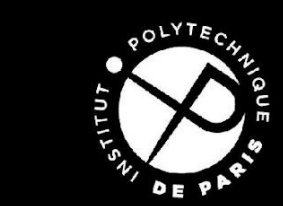
Tactful Networking as a Cornerstone for Opportunistic Human-Aware D2D Communication

Rafael Costa



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Tactful Networking as a cornerstone for opportunistic human-aware D2D communication

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Doctoral Thesis

Tactful Networking as a cornerstone for opportunistic human-aware D2D communication

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ABSTRACT

Among the mobile network challenges, there is data traffic growth, an increasing number of connected devices, spectrum limitations, and costly infrastructure updates. In this context, opportunistic D2D communication appears as a solution to offload data, increase capillarity, deliver content in specific scenarios (e.g., emergency) and foster innovative applications and services. Previous standards like LTE discussed D2D broadly. Still, recent research remarks that 5G/6G will be D2D's real enablers, given the possibility of using human-behavior big data from users' devices.

Previous opportunistic D2D forwarding algorithms extracted mobility characteristics for improving content delivery cost-effectiveness. Nevertheless, most initiatives dealt with traditional metrics due to constraints, such as limited availability of real traces or the lack of a human-centered networking vision. Next-generation solutions need a more in-depth vision of human aspects hidden into datasets. Moreover, scenarios practical to mobile carriers lack evaluation. To this end, this thesis *guides the reader through the whole process for building a novel Tactful Opportunistic COmmunicaTion Strategy (TOOTS)*. TOOTS leverages wireless encounter patterns, temporal, spatial, geographic, and direction awareness to improve cost-effectiveness content delivery in a mobile networks scenario. The proposal consists of: learning human-aspect state-of-art best practices; achieving insights to improve strategy's performance; using, proposing, and analyzing human-aware metrics; combining metrics and insights into the strategy targeting an improved performance in a more realistic mobile scenario; and finally, evaluating the strategy through its strengths and shortcomings. This thesis shows that TOOTS improved the performance of an opportunistic content delivery scenario in terms of overhead, delivery rate, and latency by following this process.

First, to achieve the results, we survey the human aspect in networking solutions for over a decade. We found that there is an evolution in how the human links to networking challenges. This broader human-aware vision culminates into the Tactful Networking perspective, which we introduce to follow, including discussions concerning application examples and insights. We complete the literature review by discussing state-of-art opportunistic forwarding strategies, including contributions, gaps, and open issues. Second, we discuss a framework for enhancing raw human data hidden into datasets. A case study with the MACACO dataset validates the framework through trace characterization results and analysis. Following, we characterize MACACO, NCCU, and GRM datasets to bring insights and to validate TOOTS. The presented and analyzed strategy's metrics come from such datasets' characterization results and insights.

Third, we introduce TOOTS, targeting cost-effective content delivery in a mobile scenario. Afterward, we present the formal definition for choosing the disseminator nodes problem (TOOTS' 1st phase). As motivation, we analyze the overhead and latency of the Epidemic forwarding. Subsequently, we introduce TOOTS' two phases: a Tactful Dissemination Policy and a forwarding algorithm.

Finally, we compare TOOTS' effectiveness on its phases with enhanced Store-wait-forward, Epidemic, and Bubble Rap algorithms through real and synthetic traces. Among the main outcomes, in a scenario with a 30 m range, TOOTS reached a 100% delivery ratio with 28% and 73% reduced delivery latency, and with 16% and 27% reduced overhead, respectively, in the

real and synthetic datasets. With a restricted (10 m) range, TOOTS was the fastest strategy and the only one that delivered 100% of the contents within the real trace.

Consequently, this thesis contributes to addressing the opportunistic content delivery problem in cellular networks by providing a cost-effective human-aware opportunistic solution. The strategy can be applied in different scenarios to assist the operator in delivering content without not necessarily using their legacy network, e.g., by exploring the capillarity of their mobile users, for data offloading and other applications.

RÉSUMÉ

Parmi les défis liés aux réseaux mobiles, il y a la croissance du trafic de données, un nombre croissant d'appareils connectés, des limitations de spectre et des mises à jour d'infrastructure coûteuses. Dans ce contexte, la communication D2D opportuniste apparaît comme une solution pour décharger les données, augmenter la capillarité, fournir du contenu dans des scénarios spécifiques (par exemple, urgence) et favoriser des innovations.

Les algorithmes de transfert D2D opportunistes précédents ont extrait les métriques traditionnelles de mobilité pour améliorer la rentabilité de la diffusion de contenu. Les solutions de nouvelle génération nécessitent une vision plus approfondie des aspects humains cachés dans les ensembles de données. À cette fin, cette thèse *guide le lecteur tout au long du processus de construction d'une nouvelle stratégie tactique de coopération opportuniste (TOOTS)*. La proposition consiste à: apprendre les meilleures pratiques de pointe sur l'aspect humain; obtenir des informations pour améliorer les performances de la stratégie; utiliser, proposer et analyser des métriques sensibles aux humains; combiner des métriques et des aperçus dans la stratégie visant une performance améliorée dans un scénario mobile plus réaliste; et enfin, évaluer la stratégie à travers ses forces et ses faiblesses. Cette thèse montre que TOOTS a amélioré les performances d'un scénario opportuniste en termes de surcharge, de taux de livraison et de latence en suivant ce processus.

Pour atteindre les résultats, dans l'étude de l'aspect humain du réseautage, nous avons constaté qu'il y avait une évolution dans les liens humains avec les défis du réseau mobile. Cette vision culmine dans la perspective Tactful Networking, que nous introduisons pour suivre. Nous complétons la revue de la littérature en discutant des stratégies de transfert opportunistes de pointe, y compris leurs contributions, leurs lacunes et leurs problèmes en suspens. Deuxièmement, nous discutons d'un cadre pour améliorer les données humaines brutes cachées dans des ensembles de données. Une étude de cas avec l'ensemble de données MACACO valide le cadre grâce aux résultats de caractérisation des traces et à l'analyse. Ensuite, nous caractérisons les ensembles de données MACACO, NCCU, et GRM pour apporter des informations et valider TOOTS. Les métriques de la stratégie présentées et analysées proviennent des informations de caractérisation de ces ensembles de données.

Troisièmement, nous introduisons TOOTS, qui vise la diffusion de contenu rentable dans un scénario mobile. Ensuite, nous présentons la définition formelle du choix du problème des nœuds de dissémination (1ère phase de TOOTS). En guise de motivation, nous analysons la surcharge et la latence de la transmission épidémique. Par la suite, nous introduisons les deux phases de TOOTS: une politique de diffusion avec tact et un algorithme de transmission.

Enfin, nous comparons l'efficacité de TOOTS sur ses phases avec des algorithmes améliorés Store-wait-forward, Epidemic et Bubble Rap via des traces réelles et synthétiques. Parmi les principaux résultats, dans un scénario avec une portée de 30 m, TOOTS a atteint un taux de livraison de 100% avec une latence de livraison réduite de 28% et 73%; et avec 16% et 27% de frais généraux réduits, respectivement, dans les ensembles de données réels et synthétiques. Avec une portée limitée (10 m), TOOTS était la stratégie la plus rapide et la seule à livrer 100% du contenu dans la trace réelle.

Par conséquent, cette thèse contribue à résoudre le problème de la livraison de contenu opportuniste dans les réseaux cellulaires en fournissant une solution opportuniste rentable et

consciente de l'homme. La stratégie peut être appliquée dans différents scénarios pour aider l'opérateur à diffuser du contenu sans nécessairement utiliser son ancien réseau, par exemple en explorant la capillarité de ses utilisateurs mobiles, pour le déchargement de données et d'autres applications.

Acknowledgement

Since I was a kid, listening to music and reading were some of my favorite activities. And from many years ago, I recall a phrase by a songwriter called Jalani Horton that says: "Every situation is a chance to grow, and every sunrise another time to sow. With our hands in soil, we're making furrow. Examine what you know." - it's all about the chances we have in life and some sort of focus and dedication. Unfortunately, not everyone gets the same level of chances - that's something I always thought about, and this thesis gave me an outstanding chance to grow. Not only as a researcher or computer scientist but, more importantly, as a human being. Life is the greatest gift of all, and the experiences we have and the people we meet along the journey are what helps us to define our path. I was fortunate to meet so many great people throughout my entire existence. If I am somehow better than I was one day, I owe this to great individuals I met. It mainly started with my parents João Carlos and Maria Celeste, and grandfather Antônio Lima. They always believed that education was the key to development. I owe sincere and deep gratitude to them for being my first advisors and magnificent supporters. I extend this gratitude to other family members who guided me. I thank my soulmate Joanna Balana for motivating me in everything I do and always taking great care of me. I bow to all my teachers - they got the power to make our society better. I was also fortunate to meet one of my advisors in this thesis throughout my academic and professional career. This person I consider not only a teacher but a true friend - Prof. Leobino Sampaio. He dedicated countless hours to advise me since my early days at the graduation. He was always there, no matter the time or circumstance. Prof. Leobino opened so many doors and put me in contact with another great person whom I knew since 2006 - Prof. Artur Ziviani. He was a very welcoming, sincere, smiling, and technically precise professor. I learned so much through him, and it's painful and unbelievable that he is not here with us anymore. I dedicate the result of this thesis to the memory of Prof. Ziviani. To his family and friends, I extend my sincere condolences, and as survivors of this crazy moment we're living, it's our duty to keep his legacy alive. Artur was the one who built a bridge for me to study abroad, advised by Prof. Aline Viana. She also gave me a lot of great opportunities and chances to grow during these last few years. I thank Aline for her great contributions and for welcoming me in France as a member of her research team at Inria. Not any less important, I thank all my close friends in Salvador and colleagues at UFBA and Inria for making my life smoother. I also acknowledge the support of PGCOMP and CAPES (Coordination for the Improvement of Higher Education Personnel). Luckily I started my Ph.D. when there were more incentives for education and research in my country. Last but not least, I thank all those who inspired me, giving me the strength to carry on - book authors, activists, scientists, researchers, musicians, songwriters, and conscious artists. Life is a miracle!

PUBLICATIONS

This thesis resulted in the following list of publications:

Tutorial

- R. L. Costa, L. N. Sampaio, A. Ziviani, A. C. Viana, Humanos no ciclo de comunicação: facilitadores das redes de próxima geração (Humans in the Communication Loop: enablers of next-generation networks), in Tutorials Book XXXVI Brazilian Symposium in Computer Networks & Distributed Systems – SBRC'2018, Brazilian Computing Society (SBC), May 2018.

Publications

- **Tutorial Book Chapter:** R. L. Costa, L. N. Sampaio, A. Ziviani, A. C. Viana, Humanos no ciclo de comunicação: facilitadores das redes de próxima geração (Humans in the Communication Loop: enablers of next-generation networks), in Tutorials Book XXXVI Brazilian Symposium in Computer Networks & Distributed Systems – SBRC'2018, Brazilian Computing Society (SBC), May 2018 [1].

- **Invited Paper:** R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Towards Human-Aware D2D Communication, in 2nd International Workshop on Urban Computing, part of the proceedings of the 16th International Conference on Distributed Computing in Sensor Systems – DCOSS'2020, IEEE, May 2020 [2].

- **Main Track - Conference Paper:** R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Extração e Análise de Dados Como Suporte a Estratégias de Comunicação D2D Cientes do Humano (Data Extraction and Analysis for Supporting Human-Aware D2D Communication Strategies), in XXXVIII Brazilian Symposium in Computer Networks & Distributed Systems – SBRC'2020, Brazilian Computing Society (SBC), December 2020 [3].

- **Survey - Journal Paper:** R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Tactful Networking: Humans in the Communication Loop, in Transactions on Emerging Topics in Computational Intelligence – TETCI Volume: 5, Issue: 1, IEEE, February 2021 [4].

- **Main Track - Conference Paper:** R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Tactful opportunistic forwarding: What human routines and cooperation can improve?, in 35th International Conference on Advanced Information Networking and Applications – AINA-2021, Springer, Advanced Information Networking and Applications, May 2021 [5].

Under Submission

- **Open Call - Journal Paper:** R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, On Building Human-aware Opportunistic Communication Strategies for Cost-effective Content Delivery, in Computer Communications – Elsevier.

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List of Acronyms

5G	**5th Generation Mobile Network**
6G	**6th Generation Mobile Network**
AI	**Artificial Intelligence**
C-V2X	**Cellular-vehicle to Everything**
CCDF	**Complementary Cumulative Distribution Function**
CDF	**Cumulative Distribution Function**
CDP	**Centrality-based Dissemination Policy**
CDR	**Call Detail Record**
D2D	**Device-to-device**
DTN	**Delay-tolerant Network**
GPS	**Global Positioning System**
GRM	**Group Regularity Model**
IoT	**Internet Of Things**
LBSN	**Location-based Social Network**
LTE	**Long Term Evolution**
M2M	**Machine-to-machine**
MANET	**Mobile ad hoc Network**
MEC	**Mobile Edge Computing**
MPLS	**Multiprotocol Label Switching**
MSN	**Mobile Social Network**
NFV	**Network Functions Virtualization**
OSN	**Online Social Network**
PoI	**Point-of-interest**
QoE	**Quality of Experience**
QoS	**Quality of Service**
RDP	**Random-based Dissemination Policy**
SBC	**Brazilian Computing Society**
SDN	**Software-defined Networks**
ST	**Sojourn Time**
SWIM	**Small Worlds in Motion**
TDP	**Tactful-based Dissemination Policy**
TOOTS	**Tactful Opportunistic Communication Strategy**
TTL	**Time-to-live**
UDN	**Ultra-dense Networks**
V2V	**Vehicle-to-vehicle**
VANETs	**Vehicular Ad Hoc Networks**
WSDN	**Wireless Software-defined Networks**

Chapter 1

Introduction

As traffic grows exponentially [7, 8, 9], next-generation mobile phone networks (5G) [10] will have to deal with spectrum bottleneck, higher data rates, lower delay, energy efficiency, and other significant challenges to serve more users and types of communication. Mobile data traffic has grown 17-fold over the past five years [8], and mobile offload exceeded cellular traffic by a significant margin in 2017. From these studies, we can infer that mobile networks would collapse without using techniques to detour traffic.

Moreover, the mobile data traffic growth links to an increase in the number of subscribers (70% of the global human population will have access to mobile networks in 2023) and connected devices [9]. For example, there will be 14.7 billion Machine-To-Machine (M2M) connections in 2023, accounting for 50 percent of the traffic. Such increase hardens the already known connectivity challenges and demands innovative solutions to unburden the legacy networks, increase capillarity, or provide connectivity in challenging scenarios (e.g., disasters or crowded places).

The increase in human subscribers exposes a weakness in previous mobile network standards, such as LTE: the main concern has always been with network parameters and not with each user's goals. For such reason, essential performance requirements had sub-optimal implementations [11]. Furthermore, computing and networking systems design are increasingly dealing with user expectations. The Multi-Protocol Label Switching (MPLS) and Software-Defined Networking (SDN) are examples of technologies that assist operators in providing QoS and QoE services through user-oriented traffic differentiation.

In the last decade, several concepts based on direct user involvement gained attention as enablers for wireless communications, e.g., User-centric Networks [12], Opportunistic Device-to-Device Communication (D2D) [13, 14, 15], People-centric networking [16], User-in-the-loop [17] and Human-in-the-loop [18]. Those initiatives targeted improved networking performance, fostering new applications, and dealing with LTE/5G challenges such as the ones previously mentioned [14, 18, 19, 20, 21, 22, 23, 24, 25, 26]. Since these mentioned concepts rely on user participation, understanding human behavior is essential [4]. Nevertheless, such perception is not trivial. There are multiple challenges associated with gathering human data, processing, enriching, modeling, extracting knowledge, analyzing, and validating [3, 4].

The main goal of this thesis was to build an opportunistic communication strategy that leverages human-aware information to perform cost-effective content delivery in a mobile scenario. This strategy envisages scenarios such as unburdening legacy networks (i.e., data offloading), increasing the network's capillarity, or providing communication in challenging situations (e.g., disasters or crowded places). An application example of such a strategy is when a network operator wants to disseminate multiple popular delay-tolerant contents (e.g., non-critical application updates) to its users while saving legacy network resources by leveraging opportunistic communication. The following sections discuss the problems, existing studies and limitations, the specific objectives, and this thesis's technical or conceptual contributions.

1.1 Building a Tactful Opportunistic Communication Strategy

Previous work on D2D opportunistic forwarding algorithms tackled the cost-effective and timely delivery of data [13, 14, 21, 22, 27, 28], i.e., delivering as many contents as possible with less overhead and delay. In these scenarios, contents (or messages) are forwarded user-to-user, from source to destination in an opportunistic fashion (i.e., relying on user devices' intermittent connectivity).

Most of such initiatives focused on proposing new algorithms that typically consider user encounters due to individual mobility [13, 14, 21, 22, 27, 28], points of interest (PoIs) [14], and time-evolving social ties between node pairs [13, 14, 21, 22, 27, 28]. Apart from that, not many initiatives approximated the evaluation metrics to broader inherent aspects of human mobility while targeting the Quality of Experience (QoE) of users and the Quality of Service (QoS) offered by the network [2].

The works mentioned above demonstrate a lack of initiatives beyond traditional techniques or limited human-mobility features. So, it becomes necessary to identify with more detail and precision the spatiotemporal routines, related consequences (e.g., wireless encounters), and movement decisions (e.g., motion direction). Among the challenges that state-of-art work had in this context were the limited availability of real-world datasets [14, 21] and the lack of a human-centered vision in computer networking.

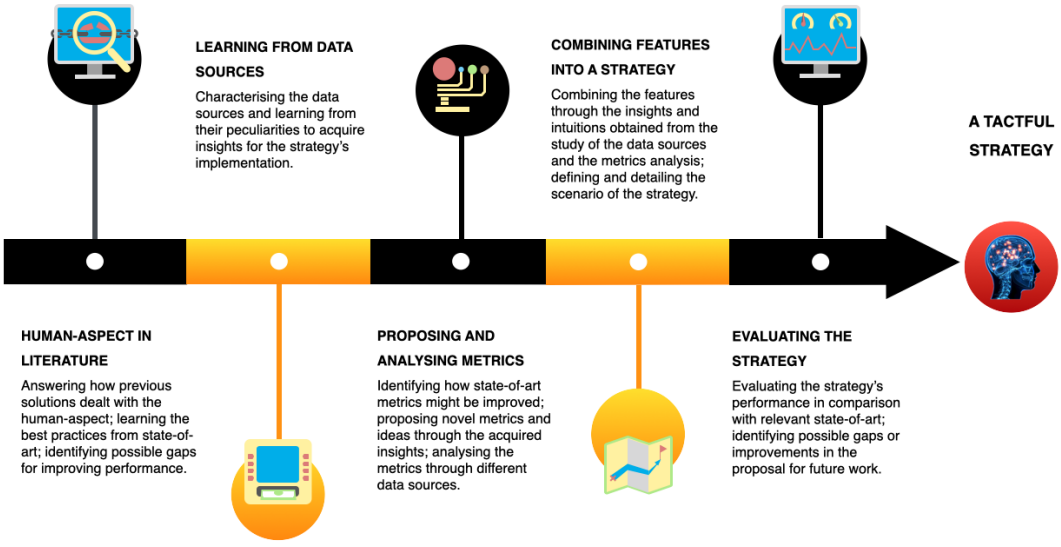


Figure 1.1: Building process of the TOOTS proposal.

Real-world datasets (i.e., with real user information) become essential in these studies, as they usually deal with aspects of human behavior [29]. The NCCU trace [30] is an example of a public available real-world dataset that features mobility traits from a population and can support the design of opportunistic routing algorithms [14].

Conversely, due to the scarcity of datasets with larger populations, several evaluations occur through synthetic mobility models [14, 29], such as the Small World in Motion (SWIM) [31] and the Group Regularity Mobility Model (GRM) [32]. The GRM keeps pairwise contact properties of real traces and accounts to play the role of group mobility, presenting group meetings' regularity and social community structure [32].

In this thesis, MACACO [33], NCCU, and GRM datasets are characterized and evaluated to extract insights and metrics later combined in an opportunistic communication strategy. The strategy focuses on metrics able to reflect human mobility features. Still, each population has particular habits that can change the wireless contact dynamics [34]. Thus, such metrics must be evaluated throughout different populations, while spatiotemporal aspects must fit each population's habits.

As previously stated, our main goal was to build a Tactful Opportunistic Communication strategy for performing cost-effective content delivery in a cellular networks scenario. Within such goal, we address the following research questions:

- Which lessons can we take from state-of-art opportunistic communication strategies when dealing with the human aspect?
- What human characteristics peculiarities can we learn from mobility datasets to improve our strategy's performance?
- How can we translate the identified peculiarities and characteristics into mobility metrics, and how can we combine those to reach superior performance in our strategy?

The main contributions of this thesis relate to *the full process for developing a tactful (i.e., human-aware) opportunistic communication strategy able to improve system performance in terms of cost-effective content delivery.* This process (Fig. 1.1) is used for building and introducing the Tactful Opportunistic COmmunicaTion Strategy (TOOTS). More details are discussed to follow.

1.2 The Rise of Tactful Networking: A Cornerstone for Future Mobile Networking Solutions

This thesis started with a deep investigation of the challenges, needs, and types of human behavior for dealing with networking challenges. In the literature review, we found the User-centric paradigm, an initiative for user empowerment as an enabler of networking solutions.

