cutvertex* values for clustering optimization. The cluster user then utilizes the overlapping node to figure out which other clients spread messages. The simulation is performed using MATLAB.

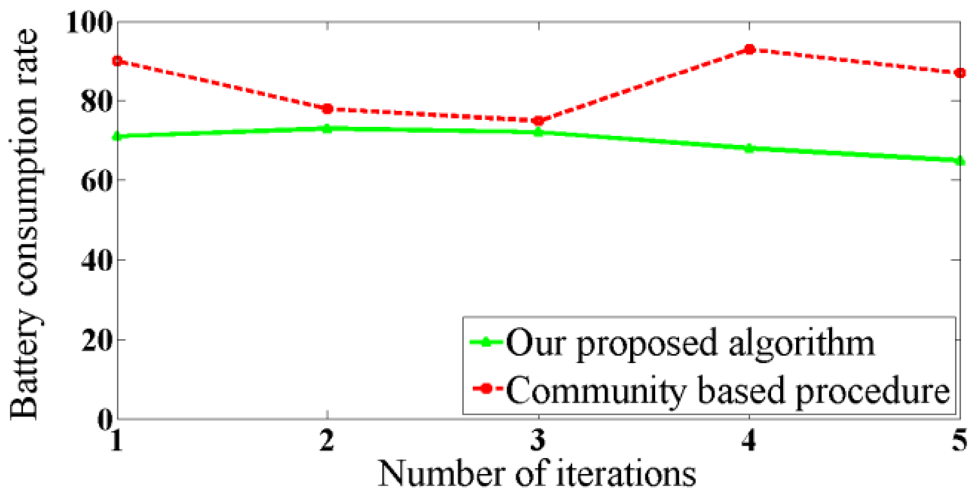

Figure 4.1: Rate of battery consumption

The use of batteries by consumers is evaluated in order to compare energy drainage. According to Table 4.1, Bluetooth consumes the most power, while D2D consumes the least. Further information is obtained from other devices during sleep mode via wireless Internet. The results suggest that more energy is consumed. The difference in D2D battery usage is around 95 percent lower than Bluetooth. Since it uses the internal power of the device, Bluetooth power consumption is significantly greater than D2D.

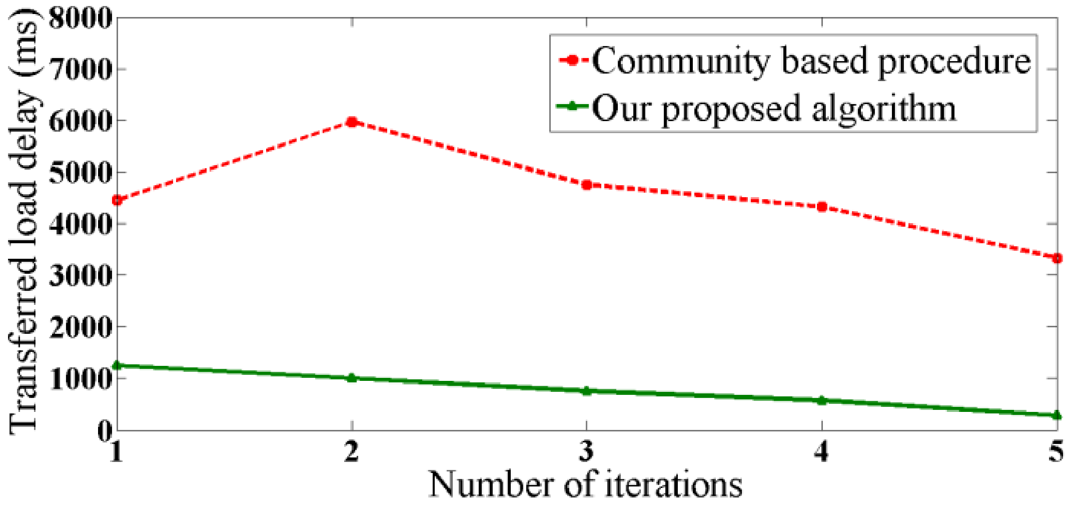

Figure 4.2: Delay during load transfer

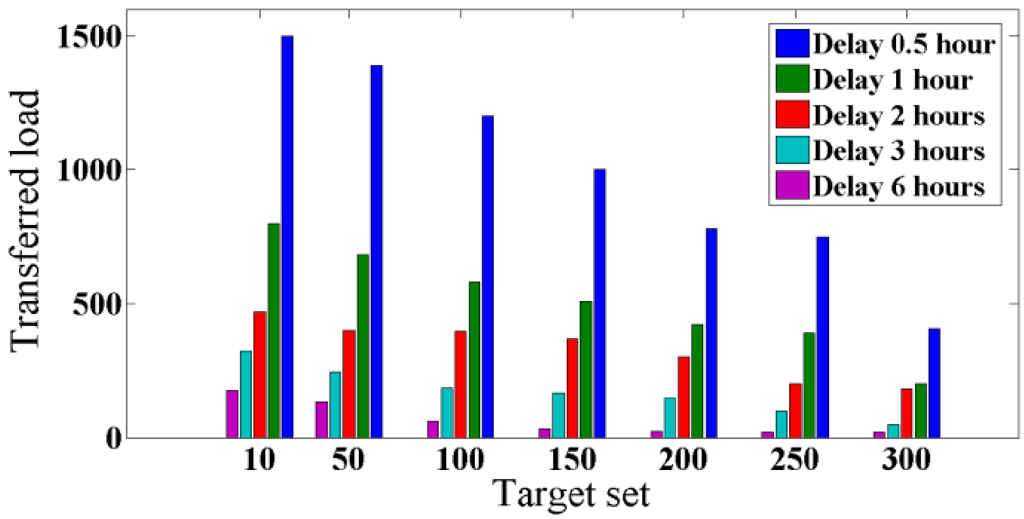

Figure 4.3: Target set with transferred load

The delay of transfer loads in milliseconds to various target groups is shown in Figure 4.3. In this figure the y − axis shows the heuristic transfer burden for several sizes of the target set. It illustrates the change of the load delay throughout a 6 hour session on the fixed target of 1000 nodes. We show the results for delays of 30 minutes, 60 minutes, 120 minutes, 180 minutes and 360 minutes. We repeat the iterations three times throughout the course of two hours. Similarly, we repeat six rounds with a one-hour delay and twelve iterations with a 30-minute reminder. The load with smaller delay scenario has the shortest delay, as shown in Figure 4.3. We see that the delay in load does not make a major impact to various delays. As a result, we concentrate on other criteria for comparison. The utilization of the battery is characterized as a decrease in power. The mean square error MSE, is dependent upon noisy group strength and the number of users in a particular cluster. Here ngs denotes noisy group strength, $nngs$ denotes non-noisy group strength, and NSC is used to represent the total number of nodes within a single cluster. The signal to noise ratio value SNR, is evaluated using $SNR = MaxBitValue^2/MSE$ to assess the unpredictability of the all users in the group against its total strength.

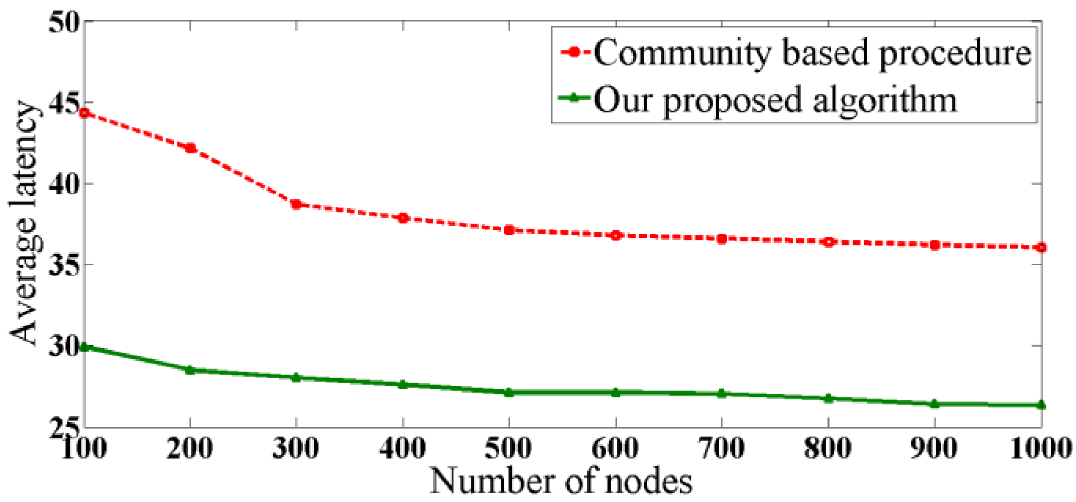

Figure 4.4: Latency for target sets

The load fluctuations and departures from the mean square error may be found in Figure 4.5. As the charge rises, the MSE also enhances. The data demonstrate that load increases gradually until the third load increases. However, the MSE abruptly rises quick when the fourth load variance comes. This is because the third load variation has numerous noisy nodes linked to it. This increases its intensity considerably faster. The SNR is also reduced in cases, where MSE increases rapidly. The minimum value of MSE is near to unity and the maximum value is approximately 14×10^7. The *x*-axis represents the load variation and the *y*-axis is shows the value for the MSE, and SNR. The results are shown four load variations. The value of SNR lies in between 0.4 and 2. Figure 4.5 shows that SNR improves smoothly up to the third change in load and subsequently drops as it is noisier. At the third repetition, the mean square error is large and the SNR starts to fall as illustrated in this figure. We have achieved the greatest SNR 1.79 for the third load, while the lowest achievable SNR is recorded for the first and second load variations. Our proposed clustering algorithm has been compared with the community-based research algorithm. The comparison is carried out using the energy drainage, latency and buffer consumption variables. The obtained result is illustrated in the Figures 4.3, 4.4, 4.6 respectively. The findings from the simulation indicate that our suggested method gives an average of about 75-80 percent less time when data are discharged from the access point, while energy optimization in five rounds increases approximately 16.7 percent. Figure 4.6 findings demonstrate that our suggested technique also exceeds latency when the number of nodes is increasing gradually from 100 to 1000. The highest delay for lower target sizes is measured as 30 percent, which further decreases while increasing the number of nodes in the target set. Our solution is based on a notion of the summary vector and overlapping nodes to facilitate quicker data transfer, as a result of this drop of latency. The buffer size of each fixed mobile node of about 50 MB has been taken into consideration in this simulation. However, as shown in Figure 4.6, we also analyze the influence of different buffer sizes on latency.

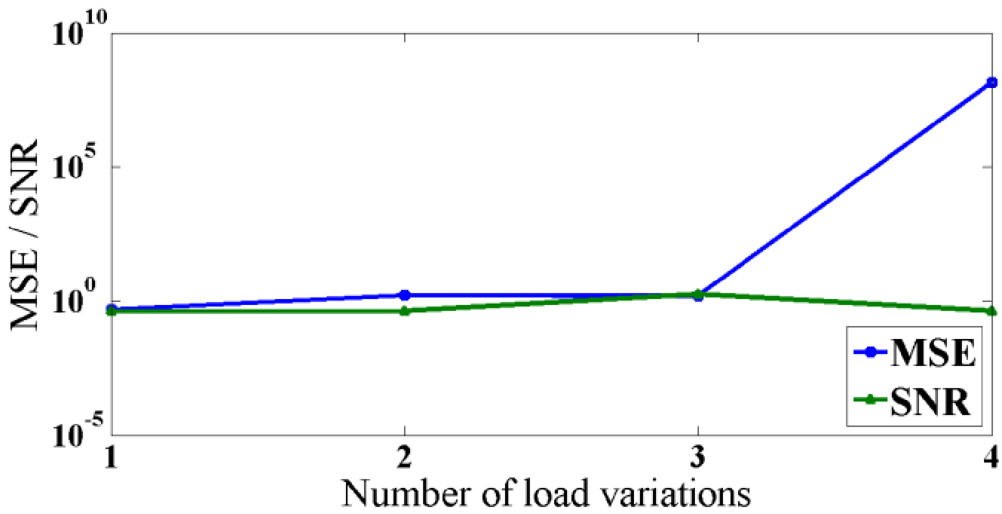

Figure 4.5: Variance in MSE and SNR

We observe the impact of our implementation while we increase the message size from 10 MBs to 26 MBs. We assumed that each of the data might be postponed by up to 2 hours. It models the delay tolerance of our data offloading model. The latency seems to rise as we continue to increase the buffer capacity. The data demonstrates that the latency rises with the improved buffer size. The findings also suggest our technique to knowing size of target communities can perform better than the community-based approach.

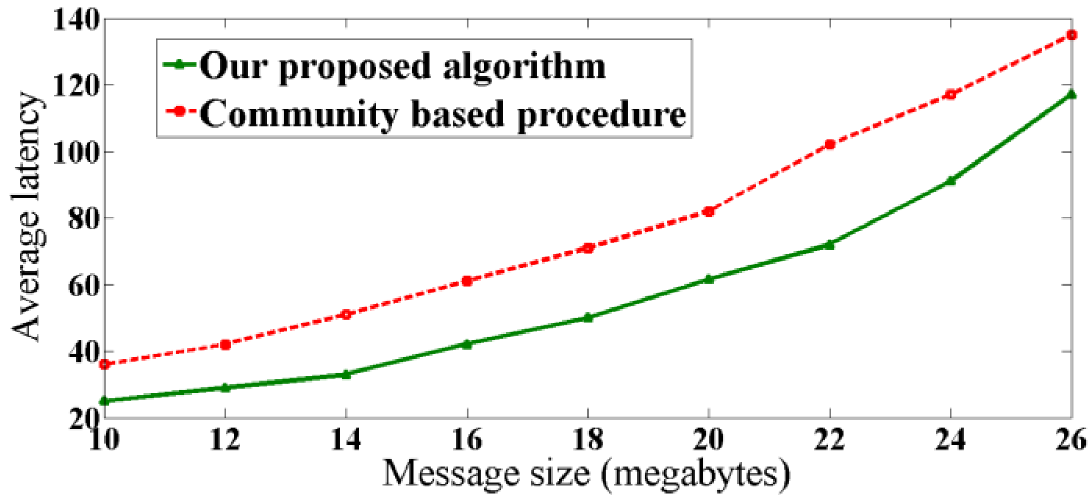

Figure 4.6: Latency and message load

4.6 Conclusion and future scope

In this chapter, we present an efficient D2D communication with the k-means algorithmic download technique. In addition to effectively downloading mobile data, the suggested method also optimizes network performance for energy, buffer and latency usage. These features help to observe the significant aspects of energy utilizations of users. The restriction of this work is that the mobility component of the nodes is not covered in depth. The proposed implementation applies fairly to the data offloading schemes of conferences, educational establishments, and residential areas in a limited geographical condition. The future part of our study will also involve use of metaheuristic algorithm for automatically optimizing the selection of data items in disconnected data and reducing the delivery time. All users may utilize the aspect as assistants for trust-based assessment and incentive assessment.