Although having the user as the central concern, the first solutions in User-centric Networks still did not see the user as an individual but rather as a network active element. Hence, frequently, only user features measured from the network point of view were considered, ignoring the intrinsic ones from human activity, e.g., daily routines and personal preferences.

Further, nowadays, mobile operators, end-user devices, and applications (e.g., social networks) gather and store a rich set of individuals' information. Along with the use of data mining and analytics, machine learning, and other techniques, this data can bring new possibilities for modeling networking solutions [3, 4]; tackling solutions for the traffic explosion problem [5, 35]; meeting some 5G/6G requirements [15]; leveraging solutions to expand network capillarity [5], and helping to achieve a network service closer to user expectations [1, 2, 3, 4, 5].

Mobile devices are attached to human daily life activities, and therefore communication architectures based on context and human behavior information are promising for the future. The ubiquity of these portable user devices opens possibilities for opportunistic device-to-device communication (D2D), a technology that, among other benefits, can assist in offloading data from the operator's network and help to increase its capillarity.

We argue that the following paradigm shift is necessary: from a network *controlling, tracking, and monitoring networking users* to a network *perceiving the needs and adapting to inherent behaviors of humans behind networking devices*. We denominate this paradigm *Tactful Networking* [4], and it calls for having, progressively, computer networks and mobile devices that understand and react to human behavior characteristics. Tactful Networking groups concepts from human behavior research, not only from computer networking but also from other areas. Examples of individuals' characteristics to be considered include mobility, personality traits, temperament traits, humor, character traits, sharing wills, age, socioeconomic status, and routines, which can be studied to offer a proper human-aware network service.

The study of human behavior is not new in areas such as psychology, physics, and sociology. Recent advances in data collection/analysis, machine learning, human-computer interaction and computational social science have shown that human-behavior investigation has also a vital importance in networking [36],[37],[38].

As for identifying and reaching this thesis's main goal, we first targeted acquiring technical background from the investigation of human aspects applied in state-of-art networking solutions. This investigation culminated in a conceptual contribution, which is the Tactful Networking paradigm [4]. Tactful Networking background was also essential for reaching the insights and metrics of the Tactful Opportunistic COmmunicaTion Strategy (TOOTS). The following section discusses motivations, problems, existing studies, and limitations related to the Tactful Networking paradigm proposal.

Regarding the investigation of human aspects applied in state-of-art networking solutions, we address two research questions, i.e.,

- How was the human aspect applied in state-of-art networking research to improve QoS, QoE, and bring innovative solutions?
- Which human characteristics can we use to leverage networking research for improving system performance and user experience? In particular, opportunistic D2D algorithms?

Opportunistic networks play an important role as enablers of emerging applications and high-demanding requirements of the modern and future mobile network generations, such as 5G [10, 39] and 6G [15]. In many of the envisaged scenarios with low-latency, high-speed data transmission, capillarity expansion, or even with delay-tolerant communication, D2D communication [40] should benefit from AI techniques boosted by human-aware information and edge technologies, such as mobile edge computing (MEC) [4, 15].

Among the challenges in this context are the increasing growth in mobile data traffic due to the emerging machine-to-machine (M2M) and Internet of Things (IoT) applications as well as the heavy multimedia content consumption and sharing [9]; network spectrum bottlenecks [15, 41]; connecting millions of devices in crowded areas, or expanding the capillarity in remote locations [41, 42, 43].

1.3 Findings and Thesis Outline

Building on the importance of designing suitable networking solutions leveraging human behavior and its challenges, we summarize each chapter's main contributions (Fig. 1.2) and outcomes. At the end of the section, we link each publication with the thesis chapters.

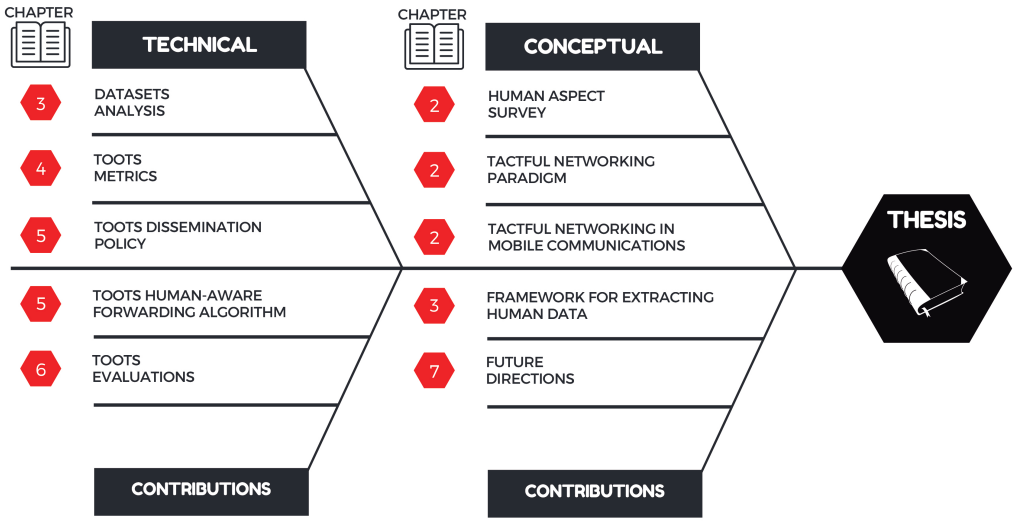


Figure 1.2: Summary of contributions per chapter of this thesis.

Chapter 2: We begin with a Survey on the human aspect in networking research covering over a decade of initiatives through a timeline. We found that, throughout the years, there is an evolution in how the human perspective deals with computer networking challenges. This broader human-aware vision culminates into the Tactful Networking perspective, which we introduce to follow in the same chapter. We also discuss several application examples of tactful networking into mobile network concepts, technologies, and communication models. Among the examples are 5G, IoT, Vehicular Networks, Ultra-dense networks, Information-centric Networks, SDN, and NFV. Finally, we review state-of-art opportunistic forwarding strategies and algorithms. Those are related to the main contribution of this thesis, which is the whole process for developing the Tactful Opportunistic Communication Strategy (TOOTS).

Chapter 3: We first present the datasets used and resume the work applied to those. Then, we discuss a framework for enhancing raw human data hidden into datasets. Data Management, analytics, and privacy tasks are discussed through best practices to deal with challenges in this context, data source examples, and other aspects. As for validating the framework, we then present a case study with the MACACO dataset with characterization analysis and results. Finally, we characterize and analyze the NCCU and the GRM datasets. We use those to bring insights and to validate the tactful opportunistic strategy.

Chapter 4: We translate the knowledge obtained into the proposal of metrics and features of our strategy (TOOTS). This knowledge consists of:

- A deeper understanding of the human aspect acquired through surveying human-behavior state-of-art in networking solutions and the Tactful Networking paradigm proposal. We learned that for trying to reach superior performance in our strategy, identifying and using inherent aspects of the human users hidden into the datasets were necessary;

- Learning the contributions and shortcomings from the state-of-art forwarding strategies;

- The insights and characterization results from datasets' analysis. Those gave us intuitions for proposing and combining the metrics into a complete strategy for reaching cost-effective content delivery in a mobile scenario.

We explain the motivations, insights, and goals behind each metric individually and how they work into the strategy. Then, we describe individually all metrics, including their mathematical formulations and characterization results in the three datasets. TOOTS uses a probabilistic approach to learn from past users' mobility, identifying node behavior through five different metrics and a time approach feature.

Chapter 5: We introduce TOOTS, a Tactful Opportunistic Communication Strategy for performing cost-effective content delivery in a cellular networks scenario. We first present the scenario we used to evaluate TOOTS, followed by the formal definition for the choosing disseminator nodes problem (TOOTS' 1st phase). As a motivation to develop the strategy, we analyze the overhead and latency metrics within the state-of-art Epidemic forwarding. Finally, we introduce the two phases of TOOTS: a TDP (Tactful Dissemination Policy) and a Human-aware forwarding algorithm.

Chapter 6: TOOTS is evaluated in each one of its steps. We start detailing the evaluation setup, followed by the 1st phase of TOOTS (TDP policy) evaluations through its combination with state-of-art Store & Wait and Epidemic forwarding algorithms. Results show that the TDP Policy was able to improve performance. Finally, we compare TOOTS (i.e., the full proposal) with traditional Bubble Rap and enhanced versions of the latter with TDP, CDP (Centrality-based Dissemination Policy), and RDP (Random-based Dissemination Policy). Results show that TOOTS was the fastest strategy and able to deliver 100% of the contents on both datasets.

Chapter 7: We conclude this thesis, including its limitations, further discussions, out-of-scope subjects, and outlook. Part of the insights, additional discussions, and open research opportunities presented in Chap 7 appear in previously published work.

Below we link each publication related to this thesis to their corresponding chapters.

Tutorial & Book Chapter: R. L. Costa, L. N. Sampaio, A. Ziviani, A. C. Viana, Humanos no ciclo de comunicação: facilitadores das redes de próxima geração (Humans in the Communication Loop: enablers of next-generation networks), in Tutorials Book XXXVI Brazilian Symposium in Computer Networks & Distributed Systems – SBRC'2018, Brazilian Computing Society (SBC), May 2018 [1] **(Chapters 2, 7)**.

Invited Paper: R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Towards Human-Aware D2D Communication, in 2nd International Workshop on Urban Computing, part of the proceedings of the 16th International Conference on Distributed Computing in Sensor Systems – DCOSS'2020, IEEE, May 2020 [2] **(Chapters 3, 4, 5)**.

Main Track - Conference Paper: R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Extração e Análise de Dados Como Suporte a Estratégias de Comunicação D2D Cientes do Humano (Data Extraction and Analysis for Supporting Human-Aware D2D Communication

Strategies), in XXXVIII Brazilian Symposium in Computer Networks & Distributed Systems – SBRC'2020, Brazilian Computing Society (SBC), December 2020 [3] **(Chapters 2, 3, 4)**.

Survey - Journal Paper: R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Tactful Networking: Humans in the Communication Loop, in Transactions on Emerging Topics in Computational Intelligence – TETCI Volume: 5, Issue: 1, IEEE, February 2021 [4] **(Chapters 2, 3, 7)**.

Main Track - Conference Paper: R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, Tactful opportunistic forwarding: What human routines and cooperation can improve?, in 35th International Conference on Advanced Information Networking and Applications – AINA-2021, Springer, Advanced Information Networking and Applications, May 2021 [5] **(Chapters 4, 5, 6)**.

Open Call - Journal Paper: R. L. Costa, A. Ziviani, A. C. Viana, L. N. Sampaio, On Building Human-aware Opportunistic Communication Strategies for Cost-effective Content Delivery, in Computer Communications – Elsevier **(Chapters 4, 5, 6)**.

Chapter 2

Rationale

Our detailed human-aware networking literature survey (Sec. 2.1) brought us the assertion on the growing importance of the user as a central element to innovative computer networking solutions. This new understanding level of the user's human characteristics culminates in what we denominate Tactful Networking, introduced herein (Sec. 2.2). As for illustrating the practical relevance of this paradigm to solve challenges, we discuss application examples (Sec. 2.3) related to network concepts, technologies, and communication models (5G, IoT, Vehicular Networks, Ultra-dense networks, Information-centric Networks, SDN, and NFV). Furthermore, focusing on state-of-art opportunistic forwarding strategies, discussions regarding their scenarios, contributions, and limitations gives essential insights to TOOTS positioning in this subject (Sec. 2.4).

2.1 The Human Aspect in Networking Research

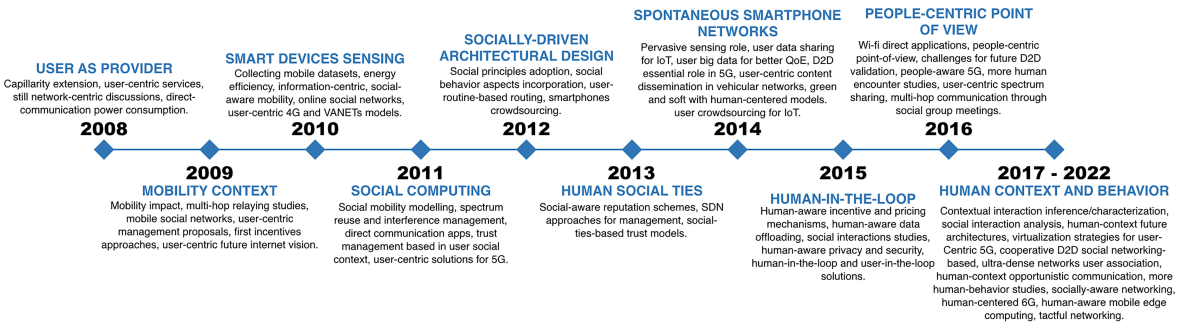


Figure 2.1: Timeline with the evolution of user-centric initiatives to human-centered future network generations.

Literature solutions based on a *user-centric* design brought more attention not only to user requirements, expectations, and QoE but also to how user participation can help to solve challenges in the context of mobile networks. These user-oriented approaches assisted mobile network design in different challenges, including energy and spectrum efficiency, routing, computing capacity, and capillarity extension.

The timeline depicted in Fig. 2.1 summarizes the research evolution from user-centric communication to more recent human-aware approaches. We highlight essential works, directions, milestones, and accomplishments for over a decade. The entire content of this section is published in [4], while here we present a resume. This section shows a considerable change towards understanding the human role in computer networks. This broader view culminates into The Tactful Networking perspective (Sec. 2.2).

Survey Methodology: As for surveying the human aspect in networking solutions, we mapped literature works over 20 different keywords related to: "User-centric" and other works published in the same direction after that. Among those, "Opportunistic Networks", "User-Provided Networks", "Human-in-the-loop", "People-Centric", "Delay-Tolerant Networks", "User-in-the-loop", "Human-centric", "Social Computing", and "D2D Communication". We then proceeded with literature classification according to several features (e.g., "Mobility & Handover", 'Routing", and "Forwarding Algorithms"). The following paragraphs describe the milestones and relevant work per year since 2008.

2008: We highlight the "user as provider" concept from user-centric communication [12], a solution for capillarity extension and data offloading through user participation. The user-centric main idea was for the user to act as a service/connectivity provider in specific scenarios: network edge, crowded places, and disasters. Despite many challenges identified [12], most discussions were still from a network, device, performance, and services perspectives, such as routing, access control, power consumption, and data privacy.

2009: The user mobility context [44] was a key topic with discussions about the main mobility aspects, the limitation of current protocols for user-centric models, and a user-centric future internet vision. The impact of user-location sensing [45] revealed issues related to control and privacy. User characteristics such as uncertainty, selfishness, and sensitivity to device resource consumption assisted incentive mechanisms [46].

2010: The importance of smart devices and online social networks (OSNs) sensing appeared in [47]. They gather user attributes and social graphs from social networks to infer other users' characteristics. This kind of sensing involves collecting mobile datasets from user devices to assist opportunistic routing architectures, such as [48]. They analyze and classify users' interactions according to their interests and activity. In [49], user contacts are mapped to social graphs for achieving better DTN routing performance. Studies in user behavior [50], preferences [51], attributes, satisfaction [52], and context started to be more common.

2011: We highlight social computing studies, such as human social aspects in mobility modeling for improving mobile network operation [53], access control, trust management [54], and privacy [55]. Among the characteristics considered were similarity of user profiles, reputation, and friendship history in social networks. User-provided networks/services relying on user-preferences targeted energy efficiency, QoS [56], among others. Urban computing was linked with social, spacial, and temporal aspects [57]. In [58], authors affirm future internet will be user-centric and context-aware. A user-centric architecture for 5G was introduced [59].

2012: Discussions about a socially-driven Internet architectural design were frequent. In [60], the role of prospective consumers (also services providers) appears as an Internet trend of user empowerment. Social aspects and other user characteristics appeared in multiple initiatives. Among those, user cooperation in peer-to-peer systems [61], energy-efficiency topology control in ad hoc networks [62], QoS-based incentive mechanism for user-centric networks [63], cellular traffic offloading through community-based opportunistic dissemination [64], and mobility-based handover [65].

2013: Human social ties studies appeared frequently. Challenges and solutions from OppNets and DTN to Mobile Social Networks (MSNs) are in [66]. Environment, context, reputation, community check, and other aspects appeared in trust management, cooperative models, and mobility analysis [67]. In [68], opportunistically created communities are determined not only by shared interests or contacts but also by mobility-related context like physical location and co-presence. In [69], user empowerment discussions in data offloading. A self-adaptive system for data dissemination in oppnets relying on a recognition heuristic with human-brain-like decisions is in [70]. Other user characteristics, such as communities, visited locations, friendship, selfishness, people's daily routines, and others, were used in MSNs, DTN, and routing initiatives [71, 72].

2014: The potential of spontaneous smartphone networks and cooperative relaying appeared in different works, making services adaptive to both user and network requirements [73, 74]. Discussions in D2D for 5G included security, privacy, interference management, resource allocation, and pricing models [75]. In the 5G context, works about reaching a superior user experience alongside new services and applications [76], green and soft future network rethinking the cell-centric design [77]. Other works included user traffic profile for allocation mechanisms [78], user-centric social-aware routing [79], user-centric communication services [80], user-provided incentive and reputation [81], QoE/QoS from user preferences [82, 83], and future people-centric networking [84, 85]. The term "User-in-the-loop" appeared in [86].

2015: Human-aspects started to be even more frequent in cooperative networking. We highlight Human-in-the-loop and User-in-the-loop approaches [20, 87], considering aspects such as human intents, psychological states, emotions, and actions inferred through sensory data. User-centric and user-provided wireless networking proposals are in [88, 89]. They emphasize people-centric networking, user interests, and social connections in different scenarios. In [90], a SDN-based 5G architecture relies on user location information. Other works included user-cooperation, geographical context, and content popularity data offloading [91], user-profile security [92], mobile users crowdsensing [93], mobility and OSNs [94], and user satisfaction as a protagonist in networking services [95].

2016: Terms like *people-centric* [96] kept appearing, reinforcing the importance of understanding the human behind a device - an individual sharing contents, experiences, and acting as a mobile virtual sensor. In [97] appears a UDN architecture closer to user requirements. In [10], D2D, UDNs, and big data analytics appear as 5G enablers. Characteristics such as user preferences, QoE, power status, movements, localization techniques, and geo-analysis appear in [98]. In [99] authors show that the structural properties of OSNs are similar to social networks formed offline. Other works included user-centric QoE prediction [100], human-behavior ICNs [101], user-centric scheduling for flexible 5G design [102], and opportunistic D2D routing relying on social group meetings [22].

2017: We highlight human-in-the-loop and user-in-the-loop works, reinforcing the need for learning, adapting, and steering user behavior to exploit the human factor in future ubiquitous mobile systems [18, 23]. User preferences or characteristics applied to energy constraints [103]; ultra-dense networks [104], mobile edge networks [105], user-centric context-aware radio access

selection for 5G [106], user-provided networks with incentive mechanisms [107], cooperation-based cache [108], extracting social relations from users' ratings [109], and cooperative D2D communication [110]. According to [111], we are moving towards the 5G era, witnessing a transformation in the way networks are designed and behave, with the end-user placed at the epicenter of any decision.

2018: The trend related to user-centric initiatives, user-in-the-loop, and human-in-the-loop continued. In [14], spatial and social awareness are combined to outperform state-of-art D2D opportunistic routing protocols. In [112], a survey on IoT future proposes a four-layer architecture, including a sensing layer. A "human-in-the-loop" 5G system in [113] combines prediction from big data analytics centered in user demand with pushing and caching. In [24], data offloading relies on user participation. They affirm that most previous works ignored user device constraints. Other works included user reliability propagation based on OSN interactions [114], user-centric D2D content-sharing [115], human-in-the-loop radio resource allocation for haptic communications [116], user-centric ultra-dense-networks [117], and user-centric cooperative caching based on network topology, traffic distribution, channel quality, and file popularity [118].

2019: The human-user context is linked with subjects such as location-based social networks [25], urban computing [25], machine learning [119], distributed spectrum sharing in dynamic networks, wireless virtualization, and handover. Many of these initiatives link to future 5G. A novel user-centric networking model where each user, based on uncertainty and their traffic model, can serve as access points for other users in their vicinity is in [120]. In [121], a 5G user-centric wireless access virtualization proposal allows users to benefit from a set of transmission points selected according to their environment and QoS requirements. This architecture represents a rupture of the traditional cell-centric scheme. In [26], handover opportunities in user-centric networks rely on user characteristics such as direction and speed.

2020 - Future: Future generation mobile networks will deal with human context, behavior, and information, considering aspects such as mobility, interactions, social ties, traffic profile, personality, and others discussed in the following section. Therefore, based on the discussions above and throughout the years, network models and solutions link with a new understanding level where human characteristics are necessary to offer better and more personalized service through tactful networking.

This section showed how the human aspect in networking research is evolving from a simplified view of "user as provider" to the use of human context and behavior, including several different users' characteristics to solve challenges. This broader human-aware view consists in part of the background for the proposal of Tactful Networking (next section).

2.2 The Tactful Networking Perspective

Traditionally, the design of computer networks happened from a service-provider perspective. There is a urgency for a proactive accommodation of human behavior, which refers to the anticipation of users' behaviors, allowing the services and the communication systems to adapt to it proactively [122, 123]. In an Internet that has become essentially mobile [9], it has

become urgent for networking services to accommodate users' dynamic behaviors, no matter how dynamic they are or how uncertain their movements are meant to be. In particular, since humans nowadays are often carrying and interacting through smart devices, mobile applications create a digital footprint that directly reflects our routines, interest, and whereabouts. Hence, our behavior and individual characteristics directly impact how we demand network resources and what kind of resources are requested.

As a result, we discuss the need for future network design to take human behavioral aspects into account to optimize network resources, services, and performance. Following, we discuss the *Tactful Networking paradigm*, the human behavior aspects that can be extracted and leveraged from digital footprints, and literature on behavior analysis. Some of these human-behavior aspects cited herein appear in solutions described in the previous section. Furthermore, we deliberate about each human traits' specific characteristics, also bringing other ones from interdisciplinary research. The Tactful Networking paradigm is a conceptual contribution of this thesis and is fully published in [4].

2.2.1 The tactful networking concept

The *Tactful Networking* research paradigm herein discussed is a reference to *the objective of adding perceptive senses to the network by assigning it with the human-like capabilities of observation, interpretation, and reaction to daily life features and involved entities.*

It is valuable to mention that the *Tactful Networking* concept is not the same as *Tactile Internet* [124, 125]. The latter regards research initiatives in which network connectivity aims to deliver real-time physical tactile experiences remotely. Conversely, being tactful is having or showing skill and sensitivity in handling with people. It also aggregates diplomacy, perception, tact, and care. Therefore, a tactful network can be more precisely defined as *a network that considers human behavioral characteristics: (i) to foresee user needs and actions; (ii) to self-adapt to the inherent heterogeneity and uncertainty of individuals; (iii) while offering a better quality of experience and improving system efficiency.*

Fig. 2.2 illustrates a tactful networking ecosystem where the human element is the epicenter of future networking solutions. His surroundings feature different aspects of his behavior that can bring valuable information to the networking domain. Mobility patterns and interactions are examples applied (Sec. 2.1).

Further, in this section, we discuss more aspects that can bring interesting insights into networking solutions. Among those, socio-demographic traits, socio-economic traits, and personality traits. More externally in the figure, we have several (but not limited to the ones herein listed) computer networking technologies or paradigms that already benefited or can benefit from the human-behavior data. Besides these and other technologies, new public-focused services (e.g., customized advertisement delivery or recommendations) or business models and opportunities can appear.

Table 2.1 summarizes some human multi-dimensional aspects to be considered. Following section features ideas behind their usability in tactful networking.

2.2.2 Behavior analysis in the literature

What tactful networking claims to consider are behaviors shaped by the fact that we are human beings. Some inherent examples are: *(i) people habitually act as semi-rational entities,*

Table 2.1: Key human aspects for tactful networking

Human Aspect	**Description**	**Services or Applications**
Context	Relates to the logical or physical context in which an individual interacts. Aspects such as time of the day, weather conditions, location-based events [126], preferences (e.g., device interfaces, geographical areas [127], tools, applications), among others, are considered.	Recommendation or customized advertisement services; context-aware prediction systems (the use of context allows decreasing the required visiting history of users and improving accuracy prediction).
Interactions	Study the features underlying human physical encounters, such as regularity [128], similarity [48], contact, or inter-contact duration in the temporal graph of encounters among individuals.	Interaction-based data offloading [91]; opportunistic applications or services [129]; proximity-based social networks [130]; prevention of cybersecurity attacks (e.g., understanding a malware propagation in mobile wireless networks) as well as of epidemic disease propagation.
Mobility	Accounts for regularity [131], entropy, confinement [132], as well as time periodicity [133] of visits. Location similarity [134], displacement profile, important location and routine inference are also related.	Network resource allocation [135] and optimization; content pre-fetching; urban planning [25]; traffic engineering [136]; prevention of cybersecurity attacks (e.g., understanding a malware propagation in mobile wireless networks) as well as of epidemic disease propagation; crime prediction.
Personality Traits	Accounts for the OCEAN traits extracted through the Big5 model [6]: Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism. Relates to the understanding of the influence that personality traits may have on individuals' behaviors (e.g., motion [137], physical/social relationships [138], preferences) or context.	Recommendation [139, 140] or customised advertisement services; incentive-based approaches; message propagation; smartphone usage understanding [37]; trust-management models.
Social Ties	Relates to friendship in on-line social networks [141, 142] and includes the study of features underlying human social interactions, such as regularity, periodicity, similarity, centrality, in the graph of social contacts of individuals.	Message propagation [22]; Influence detection; Homophily inference; Recommendation or customised advertisement services.
Socio-demographic and socio-economic traits	Relates to gender [25], age, income [126], family or marital status.	Recommendation or customised advertisement services; incentive-based approaches; smartphone usage understanding; traffic profile modeling; traffic engineering; urban planning.
Traffic Profile	Accounts for traffic volume, time periodicity, type of content, interest (including application, websites, and services).	Recommendation or customized advertisement services; traffic profile modeling; network resource allocation and optimization; load balancing.
Others	Any other human behavior facing their actions, habits, interests, preferences, and context in their day-to-day life: e.g., the human inherent and frequent will of sharing information (e.g., pictures, recommendations, opinions, arguments, and friendship).	On-line social networks; recommendation systems; pool transportation (e.g., blablacar, uber); home-sharing (e.g., Airbnb).

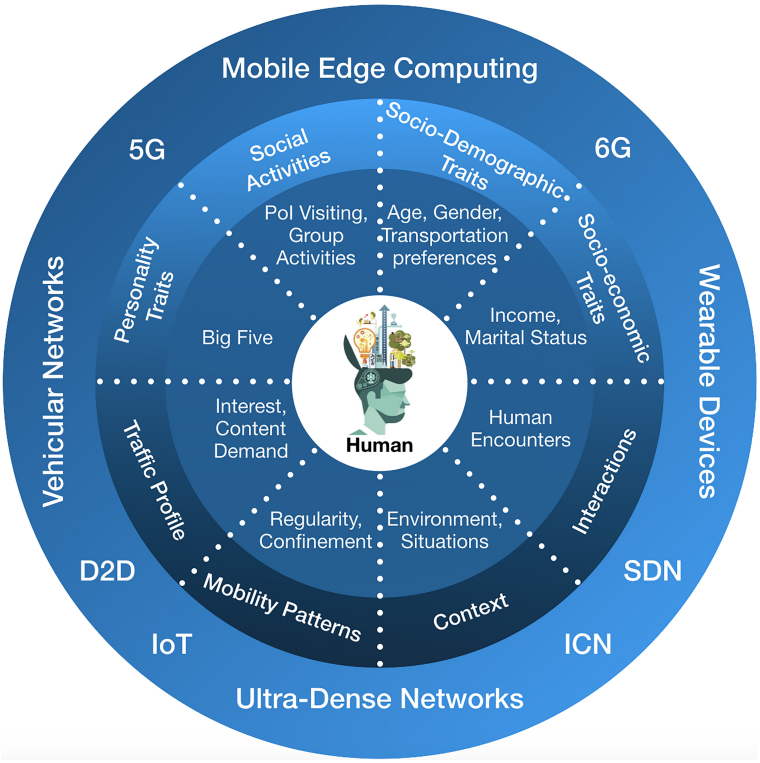


Figure 2.2: Tactful Networking ecosystem where human-related aspects are future mobile-networks enablers.

routinely moving and interacting within a reduced and predictable geographic landscape [128] and tending to meet the same people; (ii) people build their life-routine in particular areas that can also link to their personality and social ties, and (iii) human decision-making process deals with entropy and uncertainty, led by situations such as conflict, paradox, and noise [143].

Hereafter, we discuss literature works entitled to capture and analyze human behaviors.

2.2.2.1 Mobility

Understanding human mobility has many applications in several areas, such as the spread of diseases, city planning, traffic engineering, targeted product advertisements, and networking resource allocation. As routines and habits dictate our life, mobility data is relevant for inferring behavior. For instance, in modern urban planning, understanding human travel patterns on the city level is essential. Similarly, mobile operators could better adapt their resource allocation or service provision if they understand their users' displacement tendencies. Further, over 24% of Android applications build their services on top of human-mobility data. All this shows the importance of deciphering human motion.

Literature works have unraveled interesting properties of underlying large-scale mobility patterns (Table 2.2).

2.2.2.2 Personality Traits

In recent years, personality prediction has attracted interest from the computer science research community. Technologies, services, or applications can be improved to answer users'

Table 2.2: Properties of underlying large-scale mobility patterns

Property	Literature Works
Recurrence and temporal periodicity of visited locations.	[128, 132]
Confinement (a small area an individual visits).	[128, 132]
High predictability of human mobility.	[134]
Few unique network motifs (i.e., about 17) explaining the majority of daily human mobility.	[144]
Population trip distance and radius of gyration distribution following a power law.	[132]
A very high uniqueness of individual trajectories (i.e., four random time-stamped locations identify one user among 1.5 million individuals in 95% of the time).	[145]
Few trips to new places outside an individual radius and about 25% of human mobility relating to new places visits.	[146]
Tendency to minimize their efforts (i.e., following the shortest path while moving). This phenomenon repeats independently of countries, cultures, or transportation means being used.	[128, 132]

expectations and needs if such interested users' personality is known and better understood. For example, recommendations on new places to visit and novel experiences to seek could reach individuals more disposed to enjoy the information. Alternatively, online social networks or crowdsensing applications could better suggest new activities or connect individuals with similar personalities and interests.

For capturing individuals' personalities, the research community has been considering the *Big5 personality model* [6]. It delineates the OCEAN traits as follows: (i) *Openness (to experiences) (O)*: is associated with intelligence, originality, creativity, and intellectual curiosity; (ii) *Conscientiousness (C)*: describes self-control, planning, and organizational skills; (iii) *Extraversion (E)*: accounts for assertiveness, positive emotions, and captures the amount of social stimuli that we search for; (iv) *Agreeableness (A)*: describes empathy, compassion, and altruism; *(v) Neuroticism (N)*: is associated with the tendency of experiencing negative feelings, anxiety, mood swings, and emotional instability.

Personality traits levels are gathered through questionnaires built for this purpose by psychologists and available online. Figure 2.3 features examples of personality traits levels, according to the Big Five model.

Research has studied individual personality traits prediction through datasets since human migration to the digital environment renders such prediction possible, and personality is predictive of a wide range of behavioral and social outcomes. Previous work investigates the relationship between personality and smartphone usage: i.e., if installed applications, calls, and the proximity of Bluetooth devices can lead to the prediction of the Big5 traits [147, 148].

Interactions and online social ties have also appeared to predict personality traits [137, 149]. In [137], authors reveal how Openness is correlated with check-ins at popular and social venues, while Neuroticism has a negative correlation with the number of venues visited. The connection between people's social networks, the typical locations visited, and Extraversion is studied in [150]. Finally, [151] predicts Extraversion and Conscientiousness by analyzing

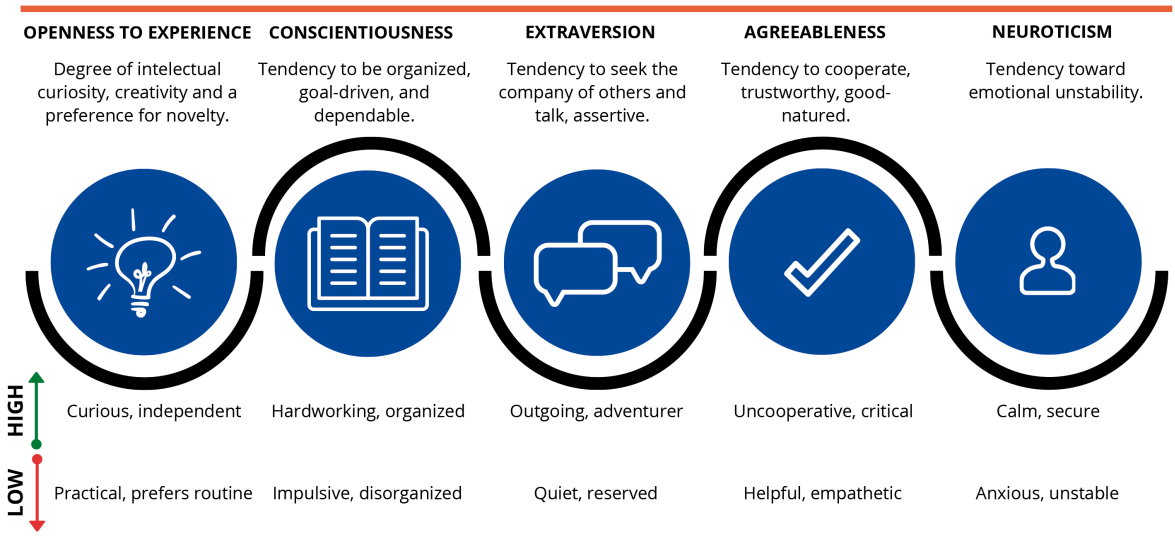


Figure 2.3: Big Five personality traits [6].

mobile HTTP(S) traffic during weekend nights and weekdays mornings, linking Openness to visited web pages diversity.

2.2.2.3 Wireless encounters

Understanding user contacts is relevant when designing new opportunistic communication protocols. In this case, the problem mainly lies in quantifying the contacts' quality according to a determined objective and correctly predicting encounters. To that end, among the findings related to the human aspect, are: (i) he regularity of daily activities [128, 132, 134]; (ii) the tendency to follow the shortest path to a certain destination [128]; (iii) the very common short and confined traveled distances [128, 132]; (iv) the prevalence of static phases spent at a few fixed locations, with rapid transitions among those [152]; (v) the overnight movements invariance in dwelling places with usually lower contact opportunities [133].

Protocols relying on human motion estimate mobile users' potential to act as data forwarders, mainly leveraging sophisticated network analysis metrics such as centrality measures. In [21, 72], authors derive social-based metrics from users' connectivity (such as betweenness centrality and neighborhood similarity) for more efficient opportunistic forwarding decisions and less overhead. In the same way, opportunistic data offloading relying on direct communication between devices appeared in [14, 22, 91, 110]. In such works, authors: (i) study how temporal communities can assist minimizing the delivery delays; (ii) nvestigate the node interactions through centrality measures to derive reliable future communication possibilities, or (iii) determine the copies amount to be injected in the network to ensure performance.

Finally, although an elevated rate of regularity characterizes human behavior, random events or decisions can happen. Such situations are hardly predictable and are unlikely to repeat in the future; they originate from the fact that users are reasonable beings, whose decisions they take are based on their motivations, which may also change over time [134, 146]. The goal of characterizing random and regular encounters have motivated works, such as [48]. In [48], a finer-grained classifier, is introduced to describe random and social interactions. The

performed analysis unveils significant differences among the dynamics of users' interactions, which authors leveraged to unveil social ties' impact on opportunistic routing.

2.2.2.4 Social ties

Social networks map vertices to individuals, while edges may represent friendship, work interactions, similarity, among others [141]. When building such a network, edges can derive from explicit information (e.g., declared friendship on Facebook) or from implicit knowledge inferred from the reciprocate behavior of the vertices (e.g., similarity), a phenomenon called homophily in the literature of complex network analysis.

Analysis of social networks usually relies on the high predictability of human behaviors [142, 153], mostly driven by routinary activities. Hence, mechanisms such as preferential attachment and triangle formation model these networks vertices connections [154], leveraging the existence of communities or highly connected hubs in the network. This high predictability makes social networks different from random ones, such as the Erdős and Rényi network [155] (where node connections are purely stochastic, being determined by a constant probability).

Most recently, location-based social networks (LBSNs) have become relevant data sources for urban computing [25]. LBSN offers unprecedented geographic and temporal resolutions. It reflects individual user actions (temporal resolution) at the scale of entire world-class cities (global geographic resolution). For instance, users who share data in Foursquare, a popular LBSN, usually have the goal of showing to their friends where they are, while also providing personalized recommendations of places they visit. Nevertheless, when correctly analyzed for knowledge extraction, this data can suit for better understanding city dynamics and related social, economic, and cultural aspects [25, 126].

2.2.2.5 Content demand

Understanding individuals' content consumption is relevant when looking for solutions: (i) to manage the recent boost of mobile data usage; (ii) to improve communication services quality or the design of adaptable networking protocols [156].

Such perception can help to identify traffic congestion periods or fill the gap between the infrastructure technology's capacity and the mobile users' traffic load.

A significant amount of work in the literature analyzes network traffic usage through voice calls and SMS messages, both extracted from traditional Call Detail Records (CDRs) [157, 158]. Although providing valuable insights, as the CDRs present time irregularity and scarcity of call traffic, they do not describe realistic data traffic demand patterns. Browsing (visited websites) behavior has also been applied in user profiling according to their traffic demand [159]. Still, other works have categorized the actual mobile traffic usage [160, 161]. Among those, [161] provides a profiling of individual users' behavior –rather than a network-wide one – and a precise temporal network usage modeling, i.e., in terms of volume as well the frequency of traffic demand – rather than only considering total volume of traffic or a normalized volume. Among the outcomes, authors show: (i) the high day-wise similarity on sessions number, traffic volume, and inter-arrival time traffic parameters; (ii) such parameters from the same hours on different days present less variability than the parameters within the same day on different hours; (iii) the high correlation between upload/download traffic volume; (iv) peak and non-peak hours can be easily identified when it comes to users' traffic demands; (v) similar sessions

number and duration occur when users are grouped by age range, irrespective of the users' gender; (vi) male participation raises as the user age increases, while the female participation decreases with the age increase.

More recently, literature works have investigated network usage concerning other users' behavior. In [161, 162], calls/SMS patterns or traffic demand of users and their socio-demographic factors (e.g., age and gender) are jointly investigated. The relation between content consumption and mobility properties is considered in studies that focus on application interests [163], data traffic dynamics [164] and service usages [165]. Finally, in [166], authors describe their investigation on the predictability of mobile data traffic generated by individual users, which is studied in isolation as well as jointly with mobility. Among the outcomes, authors show: (i) the possibility for predicting user traffic generation with an upper bound of 85%; (ii) by knowing the past activities history of an individual, apart of the traffic volume, it is possible to predict where it will occur with an 88% accuracy in average. This result is possible thanks to correlations between visited locations and traffic volumes; (iii) including location information in the prediction process allows forecasting the future consumption of mobile data traffic with 5% higher accuracy, pushing the overall performance from 85% to 90%. Such results indicate a large space for predicting mobile data traffic and adapting network optimizing solutions based on the latter, such as caching and prefetching.

This section discussed the Tactful Networking paradigm, including a more granular view from aspects of human behavior to assist future networking solutions.

2.3 Tactful Networking in Mobile Communication

This section discusses the Tactful Networking paradigm towards mobile network concepts, technologies, and communication models. More detailed discussions are in [1]. The examples given here also appear in Fig. 2.2 which shows the Tactful Networking Ecosystem.

2.3.1 5G

The *5G* emerged with the premise of providing access to an increasing number of users in a current scenario of overload and limitations. The challenges range from spectrum allocation (more efficient reuse and new spectrum) to supporting new applications and device types.

Among the enabling technologies for 5G (i.e., for achieving 5G goals, while maintaining compatibility with previous generations) [10, 167, 168] are: (i) Wireless Software-defined Networks (WSDN); (ii) Network functions virtualization (NFV); (iii) Ultra-densification; (iv) Mobile Cloud Computing; (v) Internet of Things; (vi) Device-to-Device Communication (D2D), and (vii) Green Communication (sustainable).

According to [4], in the future (both in *5G* and in *6G*), contextual information and human behavior data/insights will be combined with technologies such as those cited above to get closer to the specification, avoiding sub-optimal solutions as in LTE [11]. Figure 2.4 lists some of the 5G requirements, which can benefit from tactful networking solutions. Below we discuss which human aspects can apply and how.

5G targets a reduction in energy consumption (1000x/bit) [10] due to the battery limitations of user devices and even more restricted ones (e.g., *IoT sensors*). D2D relying on human-aware data can: (i) apply to more efficient resource management; (ii) less energy consumption (short-range connections) and latency; (iii) higher transmission rates; (iv) better

spectrum reuse (reduced reach), and (v) improved connectivity at the edge, all 5G requirements [2, 10]. D2D already appears with *IoT, V2V*, and wearable devices [169]. Human-aware D2D communication is useful in different 5G scenarios (e.g., data offloading, capillarity extension, and new applications).

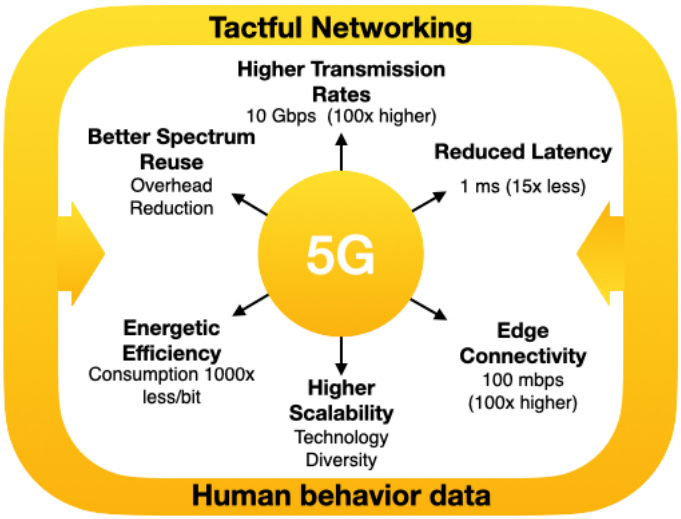


Figure 2.4: 5G requirements that may have solutions favored by knowledge of tactful networking information.

5G expects more devices (with different requirements) connections and greater scalability. Technologies such as *IoT, Vehicle Networks, and Autonomous Vehicles* bring challenges that will require changes in the network layers [4, 10]. For example, in the physical layer, the user's traffic profile and context can apply for better spectrum reuse. More efficient human-aware data transmission and signaling mechanisms emerge due to better resource orchestration as the user (and his intentions) are known. In the network and transport layers, routing algorithms can rely on mobility, personality traits, and others to reach a higher delivery rate, reduced latency, and lower overhead. For users on the move, mobility patterns can help in handover prediction along possible routes, where resources must be reserved.