CHAPTER 5
TARGET SET SELECTION USING HYBRID COORDINATION OF ACCESS POINTS AND NETWORK

5.1 Introduction

The growing mobile usage for day-to-day services leads to a rise in mobile data traffic. The opportunistic networks provide an effective way to distribute this traffic and enable data dumping. The adoption of WiFi, Bluetooth or femtocell-based technology supports opportunity communication. These communications provide a potential alternative in the light of the costs otherwise involved. Although social networking tools for download optimization are available, they confront problems in privacy and security. Social networks are used to discover influential networks utilizing graphs with users as vertices and interactions as edges. Their communication methods are thought to minimize user behavior, throughout the whole network. This difficulty is referred to as the TSS problem when recognizing the limited group of users. The subgroup of users is thought to have such a mitigating effect that either the whole universal set is satisfied or all users or most of them are activated. Its influence decreases the data traffic of the ISP utilizing the best suitable collection of offloaders. The research implies that we can analyze certain static network data to expand the mobility pattern. It broadens the scope of application in realistic mobile environments. We propose to build a hybrid approach using greedy algorithms and heuristics associations of the underlying hybrid network with infrastructure support. We also consider the overlapping target sets for intermediate analysis using summary vectors.

5.2 Motivation and related work

Several writers examined the TSS problem in mobile data download literature. We also used the situation to share the curriculum with select students in a specific segment of the course. The conventional procedure is to distribute it one by one to all the pupils. This approach takes time and demands extensive resources. In the mobile data download literature, several authors looked at the TSS problem. In this chapter, we consider a scenario where, a group of students need to be circulated with some course curriculum or a particular segment of the same. It must be distributed one by one to all students in the traditional method. It takes time and requires considerable money. Another smarter approach to do so would be to share it with certain students and ask them to pass it on to the other pupils. The basis for the TSS issue lies in its practical use. Here the limited group of users, i.e. students, must be identifying such that the whole portion of the universal set, i.e., is fulfilled. Tolerant delay networks are increasingly essential in order to discover similarities in the interests of consumers using such an approach. This download may be useful for updated situations of common interest, such as daily weather updates, local news and particular user communities. All such users can be divided into groups of similar interest. Mobile data downloading can also assist in constrained geographic disaster management systems if the rate of delivery of information is significant for a greater impact.

In the field of viral marketing, we also have TSS applications that use social network analysis. For greedy and heuristic implementation, most studies have exploited the characteristics of static networks. The networks, however, are usually dynamic. This is also an issue that is tough since a person is part of many network sets concurrently. The control of space crossing has been done with little effort. This chapter seeks to understand network and community dynamics. For literary discussions, the following classifications will be utilized.

5.2.1 Types of ad-hoc connections

The most promising technique with the usage of DTNs is data flowing from mobile phone to device-to-device networks. DTN-based devices have been examined for their small capacity and the wide range of interest in their limited storage by users [4]. DTNs with genuine human and vehicle traces are converted by optimized 0-1 knapsack with linear limitations into maximizing function problems. In order to estimate homogenous contact rate and buffer sizes, the authors proposed a GA of generic scenarios, AA of shorter life-scripting and an OA. However, the work of the two knots is supposed to follow the Poisson rates. This means that the implementation is limited to DTN-only models. In [8], additionally heuristic records address the problem of offloading maximization. The greedy method entails a reduction in record-life connections. It proposes an optimal way out for heterogeneous networks. The work done in [21] showcases the comparison of the proposed methodology with greedy and approximation algorithms. The authors use Lyapunov optimization for adaptive offloading in it. Such implementation offers offloading a fraction of computation to a dedicated server. It can also adapt according to changing environments, as has been shown in [6].

Some literature also focuses on identifying the impact of heterogeneous systems. Such research makes the network more realistic due to the categorization of network users as service subscribers and offloading helpers. In [22], the authors have approximated the upper bound for TSS, whereas its lower bound is targeted in [38]. A similar assumption of all the users to agree for sharing is done in this work too. Such users need to forward the similar information using the available shared resources. This might minimize their financial burdens and also share resources in order to prevent congestion. VANETs use such WiFi hotspots, alike in [94]. It happens because the users are believed to be forming communities during fixed instances. This helps to ensure that all such networks are given priority. Such methodology reduces the cost of transmission. The solution proposed in [11] uses the network relationship of users. It frequently checks the connectivity status among users. Using the network associations, the authors are able to determine the expected range of network transmission. There are a limited set of users who are able to reach to the final destinations across networks. These possibilities for various communities have been discovered by the authors [5]. In these instances, a node must have absolute priorities depending on a number of key features. A data transmission method, SAIS, has been proposed by the authors to be used for social-networking deployment. A realistic approach to a modest relationship of access points in relation to the total number of mobile users is the main contribution of their work. The authors also discussed the property of network implementation graph cliques.

5.2.2 Data offloading parameters

Few authors examine discharging cellular traffic with the encounter frequency inside a single classroom [104]. They utilize social communities and the frequency of meetings to assess the performance of data transmission. The authors suggested and contrasted the transfer of data based on meetings, RF meetings and random techniques. It shows best than a number of comparative techniques the results of the

RF meeting algorithm. The authors utilize data dissemination delay in the RF algorithm in order to determine the effect of using sources in the group for a given duration. The results demonstrate that the balance between the discharge frequency and delay depends on optimization. The third criterion is human movement regularity as a crucial element in evaluating opportunistic, connectivity-based downloading of mobile data. It has shown that the problem is submodular and that greedy algorithms and heuristic mobility patterns are applied. However, as with [7], it is partly assumed that certain controllers for content dissemination decide which node material must be delivered. Some research projects such as [10] also use the contact length of mobile phones to identify the opportunistic likelihood of conversation. Although the application scenario is constrained, the greedy technique is superior to the heuristic and random algorithms, as demonstrated in [11]. It generates a framework from tiny data exchange during brief durations of interaction. A traffic download system model with movement prediction is available in [39]. In order to define the coverage zones in the vicinity, the authors have employed a series of matrices. In order to calculate the chance of meeting, their technique employs several matrices. The likelihood of meetings is used to calculate the coverage via heuristics. In the ns-2 simulator, the researchers simulated the ad-hoc network.

Most of this research is concerned with identifying social participation and the status of activity via social networks like Facebook or Twitter using online social communication networks [7, 30]. The authors provide an appropriate worst-case solution utilizing the static graphical network transformation based on the trees. In order to determine dynamic communities, the authors have suggested a novel method named AFOCS. It is followed by the C Finder [105] and the COPRA methods [106] comparative analyses. Instead of static community detection, their important contribution is to analyze the dynamic community based on standard information. The authors first utilized their AFOCS method to establish the fundamental structure of the community based on local relationships. This was followed by the combination of several groups that overlap. This technique serves to make a community more useful and eliminate it. The authors in [107] proved effectively the link between overlapping communities and community identification of space crossings. The usage for data transmission in mobile social networks might be made of those space crossing communities. Finally, it has been suggested to enhance the data transmission efficiency in order to address the delivery ratio and timeliness features of the data transfer algorithm, namely SAAS.

5.2.3 Target set selection problem

In most of the literature, like [7, 12], TSS was targeted at user IDs, which can help the download or dissemination of data. The authors utilized a strengthening learning technique to identify the TSS solution. The solution is to be compared using actor-critical solution [7] and DROiD [12] to determine individual or multiple community identification. The researchers will decide, in addition to TSS, the appropriate goal size. Heuristic behavior based on recognition messages is determined to enhance content sharing for users. This is done utilizing the approach of learning time differences. The writers have utilized the degree and amount of material distribution employed by the left-wing users and the time limits for the provision of content to optimize the users. The approach is proposed in [36] for the identification of specific users as VIP delegations. The writers took use of the social elements of user movement. In order to observe the random movement of users a temporary social network is built and studied. The assembly patterns were developed in specified timeframes with the frequency of meetings. The social connection strengths in the network graphs may be determined. The VIP technique is built on random and greedy methods and has been referred to as blind promotion and greedy advocacy. The community *k*-clique algorithm was used to detect recurrent meetings that occur more regularly across the exact locations. Similar to literary methods, the qualities of centrality and proximity have been employed. However, the primary importance of degree and page ranks of users has been emphasized for the importance of nodes. In few study works, the identical data are found in limited nodes based on the deterministic features to supply the greatest number of adjacent nodes [108, 15]. The main problem is, however, that, despite their uneven relevance, each access point would have to pay the same amount of incentive as in [8, 11, 71]. When the user sends and consumes this information across these access points, it creates an overloading situation. It showcases the significance of incentive derivation problem in mobile data offloading.

In the next section, we propose a hybrid approach of greedy and heuristic behavior of users, taking into account the space crossing communities.

5.3 Proposed TSS implementation

In order to get the optimal final target set, we separate the entire TSS implementation into three algorithmic phases. The initial target set is determined for the AP at first. It is followed by optimal neighborhood selection. The ultimate algorithm merges the final output on the basis of prior algorithms. The final algorithm determines the data transfer system optimal for offloading.

Algorithm 5.3.1: Algorithm for Primary Target Set (*PTS*) identification

This method utilizes a restricted number of nodes in a given community based on the index values of similarities and the optimal values of the nodes. The user nodes will be examined on the basis of a set of interests for their similar subscription selections. The nodes falling in the range of the time-instance t access point are detected and compared to instance nodes, $t + \delta t$. All m neighbors have been discovered for each node n_i. We analyze the similarity of data subscription of neighbors as shown in [48]. Each n_i node, with the use of Betweenness centrality BC_{n_i} [47] and its total number of neighbors ρ_{n_i} with the use of equation 5.1, is assessed for BC_{n_i} Betweennesse Impact.

$$BI_{n_i} = BC_{n_i} \big/ \rho_{n_i} \tag{5.1}$$

The betweenness centrality value BC_{n_i} for the n_i node is given by equation 5.2, in which $g_{jk}\,(n_i)$ specifies the number of routes that travel through the n_i node between n_j nodes and the n_k node. Here g_{jk} is the total number of node n_j and node n_k routes. We analyze the similarity in data for each node and its near neighbor.

$$BC_{n_i} = \sum_{j=1}^{N-1} \sum_{k=1}^{j-1} g_{jk}(n_i) \Big/ g_{jk} \tag{5.2}$$

The influence function is implemented using the *k*-truss method used by the authors in [109]. This optimization guarantees the maximum use of cut vertex nodes. It is based on graph theory on the concept of influential subgraphs. The $n_i(K)$ graph is the biggest subgraph for a graph *G*, which contains all linked edges with at least $K - 2$ triangles, according to the *K*-influence subgraph theories. Thus, $n_i(ij) = K$, if each node is of $n_i(K)$, and is not of $n_i(K + 1)$, each node's n_i influence value. This corresponds to the order clique K. The nodes are classified according to the INS_{n_i} influence sizes, using the equation 5.3.

$$INS_{n_i} = \max|n_i(ij)| \tag{5.3}$$

The greatest impact may be derived from each graph's node for different amounts of influence. The fraction for a variable size window W is determined by using $F = RWKmax$ and applying the following equation:

$$R_W^{K_{\max}} = \frac{\varphi(n_i(K))/|S_{K_{\max}}|}{|W|/|S|} \tag{5.4}$$

where $\varphi(n_i(K))$ is the number of nodes in K-influence subgraph $n_i(K)$. The ultimate preference for edges must be dependent on the EgoBetweenness and Influence combined for each node computed using the following equation:

$$Utility_{n_i} = (\alpha \times F \times INS_{n_i}) + (\beta \times BI_{n_i}) \tag{5.5}$$

Algorithm 5.1 PTS, an algorithm for initial set selection by access point.
INPUT: $S = [n_1, n_2, \dots, n_i]$, $D = [d_1, d_2, \dots, d_{int}]$.
OUTPUT: PTS.
PROCEDURE

Initialize $a \leftarrow 1$, $W \leftarrow 1$, $\alpha \leftarrow 0.1$
for $a <= i$ **do**
    evaluate BI_{n_a}
    for $b <= int$
        evaluate $R_W^{K_{max}}$
        evaluate INS_{n_i}
    end for
    for each α and β **do**
        evaluate $Utility_{n_i}$
    end for
end for
if $Utility_{n_i} \geq 0.5$
    update $PTS \leftarrow n_i$
end if
return PTS

In equation 5.5, α and β are the customizable constants to prioritize on the basis that $\alpha + \beta = 1$ is required. A node n_i is chosen to be inserted into a PTS set based on $Utility_{n_i}$ maximum value. For all $BI \geq 0.5$ nodes, the same selection criteria are applied. Such optimization makes similarity effects with the adjustable constants equally important. The user set is divided into two parts according to the value of BI, with $BI < 0.5$ or $BI \geq 0.5$ values. While this method is more complicated, it nonetheless accounts for the substantial improvisations we have accomplished.

Algorithm 5.3.2: Algorithm for Optimal Neighbor Selection (*ONS*)

When optimizing the sets based on nodes' priority interests, the target set is further optimized. We basically try to prioritize few nodes over other. Such comparison based on frequent interaction in social network is associated with the state of activity regulated by the points of access. These nodes are the preferred nodes which duplicate the data to their neighboring nodes. In a user group with *V* neighbors and *E* edges, the goal of an access point is to pick a main set of users that could aid with future offloading. The second *ONS* algorithm determines a primary set of assistants. Here *ONS* utilizes first and first width searches to distinguish principal and secondary users to allow them to be downloaded with data. Such users can function as progressive nodes when target users are defined. The utility values of the last algorithm are shared with neighboring nodes.

Algorithm 5.2 *ONS*, an algorithm for optimal neighbor selection of each user.
INPUT: $PTS = [n_1, n_2, \dots, n_j]$.
OUTPUT: ONS_{n_j}.
PROCEDURE
for $e <= j$ ***do***
    if $h \in Nbr_{n_e}$ ***then***
        share the $SV - I$ & $SV - II$ with h
    end if
end for
for $e <= j$ ***do***
    if $SV - I_e \leq SV - I_j$ and $SV - II_e \leq SV - II_j$ ***then***
        update $IF(i)_e = 1$
        update $ONS_{n_j} \leftarrow n_e$
    else
        update $IF(i)_j = 0$
    end if
end for
return ONS_{n_j}

The progressive nodes are made to consider and transfer compressed messages using *SV-I* and *SV-II* summary vectors. The vector *SV-I* carries the information of the subscription interests of each node. The vector *SV-II* carries the compressed form of data optimally. A neighboring node or the next to the kin node is selected based on similarity across these summary vectors. The data is offered to a neighboring node if the size of *SV-II* is less than the data available across itself. We continue to identify a single community based on a similar type of subscription. Progressive nodes are used by summary vectors of *SV-I* and *SV-II* to consider and transmit compressed messages. The *SV-I* vector include information about each node's subscription interests. The compressed form of data is supplied best by the *SV-II* vector. Based on similarity across these summary vectors, a nearby or kin node is identified. If *SV-II* is less than the data that is accessible, the data is delivered to an adjacent node. A unique community on the basis of comparable subscriptions is still identified. This problem is defined as the optimal selection of the neighbor set. We suggest in this approach that the data be distributed as summary vectors to the surrounding nodes. It takes account of nodes that have more than one community specified via the channel. For each matrix having a node belonging to more than one community, we compute the overlap based on its matrix representation. The weight of common interests throughout the interest matrix ensures the selection of communities that do not overlap.

Algorithm 5.3.3: Algorithm for Final Target Set Selection (*FTSS*)

Now we are transforming the graph visualization into a tree to complete the final target settings. The presence of cycles in subnetworks is taken into account. This technique hampers the use of numerous routes for graph node crossings. In order to establish the best feasible shortest routes we explore the use of the notion of a minimal frequency depending on the depth of each Node. The graph users must be linked to assess the depth. The sum of the row matrix is therefore utilized to achieve the depth-based relationship. The maximum depth assessed by energy component $row_{wt}(n_y)$ determines the greatest usefulness of a low delay tolerance minimum of nodes and ensuring a maximum part of the network. The nodes are picked utilizing the best ad hoc technique. It is NP-hard to approximate the solution of target set selection, for its maximum and minimum solutions. The PTS algorithm has a complexity of order $i \times int$. In contrast to the number of users, however, the number of interests is considerably smaller. Hence, we can consider $O(i \times int) \cong O(i)$. In addition, the second method depends on the number of node neighbors. There are also extremely few main neighbors for every node compared to the total user numbers. Hence for the *ONS* algorithm is of the order $O(j)$ complexity.

Algorithm 5.3 *FTSS*, Final target set selection algorithm.

INPUT: $PTS = [n_1, n_2, \ldots, n_j]$, $ONS = [ONS_{n_1}, ONS_{n_2}, \ldots, ONS_{n_m}]$.

OUTPUT: *FTSS*.

PROCEDURE

Initialize $row_{wt}(n_i) = 0$, for all i

  for all $y \in ONS$ **and** $x \in PTS$, ***do***

    for all $x \in ONS$ ***then***

      if $IF(y)_x = 1$ ***then***

        update $row_{wt}(n_y) = row_{wt}(n_y) + 1$

      end if

    end for

  end for

update $FTSS = PTS \cap ONS$ according to descending order of $row_{wt}(n_y)$

return *FTSS*

The ultimate algorithm *FTSS* depends upon the outcomes of *PTS* and *ONS* algorithms. The frequency of *ONS* repetition is dependent upon the users determined by *PTS*. Therefore, the overall order for *FTSS* is $O(i \times j)$. The average number of neighbors, which a user can have is significantly lower to the total number of users in a realistic network. Thus, the overall algorithmic complexity of implementation is limited to $O(i \times j) \cong O(i)$.

5.4 Experimental results and performance analysis

To identify a certain subscriber category, all nodes should be categorized based on the same service. Each node is ready for comparable data to be replicated within a given period. The interrelated relationships between each community are dynamic. A few assumptions for data transmission and analysis are explored to represent the dynamic situation. We took the following assumptions for granted:

a. All users in the range of one AP belong to the same community.
b. Every node should additionally agree to share its neighbor list in a cache-similar scenario with its interests in summary vector components.

5.4.1. Simulation

The suggested optimization is compared with MATLAB literature methods. Our results are validated for data transfer if the target sets with more important nodes are of restricted size. The simulation is assessed using MIT and NUS Bluetooth data sets using reality mining data. These datasets have been used to determine social groupings and communities by identifying Bluetooth-enabled devices for static and dynamic connections in close vicinity, which evolve with time. Our suggested naïve *FTSS* algorithm was compared with greedy, heuristic and community-based methods based on literature. We assumed daily updated news of the newspaper, a fixed size of 10 Kbs, in our simulation. Since the content is the same, each packet supply is comparable to a hawker's newsletter. Our simulation is to identify the comparison of offloaders and to establish an efficient cellular data offloading objective. Such target sets assist to route the data packet at different periods, based on available opportunistic communications. In the simulation setup, we consider 1000 users from the MIT dataset. We compare the literature-based method to our fixed-size target algorithm with a maximum of 50 nodes. The 20-second deadline for a subscriber to retain and share the info with their neighbors has been examined. The cell access point needs to broadcast the data automatically to all nodes of its range after the period limits.

5.4.2. Results and analysis

A similar technique has been followed as the number of accessible subscribers has increased. We now examine the various parameters for comparing our algorithm to methods based on literature.

Traffic load comparison

The proportion of users able to get data using the finite number of users in target sets via an opportunist network is estimated in our method. We note that the selection of targets based on FTSS is more optimum than previous methods. For similar interest subscribers, our system delivers superior outcomes for optimal consumer proportions. With the increased number of subscribers of general interest indicated in Figures 5.1 and 5.2, the proportion of users retrieving the data via our suggested FTSS will grow. This improvisation is based on the possibility that subscribers engage with others in a more opportunistic network. In this simulation we analyze MIT data set users and NUS data set and the findings in Figures 5.1 and 5.2. We choose a 10 KB data packet that is transmitted in various sizes to 10 to 100 nodes.

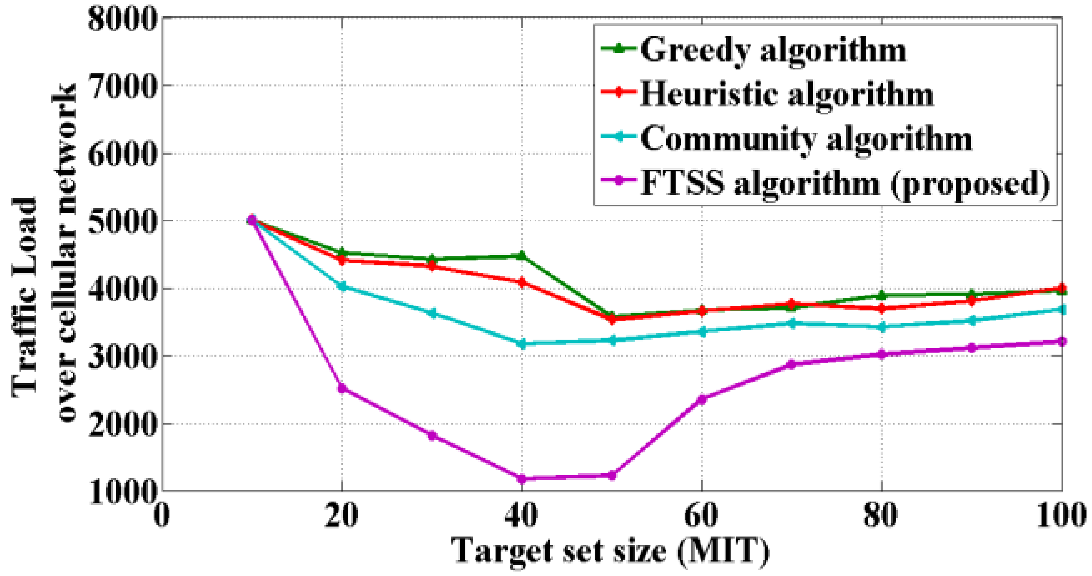

Figure 5.1: Traffic load over MIT cellular network

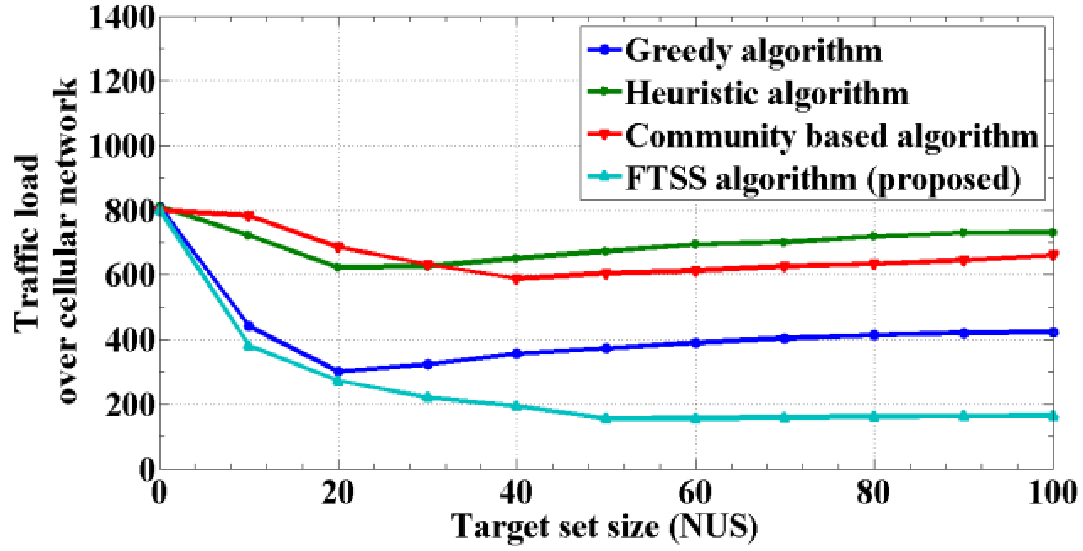

Figure 5.2: Traffic load over NUS cellular network

Initially, all traffic is controlled by the access point because the goal range does not lie with any subscriber. Thus, $800 \times 10 = 8000$ kbs of data must be sent. Since we allow additional people to help load the traffic of the access point, it reduces the quantity of traffic.

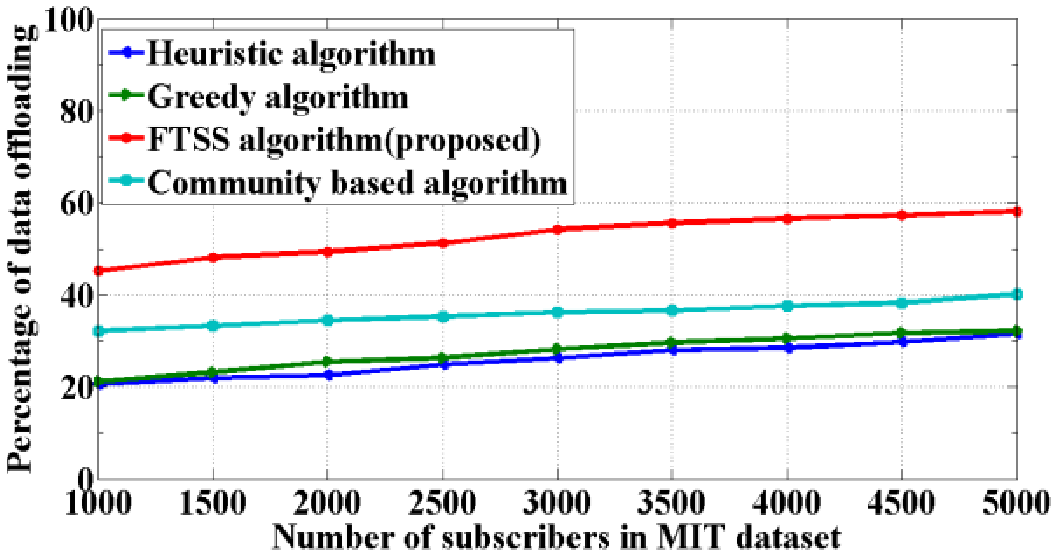

Figure 5.3: Traffic load over MIT cellular network

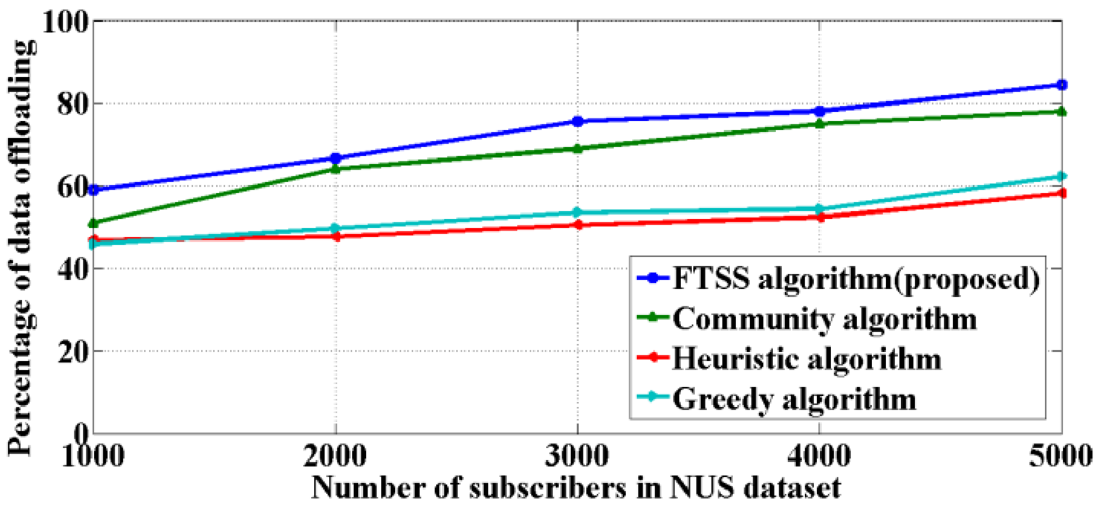

Figure 5.4: Traffic load over NUS cellular network

Data offloading comparison

The extent of the offload percentage of the respective traces of MIT and NUS is shown in Figure 5.3 and Figure 5.4. With a growing number of subscribers, it tends to grow. If we expand the MIT data from 1000 to 5000 subscribers, we achieve over 20% more data offloading compared to literary techniques. However, 10-25% higher download statistics for equivalent donations from NUS subscribers was observed.