In terms of management, although the SDN is already a more consolidated technology, the WSDN still requires many advances [10, 170]. There is a lack of a management framework capable of managing mobility, the interaction between protocols and technologies, and guaranteeing QoS and mobile services provisioning. Social interactions or relationships of trust in the social context can serve as an input to offer QoS/QoE.

2.3.2 Internet of Things (IoT)

One of the premises of the IoT services is the on-demand availability to their users, at any time and regardless of location (i.e., connected) [171, 172]. IoT will function as an extension of current networks [172, 173, 174]. Each object will interact through a network infrastructure and inter-operate with data and communications services, available resources, and other objects. Thus, the large amount of data generated and new connected devices will impact the networks. Data analysis and response to events in many cases will need to be in real-time. Thus, efficient, context-sensitive, and high-speed networks are essential.

The tactful networking paradigm is capable of leveraging IoT user data from the sensors themselves to favor types of communication (e.g., D2D, V2X). The study of the mobility profile and user routines present in the vicinity serves to choose which nodes have the best forwarding potential from the IoT sensors (or a relay node) to the cloud. Several works relate to communication types or resource scheduling that consider the social context, mobility, and others [175, 176, 177].

Human social ties (e.g., from online social networks) can serve as trust relationships and as a QoS metric in the communication and data composition from different users' sensors. Studying individual routines can help to predict the best moments for capturing or sharing sensors' data, keeping them in standby mode in specific time windows (i.e., energy efficiency). Further, IoT sensors can collect human context data to identify dangerous situations and stimulate opportunistic communication upon main network infrastructure failure. We conclude that IoT and tactful networking favor a new perspective of networks and leverage solutions that will help in people's daily lives.

2.3.3 Vehicular Networks (VANETs)

Figure 2.5: Tactful Networking human-behavior data that can leverage V2x networks in predicting situations, favouring interactions, managing resources, creating incentive mechanisms, establishing trust mechanisms, among others.

VANETs are a special case of *MANETs*, where vehicles with communication and data processing devices can create opportunistic and spontaneous networks while moving [178]. The communication pattern *C-V2X (Cellular-Vehicle to Everything)* has emerged with great potential and allows users on the road to communicate using standards such as *LTE* and *5G* [179, 180]. Through sensory information (e.g., weather and road conditions, vehicle status), vehicles will help their drivers make decisions. In Fig. 2.5, we illustrate visions of how data from the tactful networking paradigm can favor *V2X* technology.

Despite the dynamics of these networks, some aspects are recurrent and linked to their users' behavior or context. Mobility, for example, is constant but restricted as vehicles travel on specific roads or streets and are subject to certain conditions such as traffic, signs, and pedestrian crossing points. The user's mobility pattern can help to predict future vehicle positions and handover needs. Despite having a high turnover of nodes, the dynamics of encounters can be helpful to identify groups that are following a particular route, and that can interact with each other to deploy opportunistic networks and share data.

At the network layer, routing protocols must implement strategies to provide constant communication. They depend on factors such as mobility, data traffic, and road formats. User mobility analysis can help identify expected traffic and data exchange points at the intersection of roads. In the future, other sensors shall become part of user devices, including health monitors. Alarms about the individual's health status may suggest route changes (e.g., to a hospital) or vehicle interruption in case of temporary risk.

2.3.4 Ultra-dense Networks

In the last 50 years, the performance of mobile networks increased 2700 times by reducing the cell sizes and consequently the communication distance between the pairs [181]. Ultra-dense networks (UDNs) are essential for 5G/6G [15, 122, 123] and they are formed by: (i) small cells implanted in high density; (ii) macro base stations; (iii) mobile nodes (e.g., from vehicle networks); (iv) network control (potentially through *SDN*; (v) end-user devices. Among the main challenges in UDNs [182, 183] are: (i) interference Control; (ii) mobility; (iii) resource management (including energy issues).

In UDNs, mobility studies can apply to predict the selection/re-selection of a base station (*handover/handoff*) and assist in resource allocation. At the edge, human-aware D2D algorithms can increase capillarity and assist in data offloading. Other aspects such as detecting people's concentration in similar time windows/space, encounter dynamics, and context can optimize the micro-cells positioning and predict resource allocation. Further, since most of the consumption on cellular networks links to base stations (about 60% to 80%) [182], users' regularity and usage patterns can help dynamic capacity dimensioning of base stations, just as already happens in data centers, increasing energy efficiency [184].

2.3.5 Information-centric Networks

Information-Centered Networks (ICN) rely on a consumption/requisition model centered on the content holder and name-based routing. The *ICNs* offer native support for mobility, content security, non-connection oriented communication, and caching in the network layer [185, 186, 187]. For such reason, tactful networking information gives possibilities for offering a better network service in *ICNs* from: the identification of behavior patterns of content producers, seeking to minimize the effects of handoff (e.g., content unavailability [188, 189]); (ii) the use of cache policies according to the users' mobility and context; (iii) choosing the cache location from daily routines.

The problem of producer mobility is one of the most attacked in ICN [187, 190, 191, 192]. Nevertheless, a human-aware ICN model that predicts producer's displacement is a possible solution. Such a model makes it possible to implement opportunistic storage techniques on the network and prioritize storage and maintenance in the domain of that content from the mobile producer, based on a specific cache policy.

In [187, 193, 194], authors propose *ICN* on cellular networks, keeping the most popular content at the edge (base stations) and grouping users with similar interests. Despite the gains in hit rates with this approach, they adopt the same cache policies, regardless of the users' patterns. Therefore, performance may vary [195]. Human-behavior patterns can assist these proposals in choosing the most appropriate cache policies to meet groups and, thus, increase the content hit rate in general.

The cache location of an ICN can also influence the hit rate and, consequently, the service. Predicting users' mobility and routines can make content available in strategic locations and increase the hit rate. In the same vein, proposals in VANETs implement proactive caches in strategic locations, aiming at content distribution [187, 196]. On the other hand, traffic monitoring and data analysis are not enough to decide optimal cache and content replicas location in scenarios in which caches are stored on the network. In mobility scenarios strongly characterized by highly dynamic environments, this problem becomes even more evident. For these reasons, it is necessary to use short-term contextual information, involving not only nodes' availability and content popularity, but aspects from users' habits and routines.

2.3.6 SDN & NFV

Software-Defined Networking (SDN) [197] and Network Function Virtualization (NFV) [198] created a great impact not only from the data centers operational point of view, but also bringing possibilities to next generation communication models, concepts, and architectures like 5G, VANETs, and D2D. SDN enables networks management by software through the separation of control and data plans. With the advent of SDN, it becomes possible to allocate on-demand resources and services, and to provide on-demand management network applications. A paramount element in the SDN architecture is the controller. Those are central entities that coordinate network provisioning and automate its configuration. NFV is a paradigm that opens the possibility to virtualize networking functions (e.g., routers, firewalls) replacing dedicated hardware devices with software-based network devices or servers.

Several well-known challenges in SDN can apply tactful networking solutions. Among those, we can cite the placement of SDN controllers, which is critical for the network functioning. Inappropriate controller placement can affect network in terms of latency, energy efficiency, resiliency, to cite a few. Recent work [199] remark mobility-aware placement of SDN controllers as a promising open issue for investigation. In this context, user mobility data and traffic profiles can provide insightful information for on-demand controller placement and network resources management. In VANETs, we know that there is a human behind a vehicle, which follows his/her paths based on aspects previously mentioned. Human mobility (e.g., social encounters, displacements), personality traits, and emotional traits can assist SDN-VANETs [200] to predict disconnection situations, for coordinating opportunistic routing and forwarding among vehicles, on-demand topology deployment, controller placement, trust management, and so on. In fact, there is already a multitude of research investigating tactful networking-related aspects to solve challenge in the context of SDN-VANETs [200]. The use of AI and machine learning based on human-aware big data opens opportunities also in SDN and NFV [198].

Since the use of network resources include human users, they can vary in time and space. Managing these resources is a complex task, since these users traffic profiles can be influenced by different human traits. As with SDN, tactful networking can assist in solving challenges in NFV. Identifying human traffic profiles, behavior, routines, and other characteristics of mobile users assists in NFV resources management and allocation. Human-aware data is essential to predict network congestion situations to virtualized resources, among other challenges [198, 201].

Following, in the next section, we outline and discuss state-of-art opportunistic forwarding strategies and algorithms. Throughout the contributions and shortcomings from previous work,

along with a broader view of the human aspect from the Tactful Networking Paradigm, we developed a Tactful Opportunistic COmmunicaTion Strategy (TOOTS).

2.4 Opportunistic Forwarding Strategies and Algorithms

Table 2.3: Properties from opportunistic forwarding algorithms

Algorithm	Probabilistic	Social (Encounters)	Displacement Awareness	Direction Awareness	Human-Aware Time Approach	PoI Awareness
Bubble Rap		x				
dLIFE	x	x			x	
SCORP		x				
GROUPS-Net	x	x				
SAMPLER		x	x			x
TOOTS	x	x	x	x	x	x

The state-of-art opportunistic forwarding algorithms extracted metrics or decision factors from real-world or synthetic mobility datasets [14, 21, 22, 27, 29]. Human mobility hidden into the datasets is dynamic but shows regularity [133, 202] of visited locations [128], encounters [203], displacements [204], time [128, 202], space [202, 204], and other aspects [205]. Despite the high predictability of human mobility [134, 206], there is a challenge in choosing the forwarders through the combination of human-aware decision factors in the context of opportunistic forwarding.

Bubble Rap: A social-aware forwarding algorithm for delay-tolerant networks (DTN) [21]. It relies on two characteristics extracted from human mobility: centrality, which is related to social bounds (i.e., encounters), and community detection, defined as a socially connected set of people with meaningful relationships. Bubble Rap outperformed Prophet [207], a state-of-art probabilistic routing protocol that relies on wireless encounters' history and transitivity.

Despite the vast contributions and bringing attention to social-aware algorithms, Bubble Rap evaluations occurred through small scenarios, as the available traces at the time had less than 100 nodes. Furthermore, the algorithm community detection feature requires calibration and demands expensive computing, not suitable for realistic scenarios. Despite these shortcomings, Bubble Rap is the most popular social-aware forwarding algorithm, still used as a benchmark with recent research [14, 22, 208].

When it comes to the scenario, Bubble Rap was intended for a Pocket Switched Network [209], a type of DTN that uses possible contacts between users to communicate without a legacy network. Therefore, the main intention was to deliver (i.e., forward) content from source to destination with improved performance in terms of delivery rate, delivery cost (i.e., overhead), and hop distribution for deliveries (i.e., number of hops necessary to deliver the content). In the emulation of the scenario, they divided the original traces into discrete sequential contact events. For each event, the emulator makes a forwarding decision based on the proposed algorithm.

dLife: This social-aware forwarding algorithm brought attention to the observation of more granular human mobility [27]. The algorithm captures contact information (duration and degree) throughout daily hour periods to reflect human activities with more precision. The results from the evaluation of dLife showed improved delivery rate, delivery delay, and overhead.

Nevertheless, the evaluation of dLife suffered from the same lack of availability of more widespread traces as Bubble Rap. Other shortcomings were non-realistic settings on the evaluation, such as small (1 kB-100 kB) content size for offloading and nodes with 11Mbps/100m interfaces.

The envisaged scenario for dLife exploits user devices' ubiquity by allowing them to use a free short-range spectrum to exchange data whenever a contact occurs (i.e., two nodes are in the communication range). As in Bubble Rap, the goal was to deliver content from source to destination with improved performance. In the case of dLife, the evaluation metrics were delivery rate, delivery latency, and overhead.

SCORP: An opportunistic routing protocol that exploits nodes' social proximity in terms of contact's duration and interest in a given content [28]. According to the authors, there is a higher probability for users with similar habits to show interest in similar content. Furthermore, more frequent and more prolonged duration contacts can allow faster data forwarding, avoiding possible interruptions due to topology change. SCORP forwards a message when the next node is interested in the content, or the latter has a strong bond with other nodes interested in the content.

Despite the contributions, SCORP evaluations occurred through small datasets available at the time (a real trace with 36 nodes and a synthetic with 150 nodes). With that said, SCORP's performance in larger scenarios is unknown. Furthermore, the distribution of interest among the network users, the size of the contents (1 kb-100 kb), and the nodes' buffer size (2 MB) evaluated lack more realistic settings.

SCORP envisages an opportunistic data delivery in dense urban scenarios through direct communication between content producers and consumers. Despite the assumption about scenario density, as previously said, the evaluations occurred with tiny populations. SCORP's goal in the proposed scenario was to show improved performance in terms of delivery rate, delivery latency, and delivery cost (i.e., overhead given by the number of replicas of a content).

GROUPS-NET: A social-aware forwarding strategy that relies on the regularity of group meetings [22]. This algorithm is parameter-calibration-free and does not require community detection. Compared to Bubble Rap in a larger scenario, GROUPS-NET improved the overhead with a similar delivery rate.

Despite the contributions, the algorithm relies on a group-to-group path centralized calculation every-time a given content needs to be forwarded opportunistically from a source to a destination. In real-world larger populations, performing these calculations is challenging. Finally, GROUPS-NET also requires validations in other datasets than campus, where the mobility is more restricted.

According to the authors, GROUPS-NET is a multi-hop opportunistic D2D forwarding algorithm to perform cost-effective content delivery in large-scale scenarios. The algorithm can deliver content directly between pairs (i.e., origin and destination randomly selected), i.e., without the base station, enabling bandwidth offloading. Despite envisaging the algorithm for large-scale scenarios, due to dataset availability, the evaluations occurred with only one larger trace (Dartmouth [210], with 1200 users). Cost-effectiveness evaluation occurred in terms of delivery ratio and the number of transmissions (i.e., overhead).

SAMPLER: This forwarding algorithm [14] relies on social-aware, spatial-aware, and individual mobility extracted from a real-world dataset NCCU. SAMPLER had competitive results and some performance improvements (delay, overhead, and delivery rate) in comparison with Bubble Rap. This work brought attention to the possibility of investigating other features

from human mobility to achieve cost-effectiveness in opportunistic forwarding.

Nevertheless, SAMPLER requires parameters calibration, the deployment of static relay points, and calculating social communities. Furthermore, there is a lack of description details in the scenario and simulation settings, making it difficult to reproduce the algorithm evaluations for comparison. Other shortcomings relate to the lack of more realistic assumptions on the evaluation (e.g., authors consider any contact duration sufficient for forwarding a content). Parameters such as content time-to-live (TTL) and content-size are also not considered.

SAMPLER targets cost-effectiveness delivery of delay-tolerant content in scenarios where opportunistic forwarding applies for high data rate transmissions among nearby users. The algorithm's context brings the possibility of offloading traffic while the evaluations focus on the algorithm's cost-effectiveness.

2.4.1 TOOTS positioning

According to the initiatives discussed herein, we found that learning from human routines hidden into mobility datasets is essential to develop improved opportunistic networking solutions. This work's first insights came through analyzing and discussing how the human aspect is part of the state-of-art solutions.

Differently from state-of-art, in this work, we format our metrics and decision factors with a more precise link with time. Our algorithm relies on different human activities present in human mobility over periods of the day. In previous work [2], we confirmed that human mobility varies according to different periods of the day. Among the human-mobility features considered are the routines (i.e., spatiotemporal patterns), related consequences (e.g., encounters, PoI visiting), and displacement (e.g., the quantity of movement and motion direction). TOOTS relies on probabilistic spatiotemporal aspects (i.e., characteristics that are most likely to be repeated and are time-window correlated), social information (i.e., wireless contacts), PoI awareness (related to network cells), and individual's mobility (displacement and direction awareness). In Table 2.3, we resume the properties of the state-of-art solutions discussed herein.

Generic insights, metrics, and decision factors might not suit different kinds of populations. Aspects such as culture, environment, node density, and urban transportation planning can impact a population's mobility (including the contact dynamics). Each population has particular and common characteristics, calling for the need to evaluate datasets of different kinds with proper temporal aspects chosen accordingly. For such reason, to know better our studied populations, in Sec 3.4 and Sec 3.5, we characterize the MACACO, NCCU, and GRM datasets. Complementing this analysis, in Chap. 4, we present the strategy's metrics and show their characterization results.

2.5 Summary

In this chapter we first viewed how literature works dealt with the human aspect within networking solutions over the last decade. The main finding is the growing importance of the user as a central element to innovative computer networking solutions. This new understanding level of user's human characteristics culminate in what we denominate Tactful Networking, introduced herein.

The Tactul Networking concept puts the human in the foreground of future networking solutions. This research paradigm is a reference to *the objective of adding perceptive senses to the network by assigning it with the human-like capabilities of observation, interpretation, and reaction to daily life features and involved entities.* Tactful Networking gathers different human-traits applied in previous works added to other insights from interdisciplinary research to bring benefits to future networking solutions. Among those are mobility, personality traits, social ties, socio-demographic traits, and content demand. Complementing the Tactful Networking paradigm presentation, we discussed insights on how human-aware data can leverage networks concepts, technologies, and communication models (5G, IoT, Vehicular Networks, Ultra-dense networks, Information-centric Networks, SDN, and NFV). These discussions feature insights for future work regarding the tactul networking paradigm.

Finally, we outlined and discussed state-of-art opportunistic forwarding strategies and algorithms. This subject plays a major role in this thesis, as one of the main contributions of this thesis is a tactful opportunistic communication strategy (TOOTS). The main findings in this concern were:

- Next-generation solutions will need to pay attention to human peculiarities hidden into mobility datasets and how these characteristics link with time;
- There is a need to characterize and identify aspects related to the studied populations, i.e., calling for the necessity to make proper population analysis to apply personalized insights to the metrics of each solution;
- There is a need to discuss other scenarios for opportunistic D2D algorithms' while evaluating those strategies with more realistic settings.

Chapter 3

Extracting Knowledge from Mobility Datasets

Studying and characterizing datasets were essential for reaching the main goal of this thesis. The MACACO, NCCU, and GRM traces are presented and correlated with the work we applied on their manipulation. A framework for enhancing raw human data with best practices to deal with datasets challenges appears herein as a conceptual contribution. The knowledge acquired through this framework was relevant to manipulate the traces and extract insights. We validate the framework through a case study with the MACACO dataset. Finally, MACACO, NCCU, and GRM datasets are analyzed, while their characterization results come along with discussions.

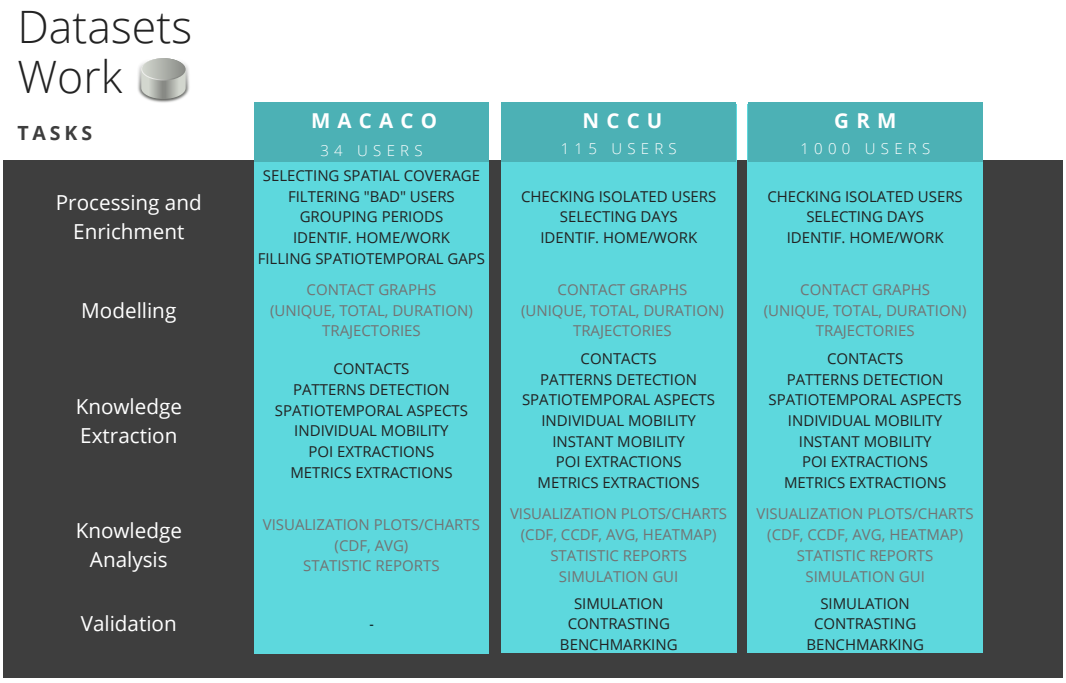


Figure 3.1: Work applied to the datasets used in this thesis.

3.1 Presenting the Datasets

As for acquiring insights, building and evaluating our opportunistic communication strategy, we worked with three mobility datasets: MACACO [33], NCCU [30], and GRM [32]. Figure 3.1 resumes the work applied to manipulate these datasets. Detailed discussions and results from such work are in Sec. 3.3 – Sec. 3.5. The described tasks in the figure are part of the discussions from the tactful networking framework for extracting human information hidden into datasets (Sec. 3.2). Following, a brief description of the datasets:

MACACO: A spatiotemporal personal dataset collected through an Android mobile phone application. The application gathers the data related to the user's digital activities such as available network connectivity (i.e., Bluetooth, APs, cell towers), battery availability, and visited GPS locations. These activities are logged with a fixed periodicity of 5 minutes for 99% of the measurements. The 1% occasional longer gaps are due to system background jobs and settings of the specific operating system version. Authors remark that the 5-minute sampling approach differs from those employed by popular GPS tracking projects, such as MIT Reality Mining [211] or GeoLife [212], where users' positions are sometimes irregularly sampled.