Average latency comparison

In Figure 5.5 and Figure 5.6 we provide latency observations of our simulations. We notice that the FTSS algorithm-based solution for both datasets also reduces average latency. The average latency of different target sets has also been decreased by around 10-12 million seconds, with the target sizes increasing from 100 to 1000, while the delay is decreasing on average. But, compared with literature-based methods, findings employing FTSS exhibit less delay.

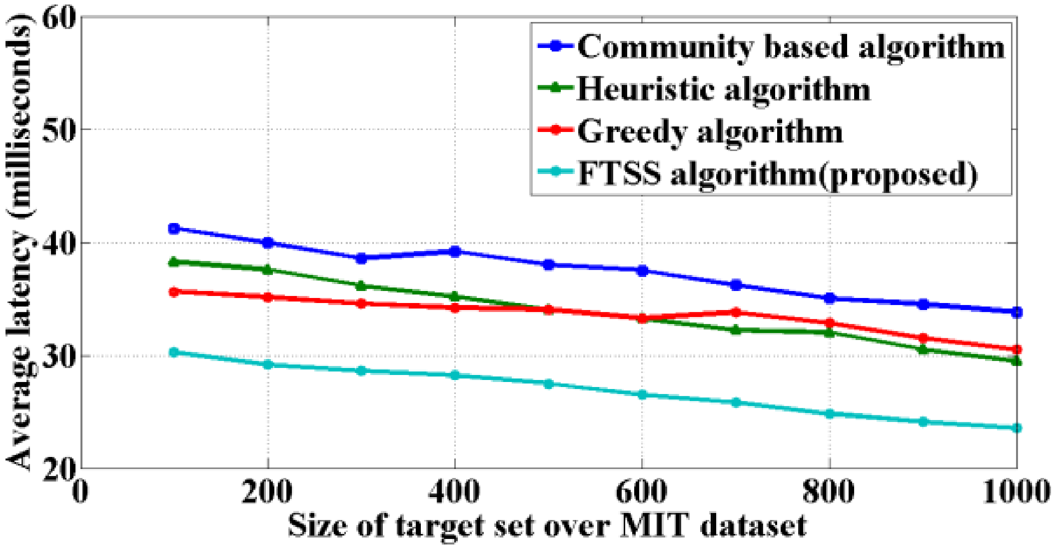

Figure 5.5: Latency impact for MIT dataset

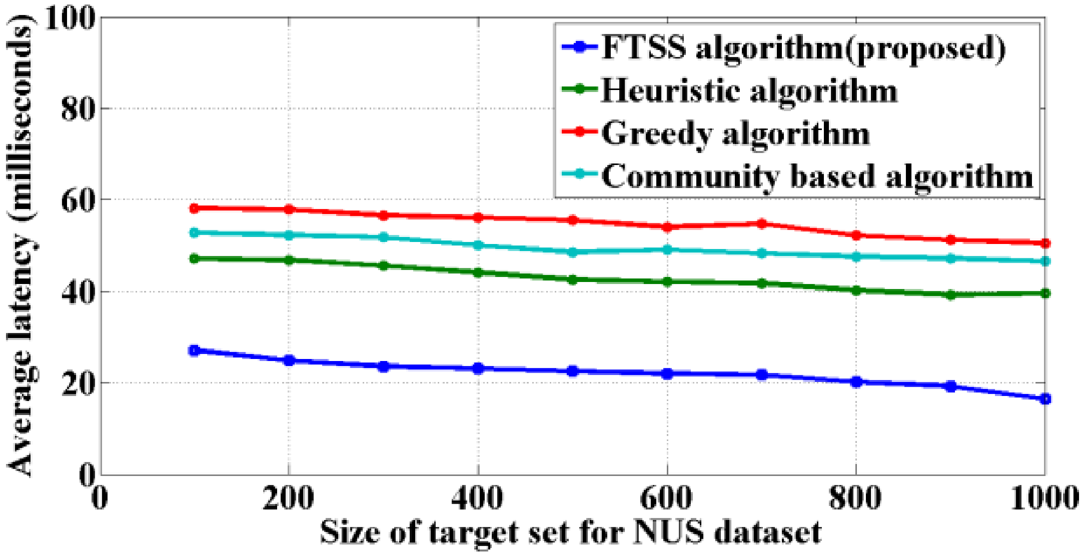

Figure 5.6: Latency impact for NUS dataset

Performance gain comparison

Finally, we examine for different message sizes the performance of our method. The overall performance advantage decreases at a fixed delay of 20 milliseconds. Figures 5.7 and 5.8 illustrate respectively the results for MIT and NUS data sets. Figure 5.7 findings demonstrate that there is a performance increase of over 20 percent for a message size of around 50 Kbs. But for both smaller and bigger MIT datasets, the benefit is minimal. Similar to the results shown in Figure 5.8, the best optimum message size is around 40 Kbs for the NUS dataset. The results nonetheless reveal less performance benefits for both lower and bigger message sizes.

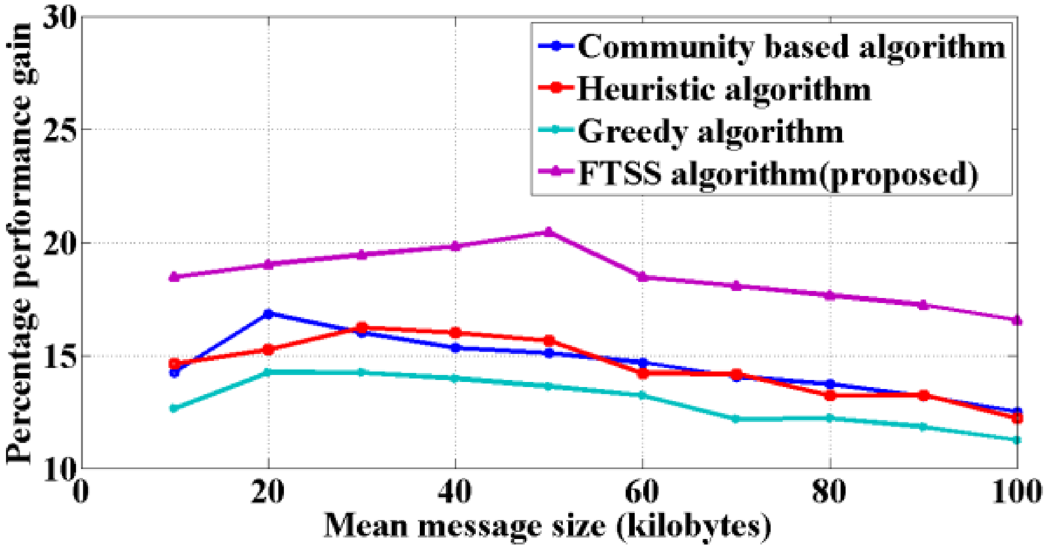

Figure 5.7: Performance gain for MIT dataset

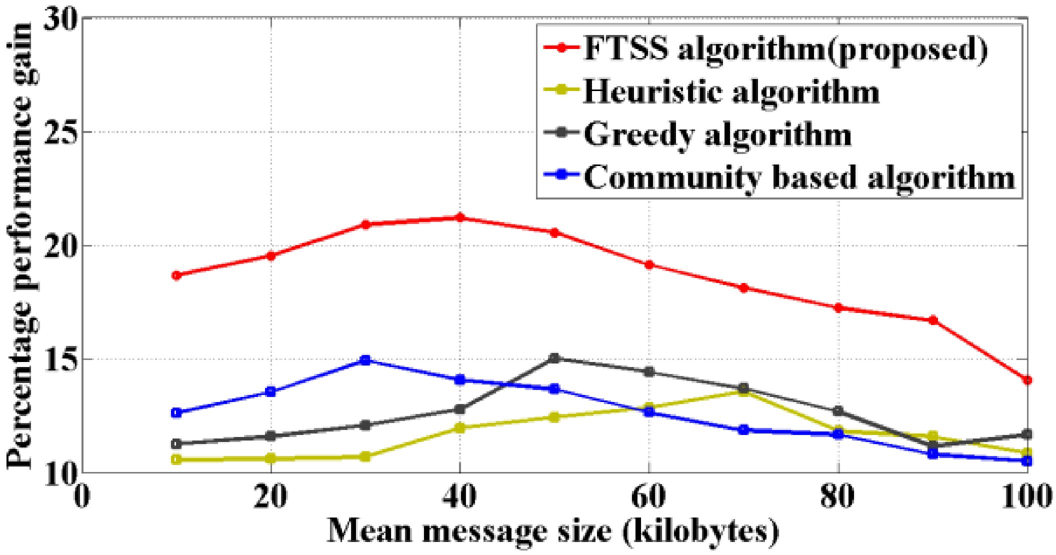

Figure 5.8: Performance gain for NUS dataset

5.5 Conclusion and future scope of work

The results in this chapter have been concluded in this chapter in accordance with the publication of this work in [110]. The reduction of data traffic by means of the integrated user service capabilities generates optimal data routing rather than the utilization of network providers' access point resources entirely. A hybrid heuristic order solution with a restricted set of limitations has been offered to us by FTSS in this chapter. It presupposes, in collaboration with access points, that all users are ready to disclose their identities and preferences. Each node also includes comparable information concerning its near neighbor. The basis for determining the best target choice in opportunistic networks lies in such a model. We conclude that our proposed FTSS implementation offers up to 35 per cent more offloading than the greedy approach-based implementation. It offers a maximum of 20 percent more offloading compared to heuristic approaches. In addition, it also offers a minimum of 5 percent latency improvisation which extends to a maximum of 23 percent latency in comparison to community-based implementation. The method provides a reduction of 5-6 percent in the target sets compared to heuristic networks at least. All network nodes can be trusted between a network or not. This will examine the influence of confidence determination on such an evolutionary network. The future guidelines for study in this field are the vehicle-oriented access points and determined reward for each helping node. There may also be different latency tolerance intervals that may also be considered in combination with the establishment of incentives for helpers to offer services. Our optimization results enable users to efficiently use and reduce data consumption. The total burden is reduced by our modeling and execution in constrained geographic scenarios.

CHAPTER 6

TRUSTED TARGET SET SELECTION AND ITS INCENTIVE DETERMINATION

6.1 Introduction

Global mobile traffic will most likely grow rapidly, pushing the present mobile network to its limits [111]. According to Cisco's annual Internet report [2], about 66 percent of the world's population will be connected by three times the number of devices employing the IP network by 2023. The primary negative impact of this expected occurrence is an overload on the cellular 4G/5G network and the resulting bottleneck [15]. It is therefore essential for large traffic to cope with new designs and viable protocols. In order to process data traffic owing to cost-effective costs, it is not possible to build cellular network infrastructure. Thus the shift to technologies such as femtocells [8], bluetooth [8, 112], WiFi [99] or D2D [113] must be utilized to meet high traffic and expensive infrastructures. This is the way we may address the cost concerns related to such mobile data offloading solutions. The data discharge techniques examined so far presume that all underlying users of the network are supported by offloaders. However, every user cannot be discovered as helpers in actual circumstances. Many individuals may act maliciously and offer their services for want of unjustified incentive. Some of the users of the network may show a positive purpose first, but support may be removed in future times. Confidence among consumers might therefore be a key download driver. The secure target selection on a trustworthy basis is critical for downloading services. While solutions have been identified [15], most of them feature an unrealistic model. The solutions either incorporate static graphic analysis [114], ISP monotony [115] or APs [116]. The researchers in [116, 117, 118] have shown that downloading mobile data can offer a feasible data offloading alternative. The major restriction of the current mobile data download is that every node eager to participate in the data download must be an honest node. In a realistic environment, the choice of neighbors change for nodes based on the trust or the incentives offerings. Thus it may help to determine the trust and optimal incentive non-uniformly. In most modeling systems, current trust determination is [116, 119]. It is difficult to apply, due to its energy restriction [98], frequent partnerships/associations [15], dynamic charts [120], buffer node area [121], or incentive interest [122]. All nodes should cooperate [116] to transfer information to perform the above-mentioned literature. This can lead to a quick and accurate trust assessment [123]. The nodes are equally likely to quit the links because of their dynamic behavior. The confidence assessment authority is partly based on the model of comparison, as presented in [127]. The node levels keep varying, as the network evolves. The network can only be guaranteed if the network has been converted into its final status. The majority of proposed network models have been analyzed on unrealistic networks [99, 114, 118, 124]. The network node level may also show malicious activity, as illustrated by [117, 15]. In social networks such a scenario occurs when the property of structural hole elements appears at a terminal node.