The regular sampling in MACACO data grants a neater and more comprehensive overview of a user's movement patterns. The full dataset covers about 190 users from six countries (including Brazil), spanning 2014 to 2018. After selecting a population and filtering out "bad users" (i.e., with insufficient data), 34 users were left. Despite MACACO being essential for extracting the first insights for our strategy, due to such a limited number of users available, we decided to evaluate our proposal throughout other larger datasets (NCCU and GRM) presented to follow.

NCCU: Is a real-world mobility trace featuring 115 users' displacements inside the campus of the National Chengchi University (NCCU) in China over two weeks. This campus measures 3764 m × 3420 m. The NCCU dataset came through an Android app named NCCU Trace Data, which recorded GPS data, application usage, Wi-Fi access points, and Bluetooth devices in proximity. According to the authors, considering the consumption of a smart handheld device, the app was configured to collect data every 10 minutes, store it locally and upload it to a server every day. In case of GPS data loss (e.g., due to weak indoor signal), they used interpolation between available coordinates (also discussed in the MACACO case study to follow). In NCCU's mobility model, each user (i.e., student) can have a sporadic schedule on a daily basis. The users can move to any area of the campus and stay in each location according to their schedule. Information about how the users move inside the campus (e.g., walking, by car) was not available. NCCU also collected users' data throughout questionnaires, including gender, grade, majors, personal interests, places on campus they would go most frequently, Facebook ID, and Facebook usage behavior. Despite this varied amount of data collected, only the anonymized coordinates of the 115 users are publicly available.

GRM: The GRM dataset comes from a synthetic mobility model (Group Regularity Mobility Model). According to the authors, this dataset can capture social (i.e., encounters) regularity from its users. The authors made available GRM synthetic mobility traces with 100, 1000, and 2000 users' movements inside an area of 1500 m x 1500 m. In this work, we use the version with 1000 users to simulate a larger-scale network. The GRM model receives as input a social

network which can be a real social network or a synthetic one generated by a social network model. This social network applies for defining the nodes that will be present in the groups of users. Additionally, GRM receives as input the simulation configurations for the dataset, including the dataset area, duration (e.g., two weeks), amount of nodes, and the number of groups. Finally, GRM's last input is a set of statistical parameters which can be extracted, for example, from other real datasets.

Before discussing the results of datasets manipulation, in the next section, we dig into the framework. We make a few statements correlating the framework with the datasets' manipulations to build our strategy (TOOTS). Those important statements are called **TOOTS positioning**.

3.2 A Framework for Extracting Human Information Hidden Into Datasets

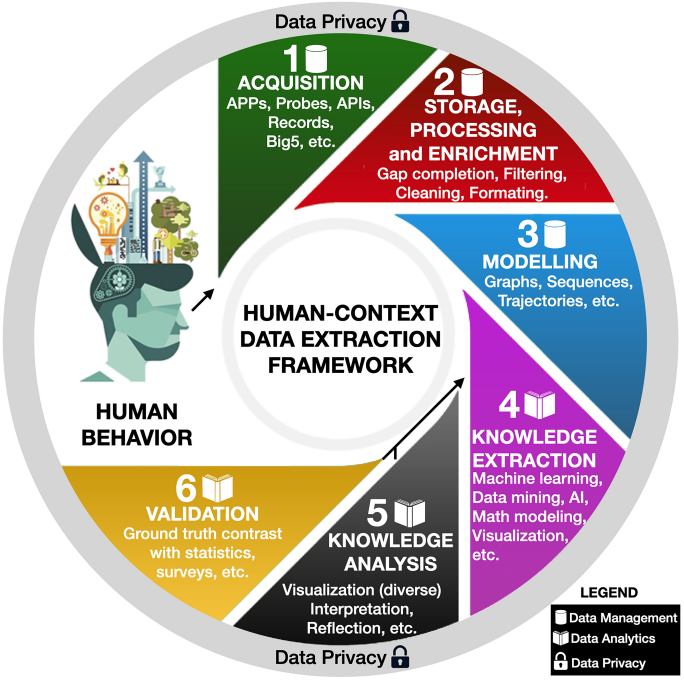


Figure 3.2: Tactful networking framework tackling management and analysis of human-behavior information to assist future network architectures.

We discussed why human-behavior data should become essential for future generations of mobile network architectures and models throughout the previous chapter. Nevertheless, the "transformation" of raw data describing human behavior (usually collected through smart devices or social networks) into helpful knowledge requires multiple iterations.

Figure. 3.2 depicts a general framework to process and preserve the privacy of human-behavior raw data as a means of considering the tactful networking concept in current networking architecture and paradigms. The framework features *Data Management*, *Data Analytics*, and *Data Privacy*, which are discussed below along with its sub-tasks.

TOOTS positioning:

1. We keep all framework main tasks here as a guide to future work in this context. Nevertheless, to be practical and attain the purpose of this work, we resume some out-of-the-scope task discussions and specify those that we applied to the datasets' manipulation. The full framework discussions appear in [3, 4];

2. Since all the datasets used in this thesis were already collected and available, the Acquisition and Storage tasks were unnecessary for our manipulations;

3. The Processing and Modeling tasks applied to the three datasets;

4. The Enrichment task is applied only in MACACO since NCCU and GRM are ready to import in the simulator.

Below we resume all framework Data Management tasks.

Acquisition (Data Management): Human behavior analysis requires data availability, sometimes from multiple sources. Among the examples of the sources, we can cite specific APIs (streaming-based or request-based), web crawlers, online social networks, mobile crowdsensing applications, infrastructure-based sniffers, mobile devices sensory data [213], mobile crowdsensing datasets (acquired through specific smartphone applications, e.g., MACACO and NCCU), operator-collected datasets (CDRs [156]), wireless networks measurements logs, and surveys (e.g., Big Five[214]). Particularities and challenges from the examples above are in [4].

Storage, Processing, and Enrichment (Data Management): After acquired, data must be stored, processed, and enriched. In human behavior information, a possibly large amount of data needs secure, scalable, and fault-tolerant storage platforms. Large-scale distributed data computation is an essential aspect for data processing, as real-time and multiple parallel requests are frequent. As processing steps, associating and integrating data may be required: Where diverse data sources regrouping different data types (e.g., posts, media, location, actions, traits, and gestures) are simultaneously exploited to extract useful information. Moreover, data may present gaps, inconsistent information, semantic errors, or missing entries. Hence, data cleaning and enrichment responsible for normalization, spurious data detection, geographical and temporal interpolation, among others, may be necessary to make up missing data and to fill the gaps, while limiting biasing the raw data. As examples, we could cite processes such as time discretization, to reduce the temporal resolution of CDR Datasets and make the data appear complete [134, 145, 204], trajectory reconstruction [133], to infer positions of the users at timestamps where the original data does not provide such information, and user filtering [204, 215] to eliminate those with not enough mobility information. Finally, dimensional reduction of multi-dimensional data may also be necessary before analysis, where feature selection has proven effectiveness.

Modeling (Data Management): Finally, data must be modeled in a format helping the extraction of spatio-temporal information or relation between different components of the data. Graphs have been the most used data format to model behaviors related to people's spatio-temporal association with environment and ties (i.e., interactions or social ties). Herein, a

vertex in a graph can represent users in a network or their visited places [14, 48, 216]. At the same time, edges would connect vertex when there is an encounter between users, or when a user sequentially visits locations [217]. Spatio-temporal trajectories or time series of chronologically ordered points are other examples of formats in data modeling: e.g., modeling collected geographic data from human mobility as a set of spatio-temporal trajectories, representing data generated by a moving individual in geographical spaces [14, 127]. Below we discuss data analytics, including knowledge extraction/analysis and data validation.

TOOTS positioning:

5. We performed Knowledge Extraction and Analysis tasks in MACACO, NCCU, and GRM datasets;

6. MACACO dataset has one exception here with the validation task since we decided to skip using this trace in the simulations due to its limited number of users.

Below we resume all framework Data Analytics tasks.

Knowledge Extraction and Analysis (Data Analytics): These are fundamental to find new insights on data. The process should typically be continuous to foster the adaptive capability of the whole system. Understanding data properties and the kind of problem to be addressed are part of knowledge extraction. Among the techniques, we can mention pattern detection and modeling, correlation and causality among associated entities, behavior profiling, data classification or clustering, data changes or irregularity detection and modeling, to cite a few. Here, machine learning techniques, artificial intelligence, HCI methods, time series modeling, sophisticated networking metrics, statistics, and empirical analysis have become essential tools. More recently, visualization techniques [218] have become very popular: Due to the complexity of big data, such techniques make data more accessible, understandable, and usable. Among the advantages, we can mention the possibility for: quick and clear information understanding; easy identification of emerging trends allowing a fast action based on what is seen; visual identification of relationships or patterns; analysis at various levels of detail.

When it comes to human-behavior diverse spatio-temporal information, there are challenges related to data association. Discovering association and relationships between datasets, detecting unusual objects, and classifying them are essential. Machine learning approaches are common in knowledge extraction with different intentions [219, 220]. Artificial Intelligence (AI) also applies in this context. Knowledge extraction can also occur through user activity in their social networks (e.g., spatial, geographical, emotional, and personality traits information) to leverage networking resource management and user prediction [126]. Data mining, natural language processing, and other techniques can be applied to extract users' information. These processes should typically be continuous with repeated iteration cycles to foster the whole system's adaptive behavior while gaining new insights, discovering mistakes, and reconsidering decisions.

Validation (Data Analytics): Data validation consists of verifying data correctness and usefulness. It intends to provide guarantees for the fitness, accuracy, and consistency of any input into an application or system. A used model validation technique for assessing how the results will generalize to an independent data set is cross-validation in statistical analysis.

Another widespread data validation method is the crossing of data (usually incomplete or reduced) with what is called a *ground truth* data (i.e., typically official or completed data). Among ground truth examples are the CENSUS data or surveys with low-error margins, or more fine-grained datasets (e.g., GPS datasets used to validate CDR trajectory reconstruction techniques). Ground truth data may not be available for all situations. In this case, repeating more experiments might be necessary, or using a simulation environment as support to validate the use of specific data in multiple scenarios or under varying conditions.

After the validation, it is necessary to shape the information for the development of services and applications. These final products are expected to help operators develop enhanced human-aware networking solutions to match user expectations more naturally.

TOOTS positioning:

7. Although our awareness on privacy needs, this aspect is out-of-the-scope of this thesis and was not applied to any of the datasets;

8. We skip the privacy deliberations from here and bring some of them in Chap 7. Please refer to [4] for all privacy discussions within the framework.

Below we resume Data Privacy within the frawmework.

Data Privacy: As we trod along the smart-devices, online services, and big data era, user-data privacy must be guaranteed to support applications and innovation while not harming individual rights and security. This data varies in different aspects, such as quantity, diversity, and quality [4]. As Data Privacy is crucial for the Tactful Networking paradigm evolution, proper techniques must suit the type of data to be stored and analyzed.

3.3 Framework Case Study

As for illustrating and evaluating the framework's methodology, we present a case study with MACACO. As described in the previous section, MACACO manipulations required more framework tasks than NCCU and GRM. For such reason, we choose MACACO here but reminding that the framework is general and the other datasets also passed through its manipulations. Following, we summarize the efforts applied to MACACO.

Selecting spatial coverage and filtering out "bad" users: In the processing and enrichment phases, the first challenge was to select a subset of users with common spatial characteristics, since we aimed to analyze their routines and contact dynamics (later explained). There is a contact when two network nodes are in a communication range at the same temporal instant. We identified a population of 62 users (Students, researchers, and administrative staff) in two universities (UFMG and PUC-MG in Brazil) where lectures were held during the day and at night. For the sake of simplicity in the performed spatial analysis, we choose to use here users from the same country, i.e., 62 users. Our selection occurred by mapping user mobility trails to geographical coordinates from the city of Belo Horizonte and the Metropolitan Region. We removed 28 users because they had little (sparse) data or inconsistent information, for example, zeroed GPS measurements, and excessive duplicated entries.

Grouping observation periods: Each user collection period (in which he used the application) is unique. As mentioned, the *trace* has data between 2014 and 2018. We discarded data before 05/22/2015, as the request interval changed from 1 to 5 minutes on that date. Aiming to select four weeks of data (20 working days), we filtered the "best" working days for each user, excluding holidays. This technique gives the chance to compare activities by days of the week since the selected population shares a social context (attends one of the Universities).

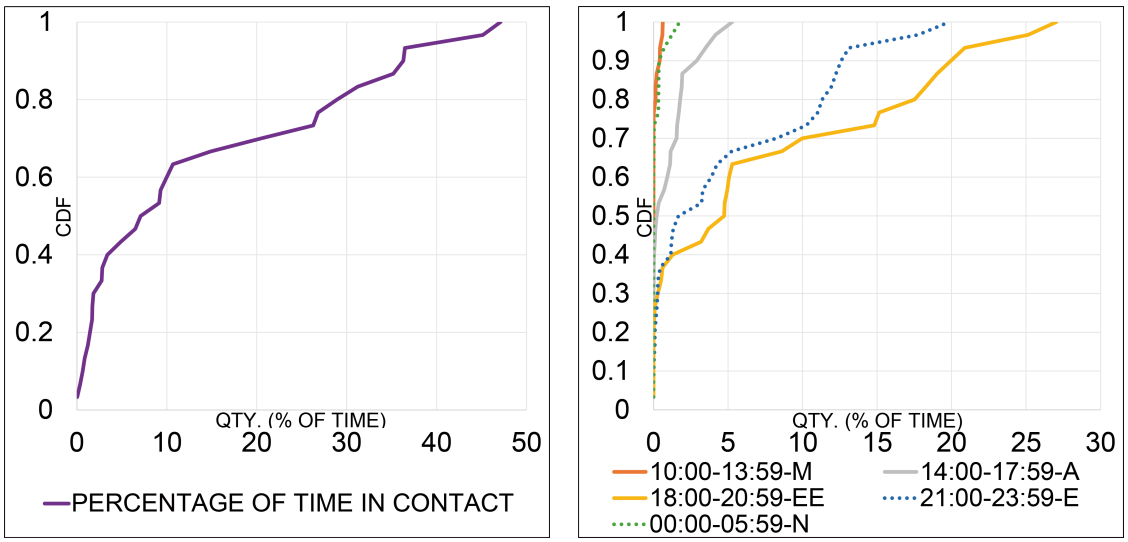
Identifying important locations: We inferred a "HOME LOCATION" selecting users who stayed in the city of Belo Horizonte and the Metropolitan region during the night, from *02:00* to *06:00*, that is, when most people are at home. We also checked the data from *10:00* to *21:00* to identify presence on the UFMG or PUC-MG ("WORK LOCATION") campus from morning till night.

Filling spatiotemporal Gaps: During the dataset acquisition, temporal gaps come from disabling the app (intentionally, or by lack of battery). In order to fill these gaps, we performed mobility inference according to different criteria. For those in the period from 02:00 to 06:00, we applied each user "HOME LOCATION" (the most frequent during the 20 days on that time window). We applied linear geodesic interpolation in the remaining gaps throughout the day. Given two pairs of coordinates, each pair associated with a time instant, the intermediate points (latitude and longitude) are calculated recursively.

After manipulating the data, we modeled it for our research goals. Evaluating the contacts is essential in an opportunistic communication strategy [13, 14, 21, 22, 27, 28]. Their occurrence (or not), duration, frequency, and other characteristics directly impact the success or the failure of such a strategy. *Since we targeted a tactful opportunistic communication strategy, our data modeling and the first analysis in the MACACO dataset (to follow) relates to the contact dynamics. As a starting point, we also decided to evaluate centrality degree [14] and radius of gyration [14], two traditional mobility metrics. We chose those since both showed correlation with improving cost-effectiveness (i.e., performance) in state-of-art strategies to deliver content opportunistically [14, 21, 22, 29].* Despite starting with two traditional metrics, we calculated those with a novel time approach (described in Chap 4).

Data modeling: We built contact graphs to study user social behavior dynamics. To identify the contacts, we calculate their occurrence and duration through each user location data (coordinates) associated with its timestamps. Based on geodesic calculations, the proximity up to 30m (i.e., the average range of WiFi Direct) is detected. As there is no clock synchronization for each measurement of each node, we applied sliding windows of 5 minutes. For example, the initial window for a user u on a day d is from *00:00:00* to *00:05:00*. If two nodes u and v were in the range within that time frame, and on the same day d, the contact occurred. If they remained in range in the next time window, that is, from *00:05:00* to *00:10:00*, the contact duration increments. As a result of this process, we generated three contact graphs:

- (i) a graph per period where the vertices are users, and there is an edge between a random user u and v if they were in contact;
- (ii) a graph per period where the vertices are users, and there is a weighted edge between a random user u and v accounting for the number of times they were in contact;



(a) Percentage of time in contact (full trace)

(b) Percentage of time in contact per period

Figure 3.3: Percentage of time in contact (total and per period) analysis of MACACO dataset.

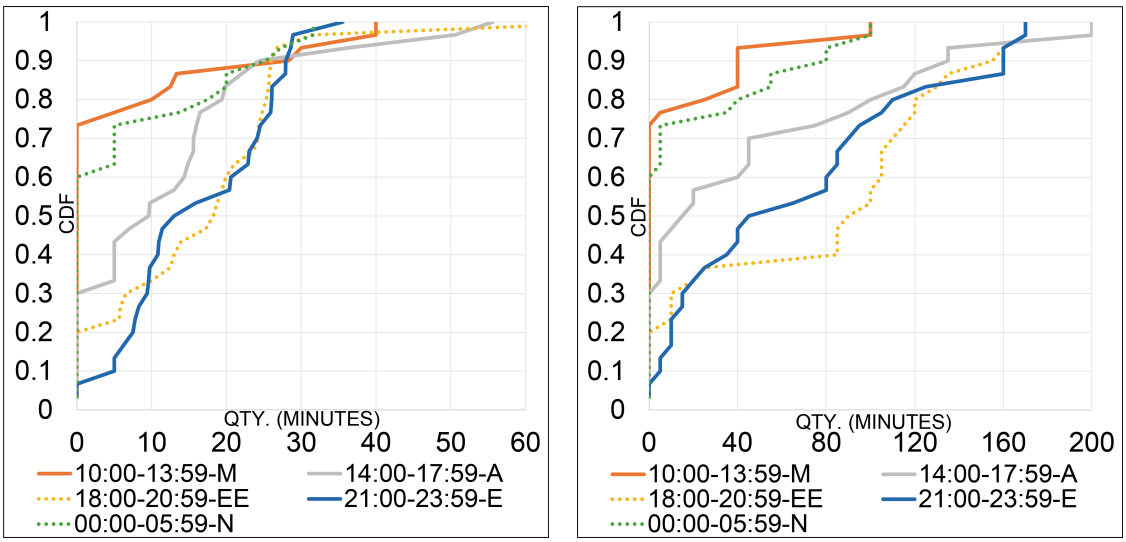
- (iii) a graph per period where the vertices are users, and there is a weighted edge between a random user u and v accounting for their total contact duration.

From these graphs, we plotted charts with unique and total contacts number, users' percentage of time in contact, average, and maximum contact duration (more details to follow). Furthermore, to evaluate the radius of gyration metric, we modeled the dataset into individual trajectories, i.e., which accounts for users' displacements identified by GPS measurements. In the following section, we present the characterization results and analysis of MACACO.

3.4 MACACO Dataset Analysis and Characterization Results

In Fig. 3.3(a) and Fig. 3.3(b), we evaluate overall user contact duration. In the first, we see about 40% of the trace with less than 5% of the time in contact. This result brought an insight: the periods of low contact incidence (e.g., when users go home) should create a significant impact on this graph. Thus, if we evaluate the trace and work with metrics with a more precise link with time, there is a potential to reach better results. With that said, we divided the day in periods (further explained in Sec. 4.1) to reflect the user activities at different moments of the day. In Fig. 3.3(b) we evaluate the percentage of time in contact per period. In this graph, we find higher percentages of time in contact during the "EE" and "E" periods.