The main focus of our proposed implementation is to find reliable, optimal offloaders as an objective selection problem and offer a trust-based offloading solution. We address in this chapter the phenomena of public confidence using the opinion metrics and addressing the issue of greater delay tolerance in parallel. We emphasize over dynamic behavior of network graphs. We investigate the significance of building random trust modeling networks in a dynamic way. We propose to gain confidence about their actual or practical behavior using heuristic dynamics. It helps identify helpers who have strong or low confidence depending on their contribution. We evaluate the download performance for our trust-based downloading model and determine the optimal incentive in comparison to the existing literature, for a realistic environment.

6.2 Motivation and related work

In the last chapter, we explored the objective of optimization by using opinion dynamics. However, the aspect of security was not taken into account. Consequently, this chapter tries to construct trust-based derivatives that use opinion dynamics to ensure a secure and optimal download. This trustworthy network idea is motivated by the use of the agent-based Ising model from physics. In the Ising-model, the magnetic dipole moments of atomic turns are seen in the two rotates representing two states of +1 or –1. These spins represent the user's and the magnet field's interaction on the basis of social features that may be linked to external information. The quantification phenomenon is inspired by machine learning techniques. This notion is essential because it can go from a stable to an unstable stage towards a dependable or unreliable influence.

In [114] and [118] the authors have worked with the type of content, its size and distribution architecture to tackle the problem of trust. In addition, they have also addressed the rapid data transmission for intelligent content replication. The investigation deals with trust prediction among mobile social networking nodes. The results also reveal that not all major customers can be identified to maximize delivery consistently. This occurs because users are dependent over distant and nearby environment. It is generally because the networks are dynamic and continue to grow, e.g. in mobile VANETs. The study rests on a disappointing community replication method based on the activity patterns of mobile users. The effort also reduces the duplication of both the content and the delivery time to a minimum. A set delivery deadline, for unconditional sharing is the basis of the community based projection. Consumers need first download the entire content as a propagator, which will lead to significant delays. The cost of energy is neglected as well. Excessive use of network resources and costly calculations are required for the implementation of application specific trust management.

In their research work in [99, 119, 125], the researchers have taken a user-focused approach to the heterogeneous WLAN offload model. A more user-dependent download model was proposed by the authors of [99] with better results than the on-site WiFi download model. The works are, however, founded on the concept that the dogleg track method for all users is same for all packet production rates and package size. The authors of [119, 125] proposed that socially-confident egoistic nodes should be discovered to address such issues related to limited geographies. They have used a reputation system based on direct and indirect information, which is shared individually and socially. In order to support the offloading methods, mobile networks address trust and security mechanisms as well as mobility management and accounting components [15, 115, 117], which advocate identifying egoistic nodes based on social connections. To evaluate the authenticity of nodes, a malicious detection module was built. This may be done by designating several nodes as special - network watchdog nodes. As a result, the model can have a longer detection time for data transfer while reducing overhead communication. The decrease of collaboration between people and society is recognized as well.

The focus of the VANETs is on the connection between privacy and confidentiality [126]. The proposed ALRS algorithm recommends that selected nodes having a particular capacity for identifying and recognizing the trust level be revoked. The authors were also able to examine the information given by other nodes using the Adaptive Trust Management System (ATMS). These systems utilize an intersection between the list of link values in which each couple of vehicles communicate their identities in confidence and share a relationship at their initial contact. The findings show that the reported event is determined appropriately. In addition, it also shows that malicious nodes are extremely sensitive to wrong events. In [120], the authors propose a stable class algorithm to address mobility and confidence management in vehicular ad-hoc networks (VANETs). The use of trust management systems in VANETs is being investigated for dealing with security attacks with the optimal utilization of network capacity in [127].

The authors have observed the significance of the trust analysis transitive relation to data offload in networks for machine communication in 5G networks [111, 115]. They have used social linkage and physical proximity for the transitive assessment of trust criteria. The subject of their work is the graphical analysis used to build relay groups to optimize visuals based on the numerous mobile relay methods. However, the authors have used the main relay systems on the basis of mutual confidence. Such a system is confined to game stadiums, retail complexes, and conferences. Based on complete confidence criteria, the authors presented a data collection method that diffuses the disturbance of one failure point in machine-type communications. This structure is based on the two-hop relay method, which is alleged to not interfere with the second hop.

Online social networking in [15] and [115] is also used in the phenomenon of home routing based on confidence (HORST). The approach comprises a firmware and a home router application. In [128], the researchers have proposed an online social networking application based on trust to share third-party home routers, which improves the cache approach towards the base station access points. The HORST algorithm focuses on the downloading, caching and transmission of WiFi information. The authors remark that transitive derivatives based on confidence are disadvantageous. They have utilized personalized trust values of WiFi access point's owners at narrower geographical distances. The content-caching process reflects the selfish and non-co-operative behavior of the user. Also there are additional charges for its implementation [113], which can be implemented in several areas of application as in [129]. The authors have used the calculation of interactive quality features in [116] based on node level and number of connections. They utilized a mitigation function to weigh an interaction feedback system. Feedback nodes may be biased in dependency. The evaluation of the level of confidence also depends on the feedback route. Some terminal nodes throughout the graphs are equally significant, despite they are loosely related to the initial source. In order to respond efficiently to significant data transmission levels of services, the performance component also needs more attention than a relationship to trustworthiness. Supposing that the network graph and data forking restricts parallel relationships, it helps to achieve the relevant networking model. The strategy to use the common interests is significantly implemented in [130].

The study done by researchers in [122] employs the wage bonus-based regime for determining incentives, regardless of the choice of restricted workers. All users are also expected to be enthusiastic assistants in downloading mobile data. Win-coupon strategy [98] is similarly driven by a bid-based consensus on strategic incentive determination. This also results in higher buffer utilization for the flow of information between users. For their centralized caching incentive system, the authors have presented a heuristic method with a polynomial complexity in [34]. The results demonstrate individual rationality and truth, however caching mechanisms entail additional storage and energy usage, which must be tackled. For research on the economics of mobile data download, the researchers in [131] have employed the use of third party WiFi or femtocells. The authors dealt with the quantity of traffic discharge and the appropriate payment to the APs for each base station. The overlapping BSs were considered but the APs were not believed to be overlapping. The application utilizes a perfect sub-game balance determined by Nash balance between APs and BSs, but it ignores the direct influence of each user. The study covers the influence of price participation and competition on the result of the market but remains inattentive to the examination of subgame anarchy and the incomplete information-based market download. In addition, the use of WiFi and AP combinations by third parties to considerably relieve network congestion and enhance quality of service was demonstrated by the authors in [132]. The situation of this application is restricted, with MNOs and residential lease-APs for money compensation deployed by residential customers. The authors discussed the question of traffic determination, whereby the MNO and its monetary charging value should be used in an AP. However, the authors have taken up the problems of wireless downloading, although again with the possible partial participation of third-party suppliers. The findings are based on the workings of assistants as possible bidders. The disadvantage of this occurrence is the erroneous bidding. The implementation of individual or community-based measures is also affected.

From the above study, we can deduce that the utilization of the trust and security mechanism, mobility management, and accountability components are handled in support of offload techniques in mobile networks based on infrastructure. The community-based prediction is based on a preset unconditionally shared delivery time. In order to increase the time for broader content, the client must first download the entire material as a propagator. There are also neglected electricity costs. It includes overuse and high calculation of network resources due to application-specific, trust-management that consumes load. It is crucial to analyze the contribution of reliable offloaders. The previous research of the existing literature shows that social identification information in the target nodes is not complete in real-world uses. The dynamic behavior of nodes and their network topologies is likewise limitedly adaptable. There are some parameters for the social element of such systems and the confidence identification is also partial. Also limited adaptability is the dynamic behavior of nodes and their network topologies. There are some factors that limit the social dimension of these systems, and trust is also inadequate. The communication is likewise dependent on confidence, but only on WSN transmissions. Some sub-networks feature social relationships based on the real situation in which static contact is considered as separate from measurable social relationships in agricultural networks.

6.3 Proposed solution and algorithms

The dynamic characteristic of a confidence relationship is always critical. Therefore, we describe our approach in an opportunistic but mobile network and the results are supported by the analysis done by us in [133, 134]. A continually evolving model allows us to study the network at different periods. Due to their dynamics, our observational models are more realistic and assessed by employing graphic features that fluctuate with time to create heuristic opinions. We feel that one ISP is complemented by multiple APs for our data providing. We have N users motivated by mobile data, such that $H = \{x_1, x_2, x_3, \ldots, x_N\}$ is always available for each of those APs. For our data offering, we believe that an ISP has many APs to supplement it. Our proposed approach only considers a limited set of users as assistants, who behave negatively based on their trust values, rather than treating all users as assistants. These are termed optimal H' assistants. We confidentially determine H' in order to allow just M people to get the data, such that $H' \subseteq H$ is available. Helpers might be beneficial or damaging in a network. With a shift in time, we see a fresh graph with different capabilities, which affects network structure and behavior.

Our opportunistic network has been thought to be better suited than mobile users for similar interest groups. But the entire network may also be seen as a social network for distinct users of interest. Our program has been restricted to identifying people so that the information in lower data size may be given as much as possible by downloading the confidence produced matrix than any other network. We considered only positive derivatives of trust and combined neutral or negative derivatives of trust. This is due to the notion that positive confidence values generate a sub-station network which is more trustworthy than the non-trust network. We also took the notion that users might work together with each other selfishly and so become trustworthy or untrustworthy based on their usefulness. Due to its long-term network contribution, user support for such a model is more or less beneficial. Together with the leaders of the subgroup, we propose this strategy for their regional trust from the point of view of the ISP. It is also useful to exclude non-trustworthy links. The frequency of the relationship of a node is a consequence of our system model that is related to certain neighbors. This node is consequently automatically rewarded with a larger frequency than the node with less connections or a comparable set of neighbors.

We prefer to use the term "reward" in our system model as a good opinion combination and thus grow more confident, while "distrust" indicates correspondence with negative or zero opinion. Given the constraints on social networking, we are seeking to build a realistic association of nodes inside a conference dataset on the Haggle project. We define the network nodes based on the confidence-based function provided by the neighboring nodes for each node in addition to dynamic network construction. This adds to the network node dependence factor. It is allocated to the adjacent matrices of the knots and their neighbors. A neighborhood opinion evaluates the relevance of a node to the neighbors when a user has a neighborhood similarity index and user rating to be appraised. Our model establishes a foundation for a confidence derivation for every node by means of two-sided dynamics, i.e. from users to helpers and helpers to ISPs or APs, and consequently completes its aim set for optimal data offload. We use a number of often employed terms in this chapter in order to portray the network and our technique accurately. We define the following terms:

Helpers: In our work we refer all users who are ultimately selected as best data provider based on the technique given and with good criteria. Overall, they are excellent users with special characteristics based on trust principles.

Community: Confidence ratings are identified in three categories: positive, negative or nil. Every user group is termed a separate community, which determines that the trust value of a certain user is a part of a certain community.

Homophily: It is the property to relate the action of a user to the same or different user. In a community, all positive users should be homologous rather than negative or community-neutral.

For the perfect target for the identification of final offloaders, we suggest a Trust Model Algorithm (TMA). Our method is based on higher trust values in an opportunistic network. The network's dynamics are taken into account. TMA users and the network as a whole utilize the shift confidence perspective. In this way, less dependable individuals are excluded and the top users may be used. Table 1 lists the list of symbols and notes utilized in the algorithm.

6.3.1 Trust model algorithm, TMA

Algorithm 6.1 **Trust Model algorithm, TMA**

Input: Helpers, $H = \{x_1, x_2, x_3, \ldots, x_N\}$, $Adj[x_N]$

Output: *TS.*

Step 1: Initialize initial Opinion as Old Opinion $\theta_t = 0$ of each Helper as Nil

Step 2: Repeat the Step 3 until Step 8 for each Helper in H after δt intervals

Step 3: Evaluate initial Opinion of each Helper as $\theta_{\delta t}$ (equation 1)

Step 4: Repeat the Step 5 until Step 7 for each neighbor of Helper using $Adj[($

Step 5: Evaluate neighbor Opinion for helper $\theta_{\delta t}(NbrHelper)$

Step 6: Update $\theta_{\delta t}(Nbr) = \sum_{r \in Nbr(a_n)} \theta_{\delta t}(NbrHelper)$

Step 7: Return Neighborhood Opinion, $\theta_{\delta t}(Nbr)$

Step 8: Update New Opinion, $\theta_{\delta t}(total) \leftarrow \theta_{\delta t} + \theta_{\delta t}(Nbr)$

Step 9: If New Opinion > Old Opinion, i.e., $\theta_{t+\delta t}(total) > \theta_t$

Step 10: Trustworthiness τ gets a positive $(+1)$ value

Step 11: Else

Step 12: Trustworthiness τ gets a negative (-1) value

Step 12: Evaluate $Total\ Trust, F = \sum_{\delta t}(\tau)$

Step 13: Sort H, according to increasing $Total\ Trust, F$ and append as H'

Step 14: Repeat the Step 15 for each helper in new the sorted list H'

Step 15: If $F > 0$

Step 16: Append *TS* to include the helper

Step 17: Return *TS.*

TMA concentrates on the overall view on these helpers' direct confidence levels in the diagram. Second, indirect confidence depends on adjacency matrix-based connections. For the last trusted user group, the total trust value is used. The problem of TSS is taken into account based on positive or negative trust in a network. All the strong and weak connections were viewed as network limits. This enables the triadic graph closures to be recognized. We can discover stable and unstable triad combinations in relation to signed networks in our technique. Our technique employs two essential features directly and indirectly to evaluate their contribution to a successful network or subset. We assess direct trust ψ_1 with opinion θ_1 in our algorithm. The more strongly integrated helpers in a network, which correlates instantly to their trust value, are taken into account. For the evaluation of indirect trust, we use the nearby matrix to identify the neighboring person. This helps to discover a homophilous pattern in our technique within the network. No nodes may be utilized to indicate key contributors to our approach since it can only be a statutory parameter.