In Fig. 3.4(a) and Fig. 3.4(b), we evaluate average and maximum contact duration. We discarded the minimum contact duration evaluation due to the uncertainty resulting from the lack of clock synchronization. There is a heterogeneity of information in each period, which reinforces our intuition that human beings behave differently according to the context and time of day, therefore directly impacting metrics coefficients. In Fig. 3.4(a), we find almost 80% of users without contacts in the "M" period. There are only about 10% of contacts with a longer duration (15 to 40 minutes). In the "A" period, the duration increases. About 70% of users



(a) Average contact duration (minutes) (b) Maximum contact duration (minutes)

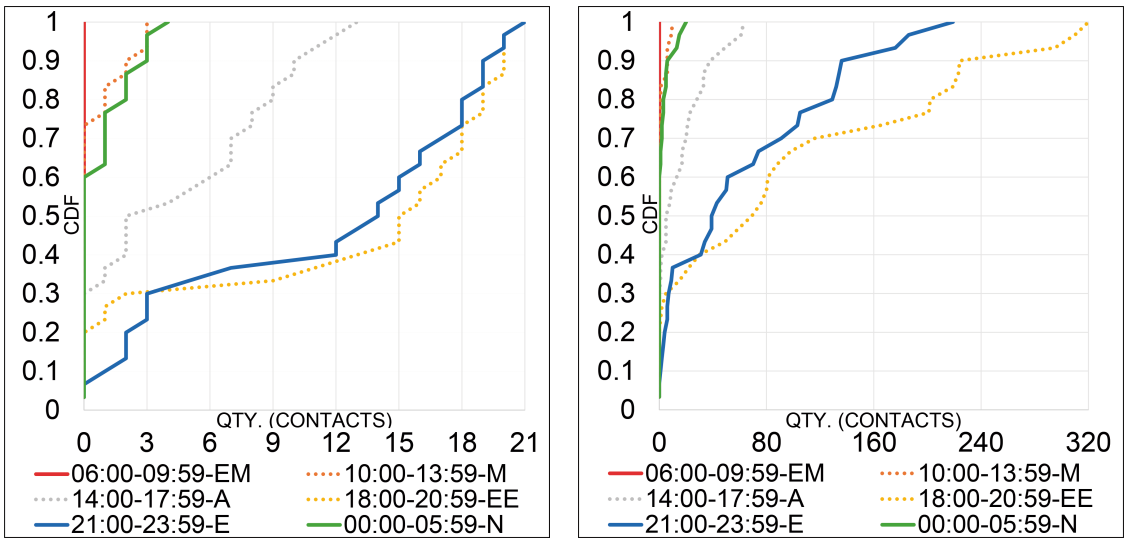
Figure 3.4: Contact duration (average and maximum) analysis of MACACO dataset.

have contacts. "A" and "EE" periods are interesting to study metrics related to geographic science, as people make higher displacements when they return home or go to University, for example. In the "EE" period, about 80% of users get in contact, with about 50% of contacts lasting at least 20 minutes. The same applies to the next period ("E"), with a higher occurrence of contact number and duration of 5 to 200 minutes (Fig. 3.4(b)). In the "N" period, there are fewer contacts incidence and shorter duration, since most people tend to be at home and do not share a social context at this time. This finding would be different in a trace where users live on the same campus, for example. Our claim reinforces here: knowing more about the humans behind the devices can lead to more proper solutions.

In Fig. 3.5(a), we plot a Cumulative Distribution Function (CDF) with the number of unique contacts. The "EM" period has zero contacts (and so removed from some other plots), while the "M" and "N" periods have a shallow contact occurrence. In the same figure, we see about 70% of users with at least five unique contacts during "EE" and "E". In comparison with Fig. 3.5(b), where we plot the CDF for the total contacts, we see higher coefficients, which is justified by the users' routines (in this case, repeating social links). During "EE", more than 20% of users have 200-320 contacts.

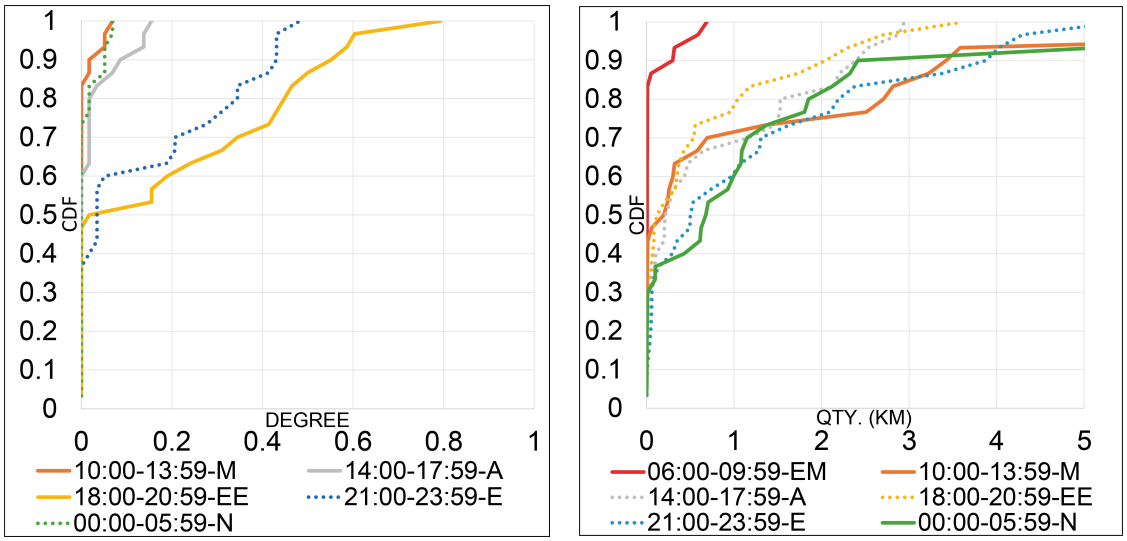
In addition to the contact dynamics analysis, we extracted the centrality degree and radius of gyration metrics to evaluate their distribution. In Fig. 3.6(a), we see how the user's "popularity" (given by node Centrality Degree, which accounts for user contacts) [14] correlates with time (i.e., varies according to the period of the day). In Fig. 3.6(b), we plot the Radius of Gyration (in meters), which accounts for node displacements concerning a center of mass. This plot distribution shows more significant displacements in the "M" and "A" periods. As in the Centrality Degree analysis (Fig. 3.6(a)), the coefficients differ per period, following our intuition.

Discussion Summary: Judging the contact duration, we find a high percentage (about 80% in "EE", and 90% in "E") of users with average contact persistence of at least five minutes. We



(a) Unique contacts number (b) Total contacts number

Figure 3.5: Contact number (unique and total) analysis of MACACO dataset.



(a) Centrality degree per period (b) Radius of gyration per period (kilometers)

Figure 3.6: Metrics analysis extracted from MACACO dataset.

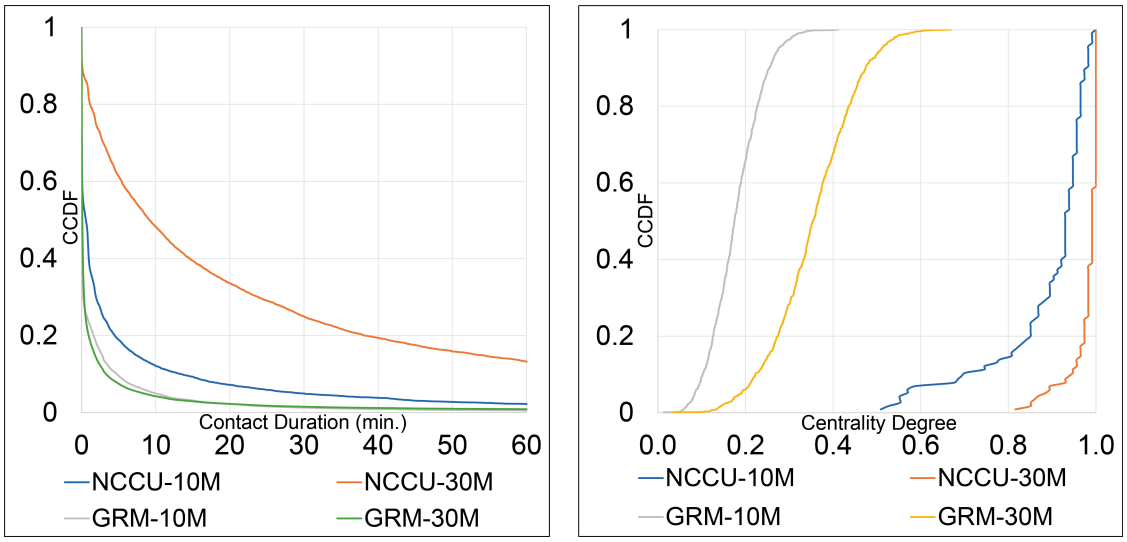
consider it as an interesting finding for transferring data opportunistically. For example, in a D2D strategy relying on Bluetooth interfaces, transferring 4MB takes approximately 18 sec. (apart from establishing a connection). A reasonable contact persistence also leads to saving device resources (e.g., battery) avoiding re-starting transmissions due to disconnections.

Regarding contact (unique, total, and percentage of the time) analysis, we found that the "EE" and "E" periods are the best to evaluate opportunistic communication services or protocols through the MACACO dataset. In those periods, we see not only a higher number of unique contacts but more repeating social links, with a higher duration. On the other hand, the lack of contacts during "EM", and the low incidence in the "N", and "M" periods could result

in higher delivery delays, and depending on message TTL, reduced delivery rate. Suppose a message creation happens during "E", but finding the destination node opportunistically is not possible the same day. Due to zero or very low contact-incidence in the upcoming periods, the delivery chance reduces. Further, due to MACACO's amount of users, we must use other datasets to evaluate larger scenarios.

Our centrality degree analysis helped to identify some popular users from the dataset in each period. As previously said, this metric is frequently applied for increasing the performance of opportunistic strategies. In a real scenario, this is a problem, as choosing the higher centrality degree nodes too often drains their resources and confronts system feasibility. The Radius of Gyration extracted from MACACO shows confinement depending on the period. We see a higher ROG in periods in which people are possibly going from home to work (or the opposite). In contrast, we see higher confinement during work or class periods (i.e., the dataset features researchers, and students). Understanding these characteristics assists in identifying the best periods for stimulating D2D content delivery. In the following section we analyze and characterize NCCU and GRM datasets.

3.5 NCCU and GRM Datasets Analysis and Characterization Results



(a) Contact duration per day

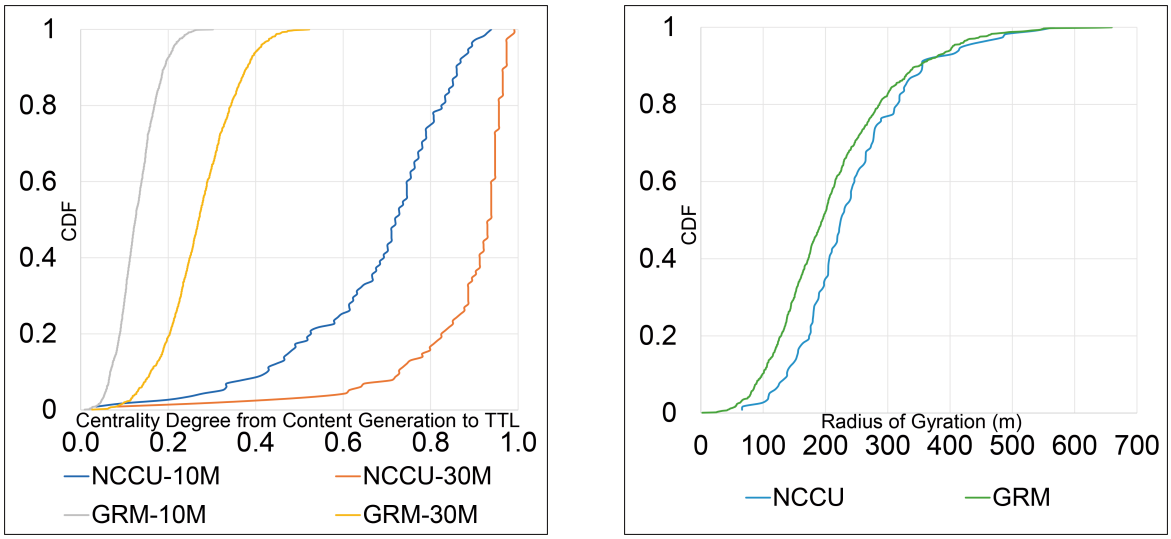
(b) Centrality degree

Figure 3.7: Contact duration and centrality degree evaluation on the NCCU and GRM datasets.

As with MACACO, the first analysis herein performed is of pairwise contact information. Previous work usually evaluated only one contact range (e.g., 10 m which is is commonly referred as the D2D bluetooth range [14]). As for evaluating how changing the contact range can impact in the results of the opportunistic strategy, and how they link to datasets social aspects, in this work, two contact ranges are analyzed: 10 m and 30 m. The first, analog to a Bluetooth range (widely used in state-of-art), and the latter as an average range for WiFi Direct, which works with up till 200 m communication range [221]. Figure 3.7(a) plots a

Complementary Cumulative Distribution Function (CCDF) of the aggregated contact duration per day on both datasets. That is, for each unique pair of users that gets into contact, we sum all their contact durations and divide by the number of days evaluated (i.e., 11) in each dataset. In Sec. 6.1, we present the evaluation setup and detail how the 11 days of data from the traces are used. In Fig. 3.7(a), we see that NCCU has longer contact durations when the contact-range is higher (30 m), while in the GRM trace the behavior looks quite similar for both ranges. The aggregated contact-duration per day in GRM dataset is shorter, with only average 5% of those with over 10 minutes. This dataset characteristic can impact a forwarding strategy's effectiveness if, for example, there is less bandwidth available and bigger size contents to forward opportunistically.

Following in the contact analysis, Fig. 3.7(b) shows the evaluation of the traditional mobility metric Centrality Degree (CD) [21] in both datasets. The plot shows the nodes' normalized CD as the total amount of unique contacts during 11 days of mobility data. We find higher CD nodes in the real-world dataset (NCCU), while the coefficients on the GRM trace are lower, with maximum degree at 0.4. A forwarding strategy strongly dependent on CD as a metric or decision factor might have reduced performance through this dataset. The plot also shows that with a higher range (30 m), the overall CD increases, which means that more encounters occur in both datasets. Nevertheless, a substantial increase in the contact durations is only observed in NCCU (as seen in. Fig 3.7(a)).



(a) Centrality degree from content-generation to time-to-live

(b) Radius of gyration

Figure 3.8: Centrality degree from content-generation to time-to-live and radius of gyration evaluation on NCCU and GRM datasets.

In Fig. 3.8(a), we analyzed the CD from the time the contents are generated (8^{th} day) till the last day of simulation (11^{th} day, i.e., the time-to-live – TTL). As expected, this plot shows lower CD on both datasets. That happens due to the smaller amount of days analyzed, reducing potential encounters guided by user routines and displacements. The results from Fig. 3.8(a) highlight the need for combining other kinds of metrics than centrality for achieving better performance and timely delivery in an opportunistic forwarding scenario. Finally, in

Fig. 3.8(b), we analyze another traditional mobility metric, the Radius of Gyration (RG). RG accounts for node displacement within the geographic space of the datasets (i.e., NCCU and GRM). The results show that due to the restricted area of the datasets, the RG of avg. 80% of the population is low (up to 300 meters) in both datasets. This finding brings insight into the possible need to combine other metrics when forwarding the content to a more distant geographical area where the destination node is. The real trace NCCU has users with a slightly higher RG than GRM. In Chap. 4 we analyze the RG per period in both datasets and extract further insights.

In the next chapter, we present the metrics and the temporal approach later combined in TOOTS.

3.6 Summary

We introduced and captured features and insights from three mobility datasets: MACACO, NCCU, and GRM. Their manipulations occurred throughout best practices learned from our discussions of a general framework to enhance human-aware hidden information. Furthermore, we validated the framework through a case study with MACACO since this dataset required more manipulation tasks than the others. Among the advantages of NCCU and GRM concerning MACACO were the higher amount of users and the fact that these datasets are ready to import at the ONE simulator. All traces were characterized and analyzed in terms of contacts and two traditional mobility metrics (centrality degree and radius of gyration). Among the main outcomes and lessons learned are:

- Depending on the dataset (i.e., population dynamics), periods of low (or zero) contact incidence can occur throughout the day. That can lead towards increased delivery delays or even expiring content time-to-live. Thus, we need to look at the time with more granularity instead of fixed time windows (e.g., last 24h) as previous work did [14, 21];

- Humans behave differently throughout the day. Thus, we decided to divide the time into different periods for more precision. Our contact evaluation plots show heterogeneous results per period, which reinforces our intuition and impacts directly the metrics' coefficients;

- In MACACO, the "EE" and "E" periods are when more users share a similar context, with about 80%, and 90% of users with average contact persistence of at least five minutes. Unraveling this kind of information is relevant for thinking about the strategy. For example, these periods are better to stimulate opportunistic content delivery of delay-tolerant content;

- Selecting users with more persistent contacts can reduce transmission interruptions and save device resources (e.g., battery). For such reason, in our Tactful Dissemination Policy (later explained), we consider contact duration;

- There are specific periods of the day with more user displacement (i.e., the radius of gyration differs by period). That is interesting to study geographic science metrics. Choosing more mobile nodes can help to take the content to consumers farther from the origin. For such reason, we decided to use the radius of gyration as part of TOOTS;

- Users "popularity" given by centrality degree correlates with time, i.e., user high or low centrality degree depends on his/her social context at each period;
- Relying strongly on the user centrality degree (as in some state-of-art works) might be a mistake since the popular users do not vary too much. That would drain the popular users' resources (e.g., battery, processing, storage) in realistic scenarios. For such reason, we use other kinds of metrics in TOOTS;
- Due to very low contact incidence in certain periods and a very limited number of users, we decided to skip the MACACO dataset to validate the strategy;
- State-of-art opportunistic strategies evaluate only one communication range [13, 14, 21, 22, 27, 28]. Results from NCCU and GRM show that varying the contact range impacts on the social metrics (e.g., centrality) and possibly on strategy's cost-effectiveness (confirmed after). *To the best of our knowledge, TOOTS is the first opportunistic strategy that brings results and discussions from varying contact range (10 m and 30 m)*;
- The NCCU nodes have a much higher centrality degree than GRM's. That highlights the need for combining others than social metrics for cost-effective content delivery in different populations;
- NCCU and GRM have a restricted area (i.e., campus). For such reason, the users' average radius of gyration in both datasets is lower than on MACACO. Knowing the population is necessary for proposing better solutions.

Chapter 4

Extracting & Evaluating Human-Aware Features & Metrics

TOOTS combines mobility metrics and one temporal feature targeting improved performance. Herein, the components of the strategy are motivated, described, and analyzed within the three datasets.

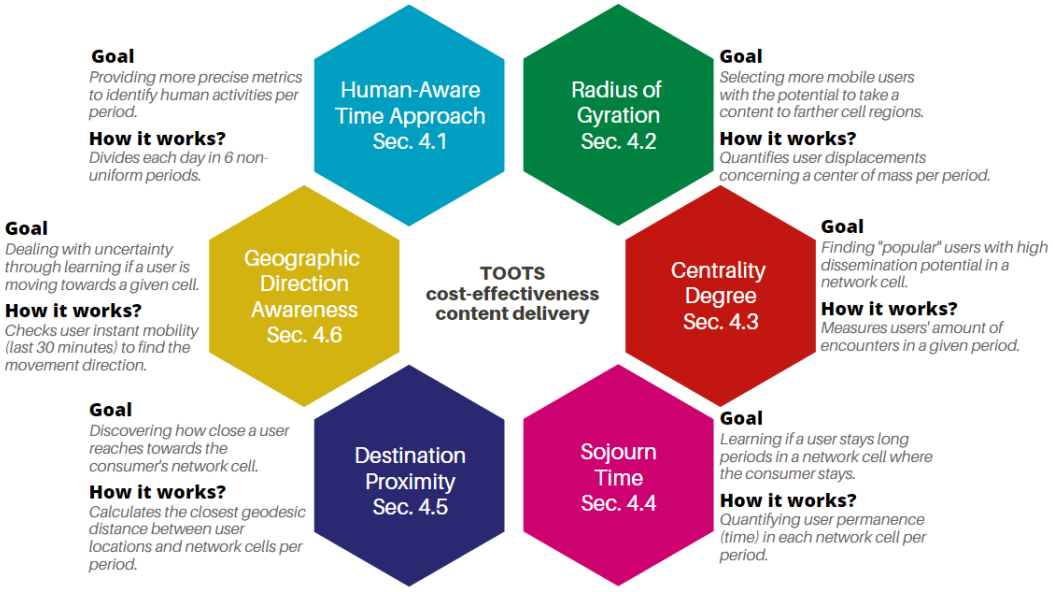


Figure 4.1: Features and metrics for reaching TOOTS cost-effectiveness content delivery in a mobile scenario.

This chapter discusses the features and metrics of TOOTS, our strategy for cost-effective content delivery in mobile networks. These metrics came from the combination of a broader view of the human aspect (i.e., tactful networking paradigm), ideas, results, or gaps from state-of-art, and the insights from the characterization of MACACO, NCCU, and GRM datasets. In Fig. 4.1 we resume these metrics, their goal within the strategy, and how they work in a "high level" explanation.

TOOTS works by learning from past users' mobility to identify human behavior extracted from NCCU and GRM datasets. The first feature of the strategy is a human-aware time approach (Sec 4.1) that identifies routines from human mobility according to the period (time) of the day. We justify this feature from the notion that humans are most likely to repeat their routines in each period (e.g., their social links, displacements, staying/leaving PoIs). Second, we feature the mobility metric Radius of Gyration (Sec. 4.2), which we use to select more mobile nodes inside a cell when we aim to take the content to a farther area. Third, we present

the Centrality Degree (Sec 4.3), which applies for identifying nodes with higher forwarding potential (i.e., popularity given by their encounters) in a network cell. Fourth, we present the Sojourn Time metric (Sec 4.4), which targets identifying users that stay more time on the same cell of a consumer. Fifth, the Destination Proximity metric (Sec 4.5) targets knowing how close a given user reaches towards the consumer's cell. Finally, Geographic Direction Awareness (Sec 4.6) targets some uncertainty, checking the last 30 minutes of user displacement to find out if he/she is moving towards a given cell.

Below we detail each feature/metric, including their mathematical formulations and results from their characterization on the datasets. They are later combined precisely in the TOOTS' Tactful Dissemination Policy (TDP) and human-aware forwarding algorithm (Chap. 5) to reach our research goals.

4.1 Human-Aware Time Approach: Identifying Routines from Human Mobility

Previous research showed that human mobility has recurrence and temporal periodicity [128, 202, 204]. This regularity in the human mobility brings low entropy to our movements [205] and make those predictable [134, 202]. With that said, through the study of predictable characteristics from human mobility (e.g., encounters, spatio-temporal regularity), network resource management and communication models (e.g., opportunistic communication) can be leveraged [4]. However, the human mobility profile changes throughout the time of the day, and the circumstance (e.g., when we are at home, at the transportation, or at work). Therefore, this work proposes a closer relationship of the mobility metrics with the human temporal aspect. Previous work showed different approaches when dealing with time to calculate their metrics or decision factors. Usually the time windows are chosen from the last 24 hours or the last 6 hours of mobility [14, 21].

Table 4.1: Proposed temporal division.

#	**Period**	**Time Interval**
EM	Early Morning	06:00:00 - 09:59:59
M	Morning	10:00:00 - 13:59:59
A	Afternoon	14:00:00 - 17:59:59
EE	Early Evening	18:00:00 - 20:59:59
E	Evening	21:00:00 - 23:59:59
N	Night	00:00:00 - 05:59:59

In our proposal (i.e., Table 4.1), the day is divided into six different duration periods. This temporal division was adopted to reflect heterogeneous mobility-profiles along the day from the users inside a campus (i.e., from real-world dataset NCCU). Note that depending on the population analyzed, the time windows might change to reflect users' activity and so more precise research results.

The time windows from our proposal are justified by correlating periods with more displacements or longer confinements. For example, during "EM" we expect to capture most users' home-work displacement, and confinement at work and shorter lunch-time displacements during "M". The intention is to increase the accuracy of the metrics and decision factors of the

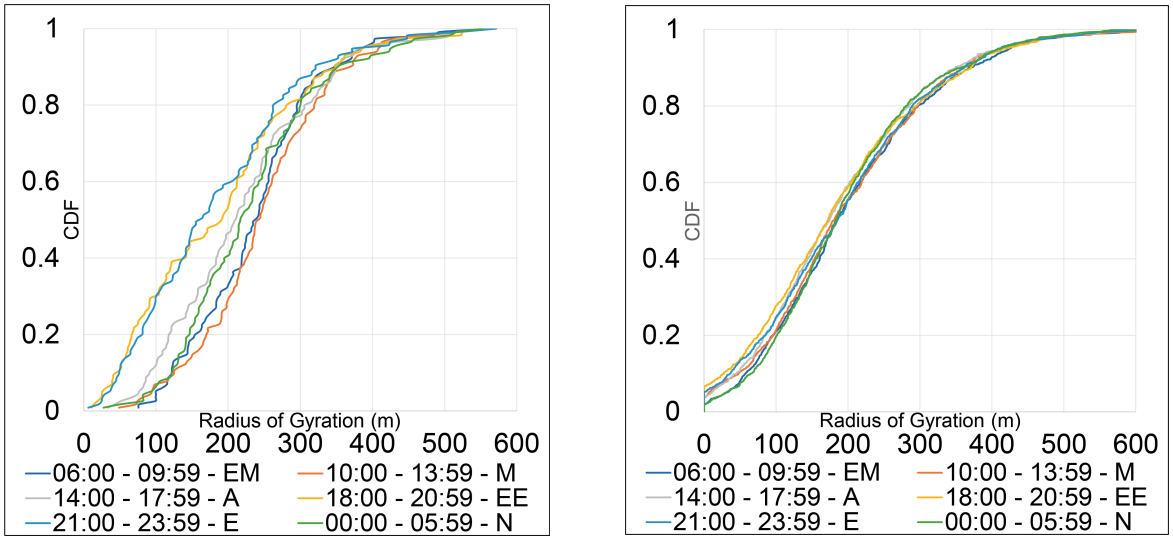
strategy, calculating those through a closer look into the human routines throughout the day. These periods can be reshaped whenever necessary.

In the following sections, we present the metrics and their evaluations based on the proposed temporal division. All plots show heterogeneity among the periods, especially in the real-world NCCU dataset. These results cope with our intuition to calculate metrics based on different periods of the day to reflect human mobility with more precision.

4.2 Coverage Area as Radius of Gyration

The Radius of Gyration (RG) [14, 128, 202] is used to quantify the mobility (i.e., in meters or kilometers) from an individual in relation to a center of mass, which is also obtained from his movements throughout a geographical space. In this work, we use RG to select more mobile nodes inside a given network cell (detailed in Sec. 5.1. Differently from previous proposals, the strategy herein learns by each period $p \in (EM, M, A, EE, E, N)$ in a week k and applies this knowledge in the week $k+1$. Therefore, $\Delta_{RG_p}(u)$ in the Eq. 4.1 is the average RG of each node u in period p. The days of the week k are represented from $i = 1$ to d, where d is equal the number of previous days (7). The amount of location points (coordinates) recorded is given by N, l_j is a location (x,y) at index j, and l_{cm} is the user's center of mass. We consider that every u has a set $L_p = (l_1, l_2, ..., l_n)$ of locations per period p of the "learning" week k. Each location l has coordinates (x, y) in a given instant, that is $l = (x, y)$.

$$\Delta_{RG_p}(u) = \frac{\sum_{i=1}^{d} RG_p^i(u)}{d}, \; where \; RG_p(u) = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(l_j - l_{cm})^2} \; and \; l_{cm} = \frac{1}{N}\sum_{j=1}^{N} l_j \tag{4.1}$$



(a) Radius of gyration per period (NCCU)

(b) Radius of gyration per period (GRM)

Figure 4.2: Radius of gyration evaluation on NCCU and GRM datasets.

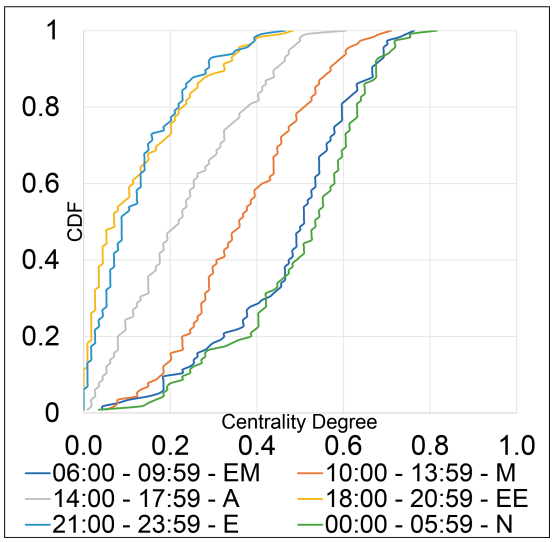
Following in our analysis, we plot in Fig. 4.2 the users' Radius of Gyration for both datasets. As NCCU dataset features user movements inside a Campus, the RG inside the area is more restricted. The same applies to GRM, which features movements inside a 1500 m x 1500 m area. The RG coefficients would be much higher if we evaluate for example a dataset with human users in a full metropolitan area, where higher displacements (e.g., home to work) are expected. Fig. 3.8(b) also reveals that NCCU users are more mobile than GRM users. In Fig. 4.2, we analyze users' RG per period on both datasets. As expected, there is heterogeneity in each period. The RG per period on NCCU Dataset (Fig. 4.2(a)) varies more, while on GRM (Fig. 4.2(b)) the difference is smoother. In Fig. 4.2(b), we see that the GRM dataset lacks different mobility profiles found throughout the day on the real-world dataset. From these plots we learn about when the users are more mobile in each dataset. Identifying more mobile nodes can assist in taking decisions on a forwarding strategy, such as in [14].

4.3 Social-Awareness as Centrality Degree

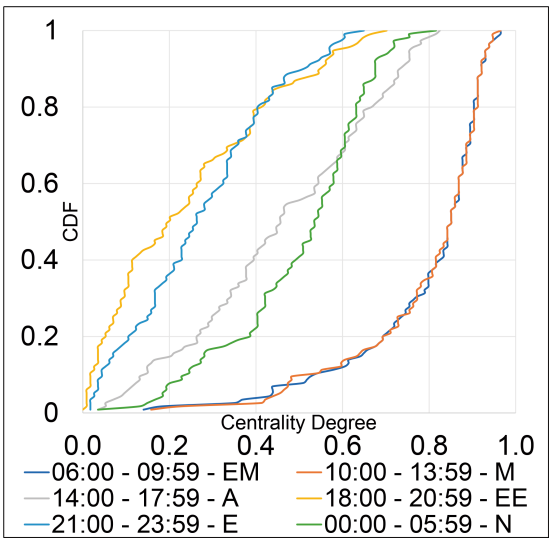
The Centrality Degree (CD) [21, 22, 29, 35, 222] is a state-of-art mobility metric used to measure users' social bonds (i.e., his encounters). A user with higher CD has further encounters and is commonly referred as "more popular" [14]. As with the RG metric, we calculate the CD by each period $p \in (EM, M, A, EE, E, N)$ in a week k and apply this knowledge in the week $k+1$. Therefore, in the Eq. 4.2, $\Delta_{CD_p}(u)$ is the average CD of a user u during $p \in (EM, M, A, EE, E, N)$. The days of the week k are represented from $i = 1$ to d, where d is equal the number of previous days (7). Finally, n is equal to the number of users (e.g., 115 on NCCU trace), while $e_{(u,v)}$ is equal 1 if exists an edge between two nodes u and v in a period p. We consider that the network is a dynamic contact graph $G_t = (V, E_t)$. The set of users is V, while E_t is the set of edges (contacts) detected, and $t \in (1, 2, ..., a)$ and $a \leq 604,800$ seconds (i.e., the learning time in seconds for week k). An edge $e \in E_t$ exists between two network nodes if at an instant t, the distance between them is less or equal the maximum communication range, which means, there is a contact. As previously stated, this work uses two communication ranges: 10 m and 30 m.

$$\Delta_{CD_p}(u) = \frac{\sum_{i=1}^{d} CD_p^i(u)}{d}, where\ CD_p(u) = \frac{\sum_{v=1}^{n} e_{(u,v)}}{n-1} \tag{4.2}$$

In Fig. 4.3 and Fig. 4.4, we analyze the CD per period on NCCU and GRM datasets, respectively. These plots complement the analysis from the previous section, and reinforce our insights related to our temporal division proposal. From what we know about the human perspective, our social behavior (in terms of contacts) differs depending on aspects such as the time of the day, routines, or activities. Fig. 4.3 certifies that and reveals also how raising the contact range impacts differently in each time window. For example, in the "N" period, the impact is smaller, as in this same time window, the users are expected to be more stationary. Nevertheless, in the "M" period, when the contact range is increased to 30 m, there is a substantial increase in the CD, where 80% of the users inside the campus have at least 0.7 CD. In Fig. 4.4(a) and Fig. 4.4(b), we see the same phenomenon observed in the RG analysis: GRM dataset users show more similar behavior independent of the period of the day. Furthermore, in this dataset, increasing the contact range to 30 m still keeps the nodes with much lower CD than on NCCU.

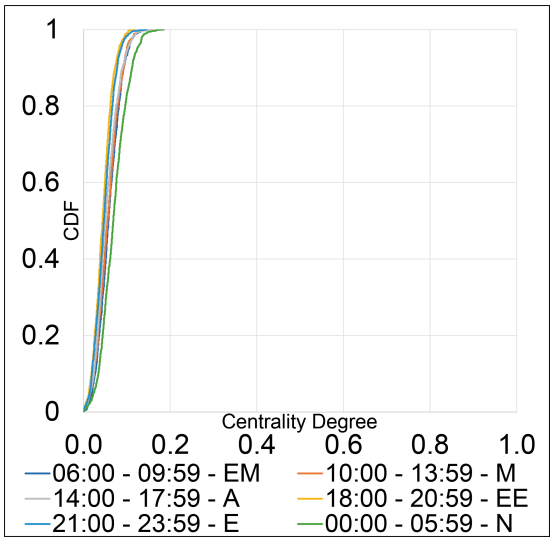


(a) Centrality degree with 10 m communication range

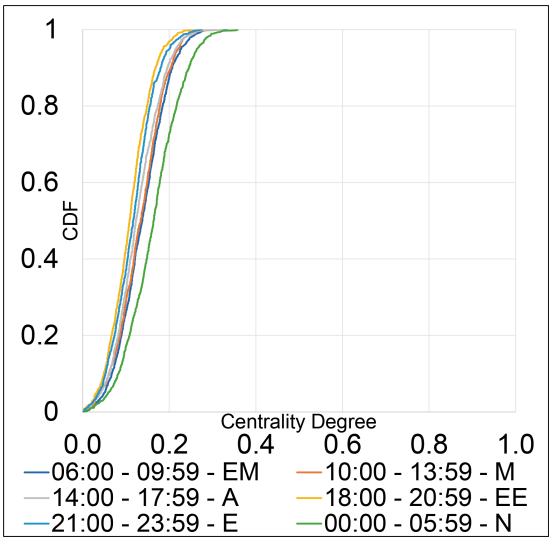


(b) Centrality degree with 30 m communication range

Figure 4.3: Centrality degree analysis with varying contact range on NCCU dataset.



(a) Centrality degree with 10 m communication range



(b) Centrality degree with 30 m communication range

Figure 4.4: Centrality degree analysis with varying contact range on GRM dataset.

4.4 Sojourn Time

We define the *Sojourn Time* (ST) [223] as the quantity of time that a user stays inside the limits of a network cell (given its range). In TOOTS, the ST is used when the strategy aims to identify nodes which stay more time in the same cell as a user who is interested in a content (i.e., he is the destination). The original cell sizes from the mobile operators in the area of the real-world dataset NCCU are enourmous in relation to both traces' area. Therefore, we

analyzed the space, and divided the area of both datasets in nine cells ("A" to "I").

Using the same method as with previous metrics, we calculate the ST of u (user) in each cell $c \in (c_1, c_2, ..., c_n)$ per period $p \in (EM, M, A, EE, E, N)$ in a week k and apply this knowledge in the week $k+1$. Therefore, in the Eq. 4.3, $\Delta_{ST_p^c}(u)$ is the average ST in minutes of u in c during p. The days of the week k are represented from $i = 1$ to d, where d is equal the number of previous days (7). The duration (minutes) is increased when the consecutive pair of coordinates is inside the geographic area covered by the cell (i.e., $(x, y) \in c$'s domain). $\Delta_t^p(u)_c$ is the total time t spent by u during p, inside cell c.

$$\Delta_{ST_p^c}(u) = \frac{\sum_{i=1}^{d} ST_p^c(u)_i}{d}, \; where \; ST_p^c(u) = \Delta_t^p(u)_c \tag{4.3}$$

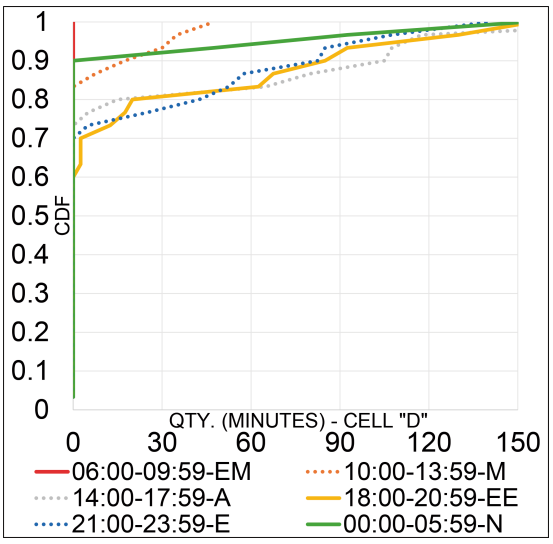
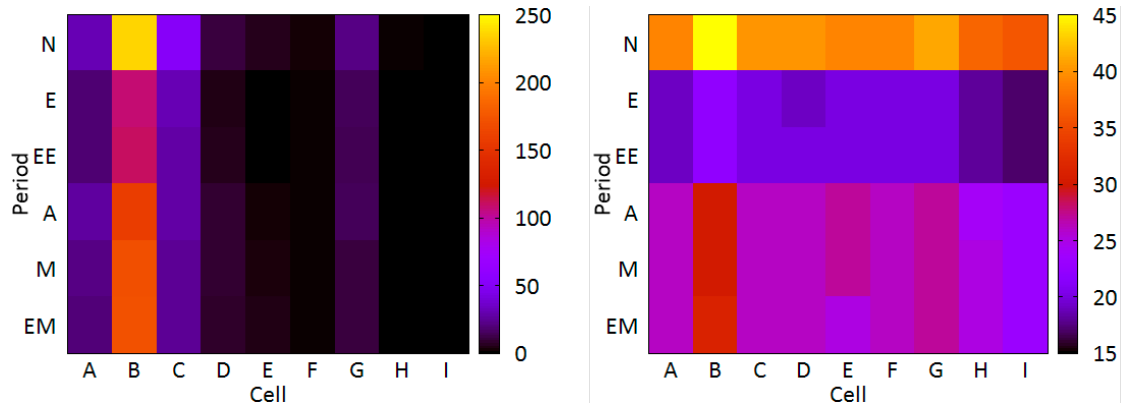


Figure 4.5: Sojourn time in cell "D" per period (minutes) on MACACO dataset.

Our first analysis in relation to the Sojourn Time metric occurred through MACACO dataset. In Fig. 4.5, we plot a CDF of the ST in one of the "busiest" cells from MACACO dataset. This plot shows that more nodes stay in cell "D" (ranging from "A" to "I") during the periods "A", "EE", and "E". During more confined periods (e.g., work, or homestay), for most users, the number of visited cells is smaller, the Sojourn Time into the confined cell is higher, while the ROG is restricted.

Continuing our ST analysis, in Fig. 4.6, we plot a heatmap with the average minutes per day and per period for NCCU and GRM datasets. We see that NCCU (Fig. 4.6(a)) has some cells with very low average ST per day while GRM which is a more dense dataset in number of users show less heterogeneity. From the heatmap we also indentify where users spend more time during the "N" period in NCCU Campus. This information, along with other techniques, can assist in identifying if a given user stays in the Campus overnight. In Fig. 4.6(b), we see that the GRM users are more distributed along the geographical space. On the other hand, as they are less mobile, they tend to visit a more limited number of cells.



(a) NCCU cell heatmap

(b) GRM cell heatmap

Figure 4.6: Cell heatmap with the average minutes per day and per period on NCCU and GRM datasets.

4.5 Destination Proximity as Geographical Awareness

In TOOTS, this novel metric uses geographical science for discovering how close a given user reaches to a network cell (based on its location as a PoI). Using the same method as with previous metrics, we calculate the MP of u (user) towards each cell $c \in (c_1, c_2, ..., c_n)$ per period $p \in (EM, M, A, EE, E, N)$ in a week k and apply this knowledge in the week $k+1$. The days of the week k are represented from $i = 1$ to d, where d is equal the number of previous days (7). Therefore, in the Eq. 4.4, $\Delta_{MP_p^c(u)}$ is the average MP in meters of u in c during p. A geodesic formula is applied to calculate the distance between node u and each cell PoI (i.e., the cell center coordinates). In $|min_{\Delta_s^c}(u)|$ we find the shortest distance (i.e., Δ_s) between node u and cell c, given all pair of u's coordinates in p. Depending on the coordinates system used in the dataset, the geodesic distance formula might change.

$$\Delta_{MP_p^c(u)} = \frac{\sum_{i=1}^{d} MP_p^c(u)_i}{d}, \; where \; MP_p^c(u) = |min_{\Delta_s^c}(u)| \tag{4.4}$$

As to illustrate this metric findings, in Fig. 4.7, we plot the MP on cell "D" for MACACO dataset. The plot shows that during "EE" and "E", about 40% of users are inside or close to the cell. Through the MP metric we also can identify the amount of users inside or close to cell "D" during working periods from "M" to "E". Examining the "EE", and "E" periods, we see users getting away from the cell, precisely at the time they suppose to leave the campus. Identifying those users and their HOME LOCATION is relevant if we need to take a content from the campus to a specific area, for example. Looking through the "N", and "EM" periods, we also identify how far the users live from the campus, as they are more likely to stay at "HOME LOCATION" during "N" and part of "EM". Fig. 4.8 plots the MP on the cell "B" for NCCU and GRM datasets. Cell "B" was chosen as it features more users activity (according to the ST analysis). Fig. 4.8(a) shows a high percentage of users inside or very close to this cell, and as the previous analysis, more heterogeneity per period of the day. The GRM analysis (Fig. 4.8(b)) repeats the behavior of previous plots, showing smooth differences per period of the day. Proximity can bring interesting insights when aiming to reach a neighboring cell.