To evaluate the utility of the network, we define total trust function F. F's value depends on the direct trust value ψ_1 and the indirect trust value ψ_2. Our TSS challenge is described as maximizing total confidence depending on trust. The TSS problem is stated as an issue of maximizing the total trust based on trust as:

$$F = \sum_{\delta t > 1} \psi_1(x_i) + \psi_2(x_i) \tag{6.1}$$

where a positive, zero or negative value can be achieved for F. The direct trust values $\psi_1(a_i)$ are assessed by $\psi_1(x_i) \ = \ f(\theta_1)$. The value of the opinion θ_1 is obtained from the following equation for x_i user:

$$\theta_1(x_j) = \sum_{x_p, x_q \in H} \frac{\rho(x_p, x_q | x_j)}{\rho(x_p, x_q)} \tag{6.2}$$

Here the number of edges between x_p and x_q, are identified by $\rho(x_p, x_q)$, whereas $\rho(x_p, x_q | x_j)$ indicates the number of edges passed by x_j, but not x_p and x_q, respectively. This enables users to identify their homophilic tendencies. The BS can assess the level of support that a given node can supply in a certain instance using this opinion value. A helper's status is represented as α_i, for an offloader. The indirect trust ψ_2 is generated from l_i lifespan, association frequency nbr_{x_i}. The ranking technique is used to obtain the maximum diversity according to the adjacency matrix. In order to identify the possible homophily, we use the weighted sums of respective entries in rows and columns of the adjacency matrix. We calculate the trustworthiness τ of a user, on the basis of difference in its opinion values. It is done using the following relation:

$$\tau_i = \theta_i^{t+\delta t} - \theta_i^t \tag{6.3}$$

Here the value of $|\tau_i|/\tau_i = +1$ when $\alpha_i = +1$ and $|\tau_i|/\tau_i = -1$ when $\alpha_i = -1$. The action status of each user is given as, $\alpha_i \subset (+1, -1)$. This helps to determine whether the user x_i in the previous time period was trustworthy or untrustworthy. In situations when any two neighbors have equal trust values, both are used for offloading. Nevertheless, if neighbors' opinions are different, then let's say: $\theta_i > \theta_j$, the node with a greater value θ is selected for offloading. We use the adjacent helping module in neighborhood optimization to make an indirect confidence evaluation in our neighborhood. The complicated computational composition of our approach is $O(N \times n)$, in which N is the total number of assistants and n the highest level of any assistant, such that $n << N$. The preceding problem of maximization is NP-hard and cannot be resolved in polynomial time except if $P = NP$.

6.3.2 Optimal Incentive Algorithm, OIA

We offer an optimum incentive method to obtain the optimal incentive for end-users. For the best categorization, our method exploits the property of many trust values in the opportunistic network. Since the TMA is dynamic, so the OIA also addresses the same issues. The change of view between users and the entire network is used by OIA. This helps us motivate neutral users with a viable encouragement. To calculate direct trust values, OIA use a global view of the helper in the graph. It employs matrix-based adjacency relationships to get indirect trust. The size of the confidence function values is used to identify reliable users as high, low or medium-scale incentives. We address this incentive distribution problem depending on network trust values to be positive, neutral or negative.

Algorithm 6.2 ***Optimal Incentive Algorithm (OIA) for distribution of incentive among offloaders***

Input: Users x_i, as trust-based helpers and their respective Trust values $T(x_i)$, K data bytes, n total number of helpers in H, m total number trust-based helpers.

Output: Incentive $I(x_i)$, for helper a_i.

Procedure

1: Set $m_H = m_M = m_L = 1$, initially.
2: ***For*** each helper a_i, repeat the following upto step 13
3: ***If*** total trust $T(x_i) > 0$
4: a_i is high trust-based helper
5: increment m_H
6: ***Else If*** total trust $T(x_i) < 0$
7: a_i is low trust-based helper
8: increment m_L
9: ***Else*** a_i is medium trust-based helper
10: increment m_M
11: ***End If***
12: Evaluate $I_{relative}$ using Equation 6.7.
13: Evaluate $I(x_i) = C \times k$
14: ***End For***
15: Evaluate $I(H)$ using Equation 6.1.

This helps to classify the offloaders according to their contribution. We analyze the outcomes of an incentive analysis, based on Nash equilibrium, in which all those trusted users in the network tend equally to influence the user. Our goal is to provide incentive I to n users so that there is a minimum value of I that meets the highest m of users (where $m \leq n$).

$$Minimize\ Incentive, I(H) = \sum_{i \leq m} I(x_i) \tag{6.4}$$

We argue that $m << n$, since every user of n uses K bytes with comparable data. These n users are supported by m users who only consume k bytes. Traffic is thus decreased according to the order of $(n \times K) - (m \times k)$, which is the greatest possible $I(H)$. In view of the number of ideal offloader values, m_H, m_M and m_L respectively, with a positive, neutral and negative total confidence, $I(H)$ is shown in as follows:

$$I(H) = I_H + I_M + I_L \ and \ I_{type} = C \times k \tag{6.5}$$

In the above equation 6.5, *type* = H or M or L with respective constants $C = \alpha$ or β or γ. The I_H, I_M, and I_L components provide incentives in this regard for very trustworthy offloaders, neutrals and non-trustworthy offloaders, respectively. Based on the positive value of total trust $T(x_i)$, we define higher confidence offloaders. Likewise, we identify null or nil medium-value offloaders and negative total, low-confidence offloaders based on trust. We assess the utilization of an x_i user in a network to determine the $T(x_i)$ value. It is given by the following derivation as:

$$I_H = \sum f[T(x_i)], where\ a_i \in H \tag{6.6}$$

The viable values of the multiplication constants α, β and γ are obtained from the theory of game based on the idea of Nash's equilibrium solution. We consider all feasible values for our classification. The values of α, β and γ are evaluated using:

$$\alpha = N/|m_H|, \alpha = N/|m_H|, \gamma = N/|m_H| \tag{6.7}$$

The value of $T(x_i)$ is dependent upon the cumulative sum of direct trust value ψ_1 and indirect trust value ψ_2 which is derived using the following equation:

$$Total\ Trust, T(x_i) = \sum_{\delta t < 1} \psi_1(x_i) + \psi_2(x_i) \tag{6.8}$$

The direct trust $\psi_1(x_i)$ is evaluated using opinion values obtained as a function of time given by $\psi_1(x_i) = f(\theta, t)$. The opinion value θ for a user x_i is evaluated using the following equation:

$$\theta(a_i) = \sum_{a_p, a_q \in H} \frac{\rho(x_p, x_q | x_j)}{\rho(x_p, x_q)} \tag{6.9}$$

where $\rho(x_p, x_q)$ represents the number of total edges between x_p and x_q, and $\rho(x_p, x_q | x_j)$ identifies the number of edges through node x_j, but not x_p and x_q. The BS can detect how much support a specific node offers at a given time using the opinion value. The indirect trust ψ_2 uses lifetime l_i, association frequency nbr_{x_i} and ranking method as stated in [19] for the maximum different set of neighbors. We evaluate trustworthiness τ of user x_i on the basis of difference in the trust values using the following equation:

$$\tau_{(x_i)} = T(x_i)^{t+\delta t} - T(x_i)^t \tag{6.10}$$

We may do a confidence-based incentive analysis using the trustworthiness value τ. Our implementation phases in the algorithm are illustrated. We study the relative incentive based on the $\alpha = \beta = \gamma$ constants to show the importance of our distribution of incentives. The relative motivation comes from the following equation:

$$I_{relative} = C \times NTH \tag{6.11}$$

where C represents the respective constant factor α, β or γ and NTH represents the total number of respective trust based offloaders m_H, m_M or m_L.

6.4 Simulation results and performance analysis

In this section, we show the findings and analysis of our proposed processing procedure in line with model specifications for a mobile ad-hoc network. To simulate this, we sought for the opportunistic PDA network on the WTD dataset in Crawdad. We only assess the energy status of users, access points status for 77 days. MANET should be done more effectively. We perform the entire network's graphical analysis with a defined delay tolerance at different intervals also. The PYTHON simulation was performed.

We have compressed the data set in such a way that only those associations may be derived where a user is linked. While the condition of the battery is ignored for our initial analysis, we are limited to estimate the confidence in the remaining data sets of 13211412 records. This state of the battery was used for energy use controls in later phases. Only such persons and access points are the foundation of our network observation on the basis of the ASSOCIATED feature. This feature signifies that the user is or is not linked to a point of access. It decreases our analysis even further to 5219839 records only. For these graph input sets, we use triadic closures of numbers of cliques, clusters and page ranking coefficients to determine confidence on the basis of opinions. We compare the reliable or unsustainable contribution of customers. In conclusion, the heuristic of network groups based on user levels and access points compares our data offloading method. These outcomes are noted as a temporary function on the basis of trust. We have also studied over time the impact of user degree changes. The confidence also varies as the user grade with changing time changes. The restriction of *ns-2* is that this simulator, in particular for MANETs, cannot be used for the energy assessment. Therefore, we use environmental statistics to overcome this problem in the [48] NETWORKX module of Python as is done in [48]. We have implemented the free space wireless radio model based on Zhou et al. energy derivation. When a node provides its neighbors with 1 bit of information, we calculate energy usage by its satisfied helpers:

$$E_{avg} = \frac{\varepsilon^{elec} + \varepsilon \times d^2}{Number\, of\ satisfied\ users} \tag{6.12}$$

When a node sends or receives 1 bit of information obtained from a 50 nJ/bit node identified by ε^{elec} the energy per bit measured in Joules per bit through electrical transmission. Here, we see ε as the 10 pJ/bit/m^2 free space constant value simulated for MANETs across a 250-meter transmission range as shown in [95]. These derivatives of energy are solely confined to MANETs.

6.4.1 Proportional contribution of positive and negative trust users

In the above-mentioned simulated scenario, initially we determine the effect of positive and negative confidence on mobile data offloading. We evaluate the effect of positive and negative confidence upon mobile discharge with the aforementioned simulated situation. Later we analyze its impact of network tolerances and energy usage with time. We show the relevance of using trust to using the results being compared with random trust simulations.

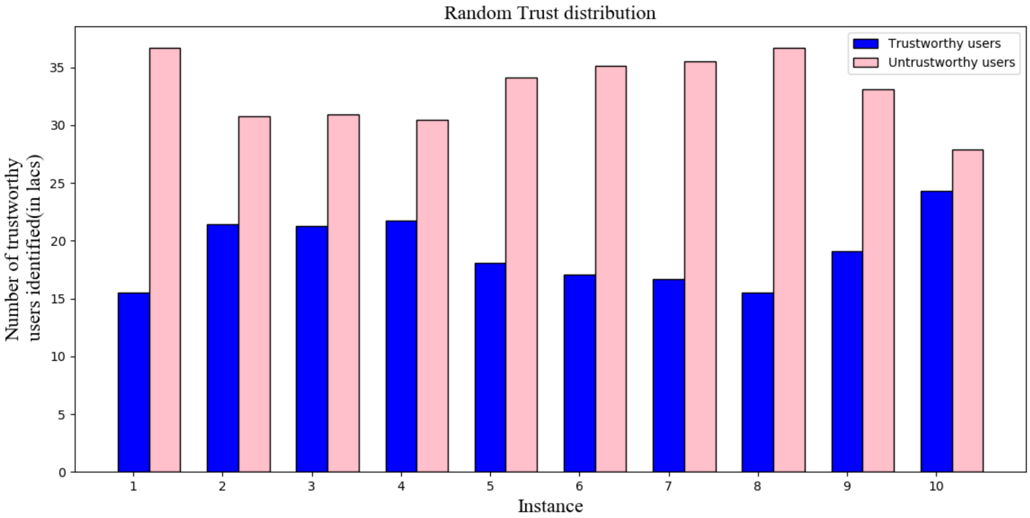

Figure 6.1: Impact of trust over network connectivity

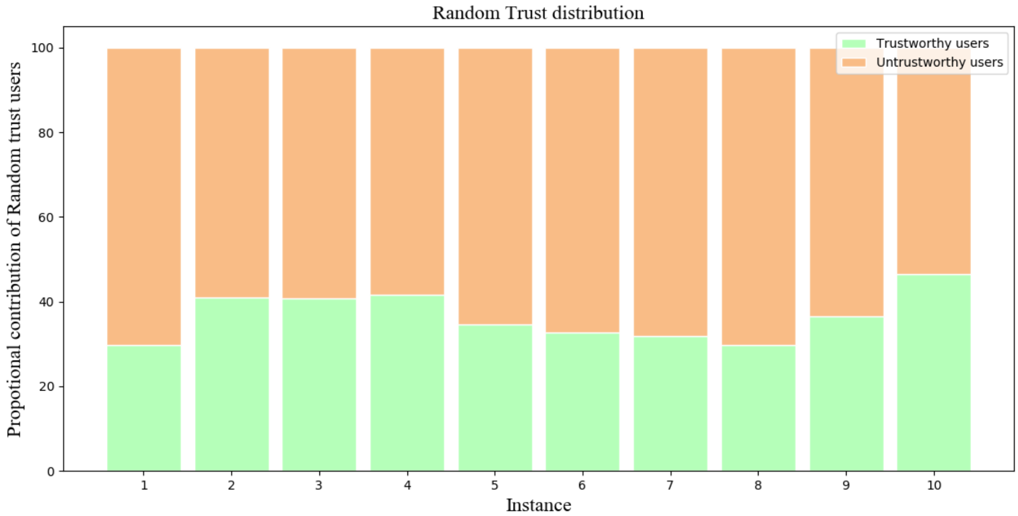

Figure 6.2: Proportional contribution of trust

We have repeated the random trust-based simulations to show the importance of trust. In the 10 random simulations conducted on the WTD data set, Figure 6.1 demonstrates the significance of reliable or unreliable users. This shows that unreliable users contribute more to realistic environments than reliable ones. Figure 6.2 illustrates also the actual observation of dependable and unreliable users' relative participation. It shows that the unreliable nodes always have above 50 percent input. These aids can offer a steady or skewed download incentive. However, a very little contribution is provided by genuine helpers who will always be less than 50% in practice, as seen in Figure 6.2.

6.4.2 Performance comparison of our proposed TMA

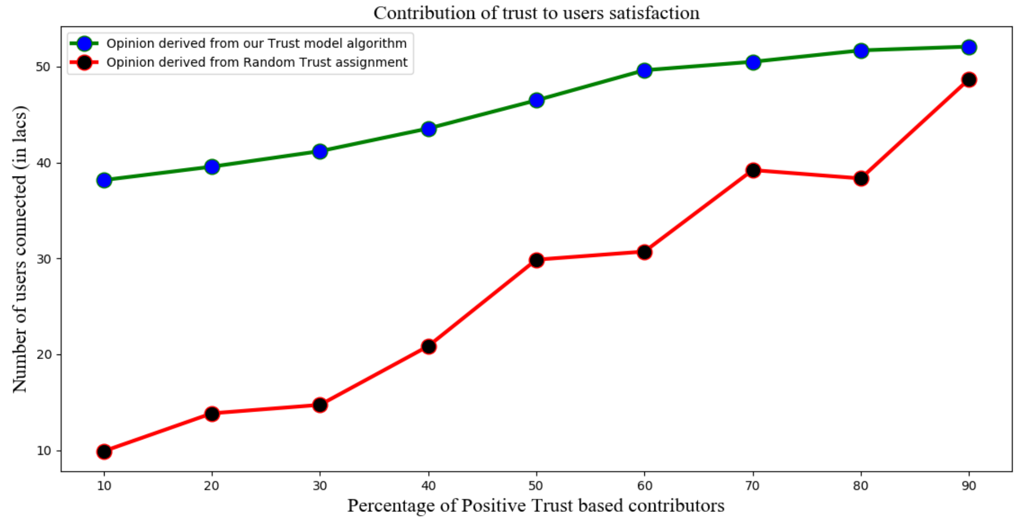

Figure 6.3: Performance of TMA-based helpers

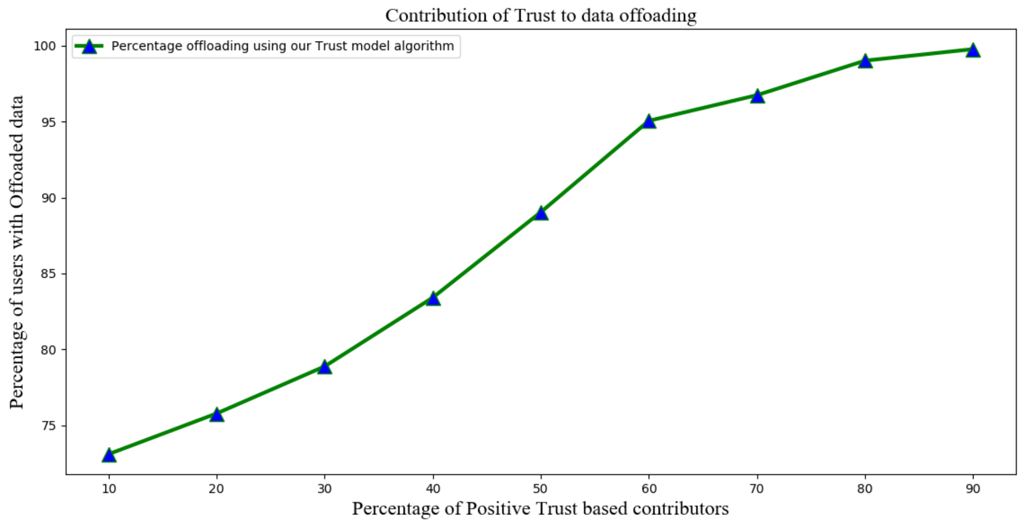

Figure 6.4: Proportional contribution of trust

As demonstrated in Figure 6.3, our ultimate goal set is dependent on our algorithm's trust level to get optimal outcomes. In order to evaluate the efficiency of our method for allocations of confidence, we compare our findings with literature-based approaches. When influential nodes are derived based on the trust function, the mobile users may obtain optimal results. In Figure 6.3 we get the same findings. With just 10 percent of positive confidential offloaders, 73 percent of the network is possible to remain connected, an ideal offloader is required. Thus, the importance of positive trust based offloader integration indicates the large proportion of effective network relationships.

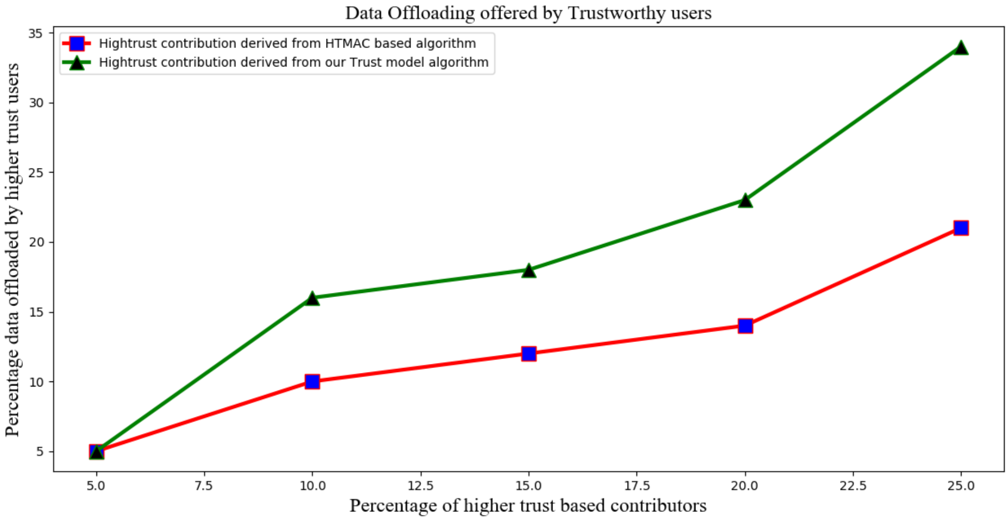

Figure 6.5: Performance comparison of higher trust-based helpers

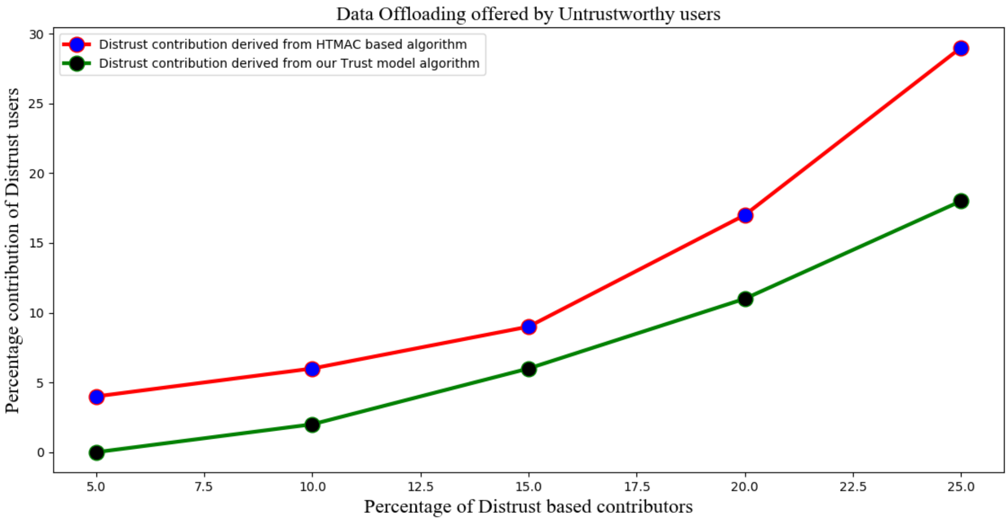

Figure 6.6: Performance comparison of untrustworthy contributors

Our trust derivation takes care of the ever changing opinion of users in the random trust assignment model, which merely takes account of the features of nodes independently of trust. As we cannot make such contributions feasible in practice, we overlook the comparisons of more than 50 percent of our trusted network operators as in Figure 6.2. In Figure 6.4, we use our method to set up trust performance for the mobile data download solution. It guarantees that over 70 percent of consumers are happy with our trust model successfully with only 10 percent of positive people.

6.4.3 Data offloading performance of TMA

We compare our results with trusted derivations utilizing an HTMAC-based method after randomly assigning trust services for users [97]. We check for trusted as well as untrustworthy individuals on the performance of our algorithm. We observe a significant improvement of data offloaded using TMA.

Figure 6.5 demonstrates that the contribution of fewer trust-based offloaders is more favorable for TMA than for HTMAC. In this instance, our lower-confidence offloaders make a contribution of at least 3 per cent. When we evaluate high confidence contributors' effectiveness, the findings shown in Figure 6.6 are observed. It demonstrates that the contributions of highly trusted TMA-driven offloaders are rising with an increasing percentage. In comparison with the HTMAC we get a maximum 13% higher contribution from 25 percent high trust-based offloaders. We are therefore in a condition presently to infer that chosen offloaders with our TMA offer better outcomes with regard to offloaded data. We also examine the findings for their delay in time and energy use afterwards.

6.4.4 Time delay performance of TMA

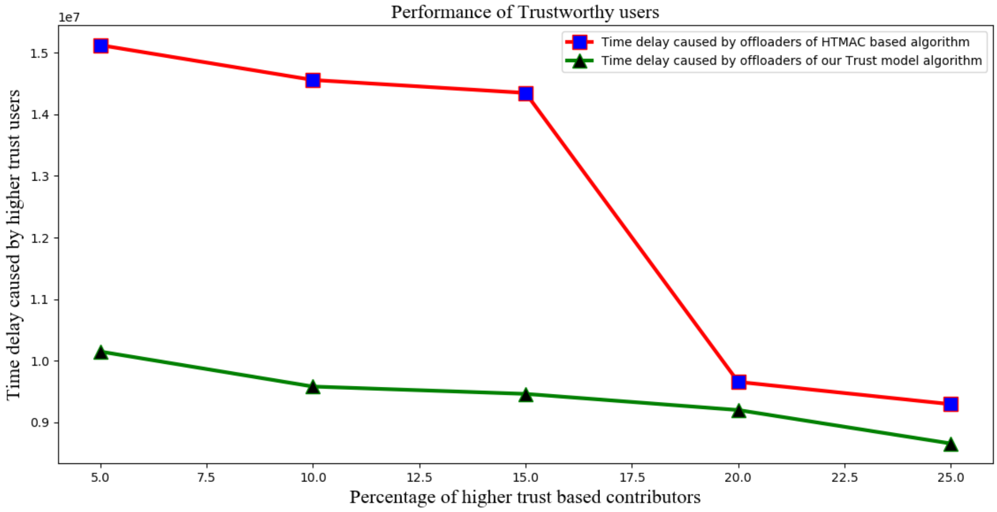

Figure 6.7: Time delay using TMA-based trustworthy users

In this subsection, we examine the latency in transmitting TMA offloaders to ensure greater offload contribution. We discovered that our TMA also reduces the time lag considerably. Although beyond 20 percent trust-based users our proposed TMA has at least similar time delay to that of HTMAC as shown in Figure 6.7. But for less contribution from 5-15 percent of trust-based contributors, our TMA behaves significantly better than HTMAC. We may thus also assume that the offloaders that use TMA are more quickly downloaded.

6.4.5 Energy consumption performance of TMA

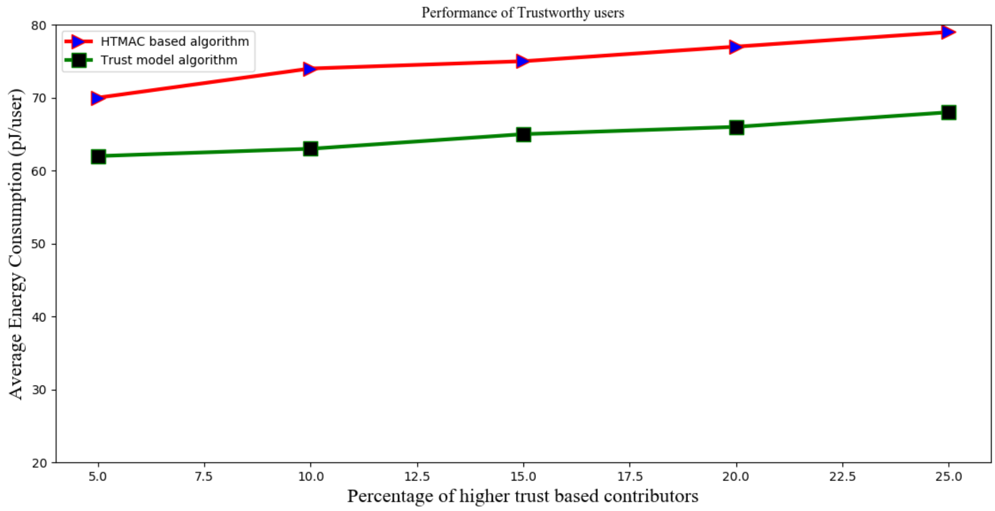

Figure 6.8: Energy consumption comparison of TMA and HTMAC trustworthy users

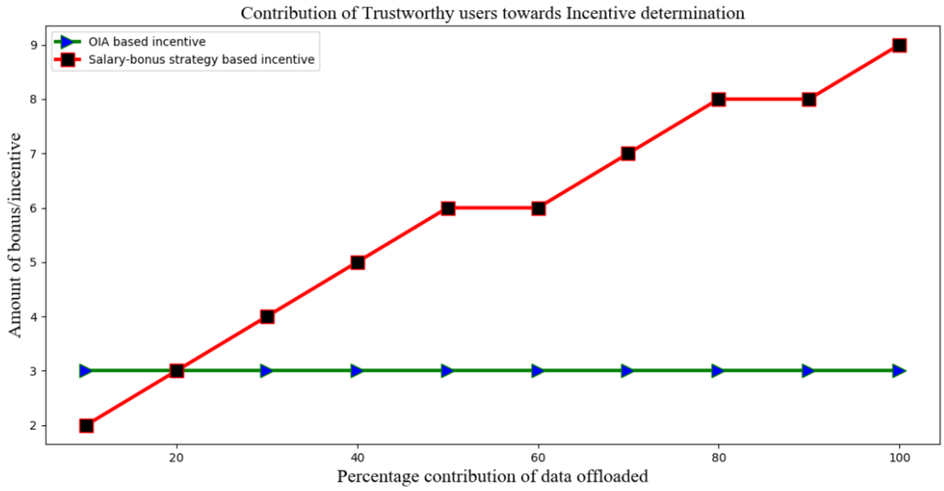

Figure 6.9: Comparison of proposed OIA with salary-bonus based scheme

Ahead of delay observation in data transfer, we evaluate average power utilization for each satisfied assistant on the network with respect to buffer capacity. Figure 6.8 shows the results. TMA is superior for energy utilization to HTMAC. Only 8 pJ/user energy is consumed with just 5 percent of TMA offloader contributions. Through our findings, we find that with the mere incorporation of 25 percent of our TMA-derived offloaders; a user is consuming a maximum of 15pJ or energy. Thus we can reduce the energy usage of about 10-12pJ/user in comparison to HTMAC derived offloaders. As we go on to increase the contribution of offloaders derived from our proposed TMA, a considerable amount of energy could be saved. Although results are shown for a single helper, we observe that there is a considerable improvement in energy for bigger realistic networks. With an increase in TMA trust-based assistants, we obtain an energy-optimized network with comparably reduced energy use.

We compare our OIA with the salary-bonus-based implementation of the system to highlight the importance of trust based encouragement derivation. Figure 6.9 shows that our system provides almost consistent incentives for the various percentages of downloaded data for all helpers. However, when we add additional offloaders for contribution, the bonus-based system tends to keep on raising the bonus. It demonstrates that our incentive is usually higher than the pay bonus system for restricted offloaders. Our OIA-based offloaders tend to have a continual and constant incentive for various download possibilities. Over 20 percent input from the OIA-based derivation, the results are significantly better.

6.4.6 Energy consumption performance of TMA

After comparing our proposed OIA with salary-bonus-based data download scheme, we now target ideal offloaders according to their confidence values. We show the contrast between incentives for positive, negative and neutral offloaders based on trust in Figure 6.10. The relative incentive values of the corresponding total trust values are calculated using uniform constant values $\alpha = \beta = \gamma = 1$. It demonstrates that the share of offloaders based on their confidence levels is increased as we proceed. The motivation for such assistance is enhanced as well. However, Figure 6.10 shows that after sorting trust-based helpers, the greatest contribution is received. They require more than neutral or negative trusted assistants to be encouraged. Both results suggest that the incentive mechanism based on trust allows us to get superior results with a moderate bonus for aid workers.

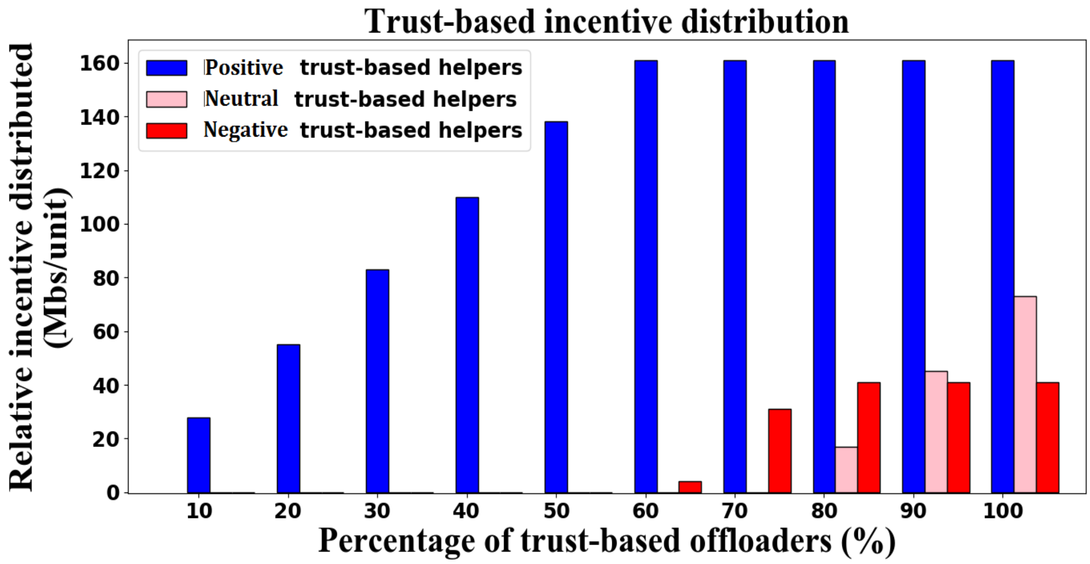

Figure 6.10: Relative incentive analysis for optimal offloaders

6.5 Conclusion and future scope of work

From the entire implementation, we conclude that trust is an essential characteristic for determining more effective offloaders in networks, which are opportunistic. This helps to efficiently download mobile data by employing offloaders to allow intelligent information systems based on applications. Few people tend to act mischievously and can withdraw their support from the network. This results in an awkward behavior. So depending on the degree of assistance is not always more advantageous, particularly in realistic user networks. Therefore, the evolutionary character of the opinion should be considered for those users who remain confident or fail through time. We have proven effectively that the performance of a trusted offload model is superior to non-trust-based derivations and random trust-based derivations. In order to obtain incentive distribution, our contribution to TSS identification may be further studied. This data may be given with extra data offers for the efficient assistance. This approach may also be used to create network-based application categorization criteria. We conclude that the trust-based evaluations optimize the target set and help the ISPs to incentivize the users more appropriately, based on the findings of result analysis. The incentive mode can better replace a confidence-based entry based on our more realistic model observing the dynamic properties and evolutionary graphical analysis. If we encourage such helpers that are based on the Nash balance method, we obtain better outcomes. Our results indicate that the planned OIA provides significantly fewer incentives and reduces network traffic overall. In addition to being 20 percent more dependent on trustworthy offloaders, the incentive is significantly lower than the literary wage-bonus plan. This approach provides extremely high outcomes optimization in conferences or hotspot-based areas for restricted geographical situations. This also applies to VANETs, though. Trust is thus a key feature in determining more efficient offloaders. It is not limited to opportunistic network only. Efficient offloaders help in significant reduction of network traffic. At the same time, the excessive incentive distribution can be reduced by using the trust-based optimizations. The data traffic for the incentive distribution can help to offer the network bandwidth using the downloading potential of the existing resources of users. The results from this chapter help us to better assess the outcomes for other input constants in future studies. The overall impact of incentive analysis may be incorporated to design efficient data offloading network protocols. Although the scope of this chapter is restricted to incentive determination alone, it may also be utilized to determine the influence on social network analysis and viral marketing.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE OF WORK

7.1 Conclusion

In this thesis, the probable methodology to address mobile data offloading solutions has been studied. The primary objectives of our thesis were categorized as the identification of optimal offloaders in networks which acknowledge the dynamic behavior of users, evaluation of opinion dynamics and trust for the users' analysis and optimal incentive offerings for them. We have been able to address all these issues in this thesis with appropriate algorithms with less overall computational complexity. Our overall research work is dependent upon the practical approach for solving hard combinatorial optimization problems using the hybrid implementation of greedy and heuristic algorithms which can nearly find an optimal solution with reasonable requirements of space and time. In the first chapter we have briefed about the need of research in this area followed by a detailed survey of the present literature related to mobile data offloading and its several types.

In the third chapter, we have tried to optimize the target selection problem using the opinion dynamics. We have tried to incorporate the impact of individual and group-based associations. This association has been reflected in terms of opinion dynamics of the users. In the fourth chapter, we have aimed to use the energy statistics and buffer usage so that minimum memory of the devices get engaged to develop trust amongst users.

In the fifth chapter, we have identified the NP-hard target set selection problem as the optimization problem. We have analyzed our hybrid approach comparing it with greedy, heuristic and community based approaches for such optimization. We have implemented the collaborative approach of the users and the ISP access points over two state-of-the-art datasets namely, MIT and NUS datatraces. We have showed theoretical guarantees of our hybrid model and analyzed the optimization problem from the viewpoint of a user as well as the service provider. The major contribution is the addressing of dynamic behavior of users in a network. The work done here justifies the impact of using hybrid approach of network heuristics with suitable greedy implementation restricting the users to belong to unique groups.

In the sixth chapter, we forward the determination of target set selection for it trust based evaluations. We take the findings of the previous chapter, a step ahead to derive trust on the basis of opinion dynamics. The trust derivations were again modeled using the ferromagnetism properties of Ising model in physics.. We derive positive, negative and neutral trust-based users on the basis of their contribution in the network. This helps to retrieve optimal offloaders on the basis of security aspect. This approach helps in establishing security across our target set users. Although, we have present the results in view of smart agriculture based implementation. However, the similar aspect is fruitful in for application in viral marketing and several others. Towards the end, in the chapter we move a step ahead with our findings for optimal offloaders. We discuss the incentive offerings for such optimal offloaders in this chapter. We categorize the users and evaluate the performance on the basis of all possible aspects of game theory. We observe the Nash equilibrium based distribution of incentive. Such a model increases the participation of more optimal users for more network stability and reliance. This helps more and more users to actively participate in offloading considering the stability aspect of our model.

7.2 Future perspectives of our implementation

There are several challenges faced by the researchers, in the results analysis of such network offloading implementation due to the concurrent involvement of ISPs and the users. It is very difficult to collect global network information. There are a few security and privacy concerns of the users also, which inhibit them to take part in offloading. In our thesis, we have tried to limit the boundaries of ISPs and users. We have also addressed the security concerns by categorizing the users as trustworthy or non-trustworthy users. Towards the end, we have proposed an unfair incentive policy which motivates users fairly. We limit our thesis to use opportunistic network because most of the literature like [15, 124] suggests opportunistic offloading to be a better viable solution for offloading than the other methods, mainly considering the advantage of energy and cost constraints. The cost is significantly reduced and there is no extra energy requirement of such networks. This research work could be extended to evaluate the performance of opportunistic networks in comparison to other data offloading techniques like using small cell networks, WiFi networks, and heterogeneous networks. A cooperative model proposing to offer switching between cooperative communication and WiFi offloading can also be visualized as a solution towards optimal data offloading. The constant bit rates used in our implementation can also be varied for appropriate bit rates for different data offloading options. In addition to data transfer rates, the operating frequency of each of these methodologies is different. The power consumption and operating ranges of femtocells, bluetooth and WiFi are different. Following the Shannon's law, the femtocells claim to have better system capacity. At the same time, the SNR values are also better in case of femtocells than in comparison to WiFi due to the reduced distance in between the sender and the receiver. Thus the comparison of such heterogeneous networks with opportunistic networks may be viewed as the future scope of implementation of our thesis work. It may be extended with classified incentive offerings also. The service providers should offer impartial incentive schemes for the motivation of such users so that they are encouraged to participate willingly in data offloading. The mobile data offloading solutions offer a varied scope of applications in the present era of big data and machine learning. As the need of hour enhances more over the services dependent on internet, the data traffic is expected to rise further. To keep pace with the need of evolution as well as the growing demands of the users with sustainable infrastructure requirements, more contribution towards mobile data offloading is essential. Although there is a plenty of research ongoing in the infrastructure developments where the generations of mobile data is changing so rapidly, yet the demands need to satisfied and hence there are more issues that the research will continue to face. A minimal contribution towards more optimal resources available in the existing network infrastructures contributes significantly for sustainable energy requirements. As the total energy requirements are suspected to rise further, our contribution could be attributed to significant aspects in green energy. The future directions of our research may be termed evolutionary in terms of varied aspects of applications. In the recent pandemic like situations where most of the work is supposed to be carried out using online services, there is yet another aspect of need of feasible data offloading solutions to reduce the data traffic. The overall reduction in mobile data traffic helps to reduce the energy requirements for ICT based applications.

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APPENDIX A

Author's publication list

1. P. Sharma, S. Shukla. "Optimal Target Set Selection via Opinion Dynamics ", in *Proc. 5th IEEE Int. Conf. on Par. Dist. and Grid. Comp. (PDGC)*, pp. 806-811, 2018.
2. P. Sharma, S. Shukla, A. Vasudeva, "Trust-based incentive for mobile offloaders in opportunistic networks", in *Proc. of the Int. Conf. on Smart Elec. and Comm. (ICOSEC)*, Oct. 2020.
3. P. Sharma, "Energy efficient target set selection and buffer management for D2D mobile data offloading", *Int. Journ. of Data and Netw. Sci.*, 2020.
4. P. Sharma, S. Shukla, A. Vasudeva, "Data offloading via optimal raget set selection in opportunistic networks", *Mob. Netw. and Appl.*, pp. 1270-1280, 2021.
5. P. Sharma, S. Shukla, A. Vasudeva, "Trust-based opportunistic network offloaders for smart agriculture", *Int. Jour. of Agric. and Env. Inf. Sys.*, vol. 12, no. 1, pp. 37-54, 2021.