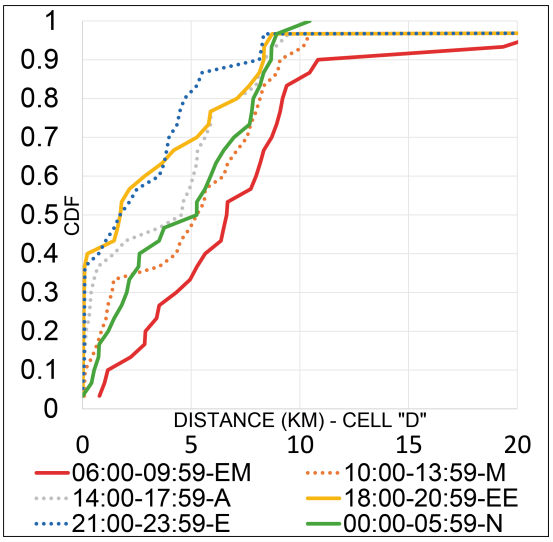
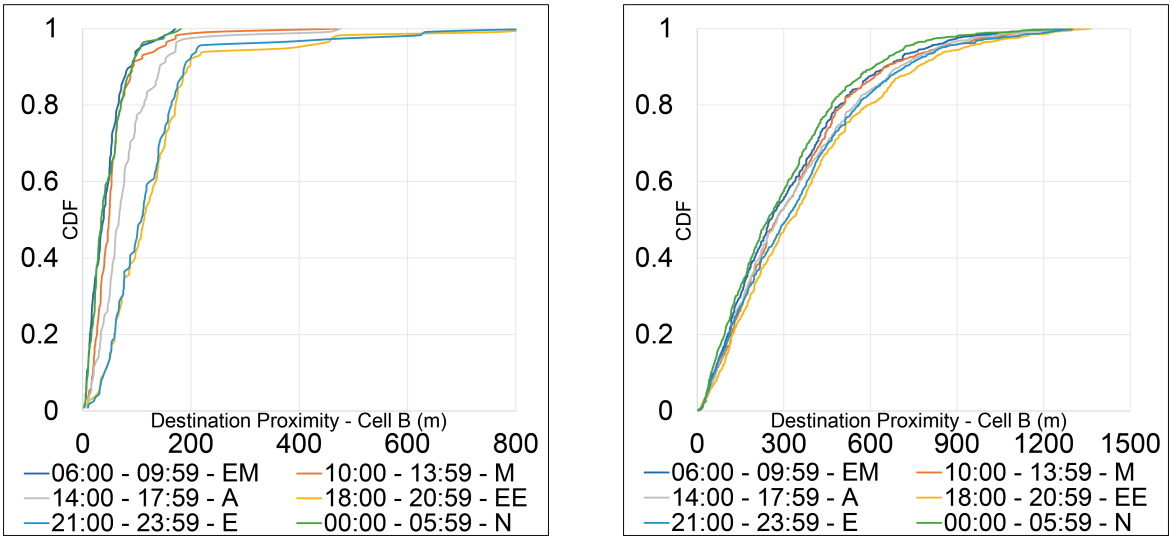


Figure 4.7: Destination proximity to cell "D" per period (in km) on MACACO dataset.



(a) Destination proximity (NCCU)

(b) Destination proximity (GRM)

Figure 4.8: Destination proximity per period (in m) analysis on NCCU and GRM datasets.

4.6 Geographic Direction Awareness

In this novel metric of instant mobility, we check if for a node u, its recent displacement was towards a cell c. The metric calculates the mode (i.e., the most common result from a set) of the geodesic directions between u's pairs of coordinates and the cell center coordinates in the last 30 minutes. In a condition of TOOTS' algorithm, nodes u and v check their recent displacement direction towards c and compare the results (more details in the next section). As the Geographic Direction Awareness is an instant mobility metric, its results are not plotted here.

4.7 Summary

We introduced and discussed the metrics and features of TOOTS. The main outcomes and lessons learned are:

- State-of-art opportunistic forwarding strategies dealt with fixed-length time approaches (e.g., 24h and last six hours). We saw heterogeneity in the metrics or contact dynamics in every single period through our novel human-aware time approach. We expect that this time approach leads us to more precise metrics and consequently improved strategy's performance;

- The average radius of gyration (in meters) on both NCCU and GRM datasets is quite close. These datasets feature a restricted area size. Traces covering larger areas would be interesting to evaluate this metric and the forwarding strategies. Nevertheless, we learned that the real dataset shows much more correlation with the displacements heterogeneity throughout the daily periods. With that said, we need to understand clearly their dynamics of synthetic datasets, which can impact the results;

- In state-of-art, centrality degree correlates well with improving forwarding strategies performance. We learned here that varying contact range directly impacts the centrality degree in terms of the number of contacts and their duration. We target a more precise centrality degree since the user popularity depends directly on his/her social context in each period of the day;

- The Sojourn Time metric gave us exciting results and is beneficial not only to identify the permanence in the network cells but also to discover important user locations (e.g., home, work, sports practice). ST and user context can bring great opportunities. For example, we could stimulate or not the opportunistic forwarding in a region by learning from this metric;

- Destination proximity can also be combined with the Sojourn Time to understand user dynamics concerning specific PoIs. This metric is used for a reason already explained in our strategy but can apply to many other intuitions from particular human mobility habits. We also learned that the NCCU campus has users concentrated in certain areas, while most of it has few visiting. In the GRM, the users spread within the area and are much less mobile.

- The geographic direction awareness focus on some human uncertainty. Human mobility has much recurrence, but individuals could tend toward disorder or randomization, called entropy [4].

For each metric presented we included its mathematical formulations and its characterization and discussions within MACACO, NCCU, and GRM datasets.

Chapter 5

TOOTS: A Tactful Opportunistic Communication Strategy

Herein, we describe the Tactful Opportunistic Communication Strategy for performing cost-effective content delivery in a cellular network scenario. We start by presenting an application scenario for TOOTS evaluation, followed by the formal definition for the problem of choosing disseminator nodes (TOOTS' 1st phase). To motivate the building of the strategy, we evaluate the overhead and latency of state-of-art Epidemic Forwarding. Finally, we introduce TOOTS in its two phases: a Tactful-based Dissemination Policy and a forwarding algorithm.

5.1 Scenario

In Fig. 5.1 we describe a scenario in which TOOTS assists a cellular operator to deliver contents opportunistically. This cellular operator owns a mobile edge computing (MEC) [224] site. In the literature, D2D is also linked with recent networking architectures, such as Mobile Edge Computing (MEC). According to '[225], traditional centralized network architectures cannot accommodate nowadays user demands due to heavy burden on the backhaul links and long latency. MEC appeared as a solution for this problem, bringing capabilities to the edge of cellular networks. MEC architecture works with servers located in proximity to operator base stations. User requests are handled by these MEC servers or forwarded to remote data centers and content distribution networks. Data is transferred to/from end-user devices through the cellular network base stations. D2D is a MEC enabler, being able to cache and disseminate content, offloading radio access network [225, 226], furthermore, in some cases, increasing network capillarity given by users' mobility. Yet according to [226], user mobility brings design issues, and large data sizes and strict computation requirements should be fetched to nearby users via D2D communications for higher energy efficiency.

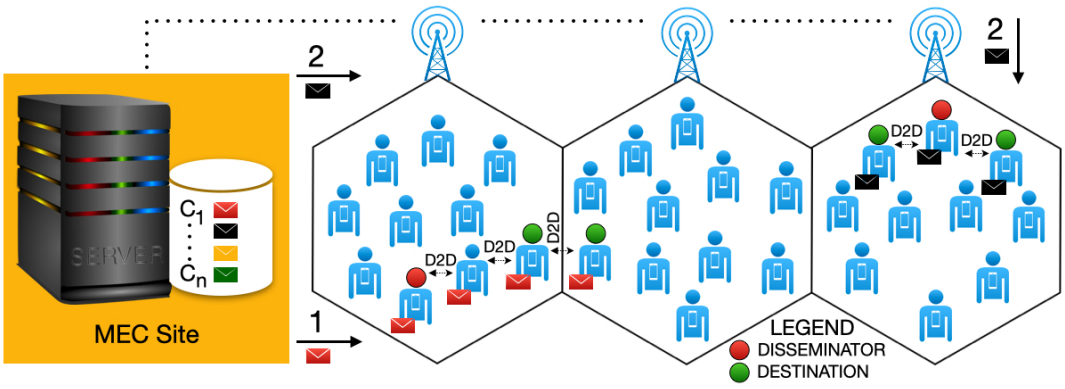


Figure 5.1: A scenario for TOOTS evaluation.

The TOOTS' goal in the proposed scenario is performing cost-effective content delivery through leveraging opportunistic D2D communication among the users. In such a scenario, TOOTS can assist to:

- Detouring delay-tolerant traffic from operator's legacy network;
- Increasing network capillarity given by users' mobility;
- Assisting to deliver content in challenging scenarios, e.g. disasters, crowded places, and rural areas.

As well known in state-of-art research cited in Chap. 2, users in opportunistic networks may act in a greedy way, and so incentive mechanisms are necessary for this kind of environment. Using and building incentive mechanisms are out of the scope of this thesis, thus we simply consider the users receive operator incentives (e.g., data plan savings, discounts) for their cooperation. In the mentioned scenario, content delivery task starts upon gathering a set of users content-requests. All the forwarding decisions are distributed (i.e., in the user devices) and rely on individual metrics locally calculated. The strategy relies on a seven-day period for learning from users' mobility. The gathered set of user requests for a given content is used to run the proposed Tactful Dissemination Policy (TDP) (Sec. 5.4), which chooses disseminator nodes. In Fig. 5.1, we illustrate the opportunistic delivery of two distinct contents through the disseminators chosen by TDP. Thereafter, the nodes carrying a content run locally an algorithm (Sec. 5.5) which takes a forwarding decision. Each node can assume the following roles:

- Ordinary - a node that belongs to the network but did not get involved in any activity related to the opportunistic communication strategy. Let $O(t)$ be the population of ordinary nodes at time t.
- Disseminator - a node chosen by the operator to start the disemination of a content. Let $D(c)_t$ be the set of disseminator nodes for a content c at time t. The disseminator nodes are the first set of propagators.
- Propagator - a node that received the full content and is now acting as a relay for it. Let $P(c)_t$ be the set of propagators for a content c at time t.
- Consumer - a node that is interested in the content and sent a request to the operator to obtain it. Let $C(c)_t$ be the set of consumers for a content c at time t.

Each node of the network has one of the roles above for a content, therefore, the sum of all nodes of each set is equal to the total number of nodes in the network,

$$O(t) + D(t) + P(t) + C(t) = 1$$

Despite not being a role, we also have a set for the Satisfied Consumers. Let $S(c)_t$ be the set of satisfied nodes for a content c at time t. A satisfied consumer is a node that was a member from the Consumer set, and received the data from a propagator at an instant t or he was also chosen as a Disseminator.

We assume the operator receives requests at time t from consumers interested in a content stored in the MEC site. The first step is choosing a set of disseminator nodes, replicating the content in the network to satisfy the maximum number of consumers possible. At the following section we define formally the problem of choosing these disseminator nodes.

5.2 Formal Definition for the Problem of Choosing Disseminator Nodes

In our network, we have a dynamic contact graph $G_t = (V, E_t)$, where V is the set of users (mobile nodes), and E_t is the set of edges existing at a time slot t, where $t \in (1, 2, 3, ..., n)$. An edge $e \in E_t$ exists between two users if those are at the defined communication range at time t, that is, they are in contact. The length of the time slot represents the minimum duration in which there is no change in the topology that can make the two users fall apart (out of the communication range). Suppose the operator receives requests from a set of consumers $C \in V$ at an instant t to obtain a content c. We consider a consumer is covered if he/she receives the content until its time-to-live of Δ time slots. We assume all users $u \in V$ are willing to collaborate through some incentive mechanism (e.g., data plan savings, bill discounts, free access to paid content). These ordinary non-consumers users can keep their status or becoming *disseminators* or *propagators* after receiving the full content. In the first, the content is sent by the operator to the disseminators, and in the second the content is transferred from a disseminator or from another propagator. We denote $D(c)_t \in V$ as the set of disseminators of a content c at time t. Initially, before t starts flowing, there are no disseminators, as the operator must choose them accordingly after putting together the set of consumers C for the content. Thus $D(c) = \emptyset$. We denote $P(c)_t \in V$ as the set of propagators at time t. A node $u \in P(c)_t$, that has the full content is a propagator, so let $\alpha(u)$ be the minimum total contact duration between $(u, v) \in V$ required so u can transfer the full content to v. As v has to receive the full content from u, the aggregated contact duration between (u, v) must be greater than $\alpha(u)$,

$$i.e. \sum_{t=1}^{\Delta} \|(u, v) \in E_t \text{ for some } u \in V \geq \alpha(u), \tag{5.1}$$

where the indicator function,

$$\|(\text{statement}) = \begin{cases} 1 & \text{if } \textit{statement} = \text{true} \\ 0 & \text{otherwise} \end{cases} \tag{5.2}$$

Therefore, the set of nodes v covered by a content propagator $u \in P_t$ for a content c when there is an edge between these nodes is:

$$\sigma(c) = \left\{ v \in V : \sum_{t=1}^{\Delta} \|((u, v) \in E_t \text{ for some } u \in P_t) \geq \alpha(u) \right. \tag{5.3}$$

Now, let's consider a set of disseminators $D(c)$ of a content c. This set of disseminators will be chosen by the operator. After they are chosen, they will be equal to the first set of propagators, $P_1(c) = D(c)$. Operator's objective is to cover all *consumers* with a minimum number of $\lambda(c)$ disseminators. Thus, our content dissemination (CD) problem is to minimize the cardinality of the set D_1 in a way that it covers all consumers in V for the content c, formally;

$$\begin{array}{cc} \text{Minimize} & \text{D(c)} \\ \text{subject to} & \sigma(c) = V \backslash D(c) \end{array} \tag{5.4}$$

Our Content Dissemination (CD) problem, similarly to the Content Replication in [29], is NP-Hard even for the most simple case of a static social graph where the full content can be

transferred in one single contact. The CD decision problem is to find if there is an initial set of disseminators D_1 of size at most $|D_1| = k$, where k is a positive integer which covers a maximum number of consumers of a content c. To maximize this coverage, D_1 must be a minimum dominating set of size k. As the decision problem of the minimum dominating set is NP-Complete, therefore the hardness of the CD problem is NP-Hard. In the following section we evaluate the traditional state-of-art Epidemic Forwarding algorithm as a motivation to build TOOTS.

5.3 Motivation: Overhead and Latency Evaluations

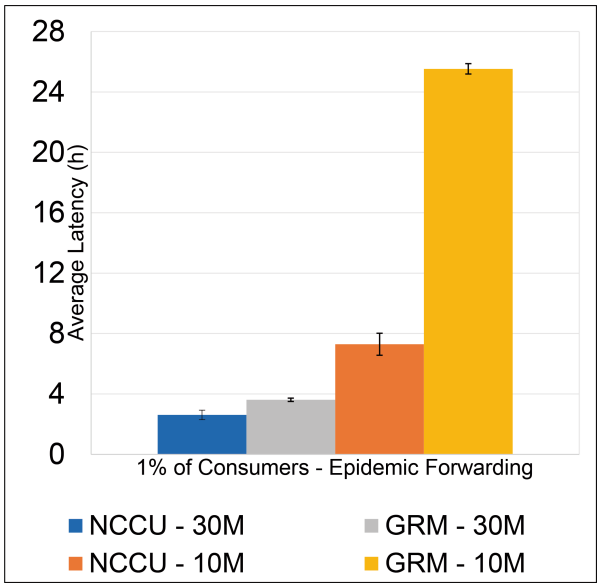


Figure 5.2: Epidemic forwarding average delivery latency performance evaluation on NCCU and GRM datasets with 1% of consumers and varying contact range (10 m and 30 m).

The Epidemic forwarding is a well-known state-of art algorithm. In opportunistic networks, it works by always trying to forward a content to an encountered node which does not have it. This algorithm is known by higher delivery ratio, smaller delivery latency, but also a heavy network overhead. In Fig. 5.2, we evaluate the average delivery latency of the Epidemic forwarding algorithm with a consumer set size equal to 1% of the number of nodes from each dataset. This scenario with a limited size consumer-set is challenging. Depending on how a strategy works and on dataset's characteristics (e.g., encounters between nodes), the results can show lower bound performance. In our experiments, the contents were generated once an hour, during 24 hours, with random source and destination nodes. Each content has a 72 h time-to-live. The experiments were repeated 30 times through the Opportunistic Network Environment (ONE) Simulator [227]. The confidence intervals are shown in Fig. 5.2. Despite largely evaluated by previous work, here the Epidemic forwarding performance is illustrated within the NCCU and GRM datasets, with varying contact-range (10 m and 30 m).

When the contact range is 30 m, the Epidemic Forwarding average delivery latency is respectively 2.6 and 3.6 hours on NCCU and GRM datasets. In both datasets, the algorithm delivery rate performance was 100%. On the other hand, the average network infection (over-

head) was respectively 98.44%, and 99.62% on NCCU and GRM. With that said, most nodes received the content and became forwarders. For reaching superior performance in terms of delivery rate and delivery latency, Epidemic forwarding flooded the network with many copies of the same message. This is not feasible in real-world scenarios and is highly costly, particularly in opportunistic networks where the devices have limited resources (e.g., battery, storage). Another finding (which is also a characteristic) from the Epidemic Forwarding experiments was a high average of hops (i.e., intermediary nodes) from the source to the destination. In this scenario, Epidemic had the average hop count of 6.62 and 8.85 respectively on NCCU and GRM. This peculiarity motivated and brought an insight to TOOTS development: taking the contents closer to its consumers for reducing the number of intermediary nodes, and potentially the overhead, and delivery latency through the combination of intelligent dissemination and forwarding decisions.

As expected according to the results from the pairwise-contacts evaluation (Sec. 3.5), when the contact range is more restricted, the delivery delay increased in both datasets. In the experiments with 10 m range, the overhead was quite similar on NCCU (98.47%), but smaller on GRM (86.50%). Still, the average delivery rate on GRM was 97%, meaning that with the restricted contac range on this dataset, even the Epidemic Forwarding could not deliver all the contents in the time-to-live. In Fig. 5.2, we see that the contact range restriction causes more proportional delay on GRM than on NCCU (on GRM, there is a 7-fold increase). This is justified by a characteristic showed on the previous section. GRM has nodes with very low centrality degrees, and also shorter contact duration per day. With that said, epidemic struggles with less contacts, and so, it takes more time to "flood" the network and to make the content reach the destination. Through the evaluation of the Epidemic Forwarding, we see that a restricted contact range, and the characteristics of a population in terms of their contact can affect strategy's effectiveness. In the next section, we introduce TOOTS, including its algorithms.

5.4 1st TOOTS Phase: Tactful Dissemination Policy

Herein, we describe our proposed Tactful-Based Dissemination Policy (TDP) (Alg. 1). This policy chooses disseminator nodes according to their social behavior (i.e., in terms of encounters) in each time window (previously described). The TDP's intention is trying to start the offloading task placing the content closer to the consumer nodes, possibly reducing the overhead, and delivery latency. Thereafter, we explain how the user routines in terms of encounters are leveraged in the policy for choosing the content disseminators. Considering the network as a dynamic contact graph $G_t = (V, E_p)$, there is a set of users V (i.e., mobile nodes), and a set of edges E_p found during the period p of the week k. We assume that there is an entity that at the end of each week k, receives the information below from each node (i.e., operator subscribers) $u \in V$.

- **(a)**: $\sigma(u)_p$ - the set of users v encountered by u for each period p.
- **(b)**: $\Delta_{C_{LID_p}}(u)$ - the average local improved centrality degree metric [29] of a user u for each period p. The C_{LID} coefficient is calculated based on the node's number of contacts, how long (duration) they took, and how early (earliness) they happened. Therefore a

higher C_{LID} is given to a node with more contacts which had longer durations, and occurred earlier (i.e., in a period p)

Algorithm 1: SelectDisseminators

input : G_t, C, c, p
output: D(c)
1 **begin**
2 $D(c) \longleftarrow \emptyset$
3 **while** $C \neq \emptyset$ **do**
4 let $u \in V$ maximizing $|\frac{|\sigma_p(u) \cap C|}{|C|} + \Delta_{C_{LID_p}}(u)|$
5 $D(c) \longleftarrow u$
6 $C \longleftarrow C - \sigma(u)$
7 **end**
8 Return $D(c)$
9 **end**

In an instant t of the week $k+1$ when there is a set of users (consumers) $C(c) \in V$ requests for a content c, the TDP (Alg. 1) runs for choosing the disseminator nodes. The policy uses the $\sigma(u)_p$ from the week k for trying to select users with past direct contacts with the consumers. According to [128], due to our human routines, there is regularity in our contacts and interactions. The Alg. 1 prioritizes these direct contacts (i.e., as they are most likely to repeat) for trying to save network and user device resources. Furthermore, the C_{LID} is used for identifying nodes' popularity and coverage through contacts duration and earliness. The use of this metric is justified by the fact that in such opportunistic scenario, a contact that happens earlier in a time window and lasts enough to transmit a content might help decreasing the delivery latency. Further, depending on the size of the content, trying to transmit through short-duration contacts can lead to resources wasting without full content forwarding.

The Alg. 1 runs for selecting a disseminator set $D(c)$ and starting the delivery of c (content) in the period p. The disseminator set starts empty (line 2), as the content delivery task begins only upon having a set of Consumers C interested in a content c. The policy selects (lines 4 and 5) the user u with the higher coefficient from the direct contacts with Consumers ($\sigma_p(u) \cap C$), normalized by the size of C, summed with u's average C_{LID} in p (i.e., $\Delta_{C_{LID_p}}(u)$). Thereafter, all Consumers that had direct encounters with the selected node u are removed (line 6). With this, we avoid the possibility for selecting a next user with similar coefficient for direct contacts and which covers the same nodes. The Alg. 1 loops (line 3) while the consumer set is not totally covered ($C \neq \emptyset$). All users in the datasets encounter at least one node (i.e., there are no isolated nodes) during the week k. With that said, if a isolated consumer is identified within a population, for obvious reasons, opportunistic communication is not a good choice to deliver content for such node. In Sec. 6.2, the TDP is evaluated with varying consumer set sizes (1%, 5%, and 10% of each dataset total nodes).

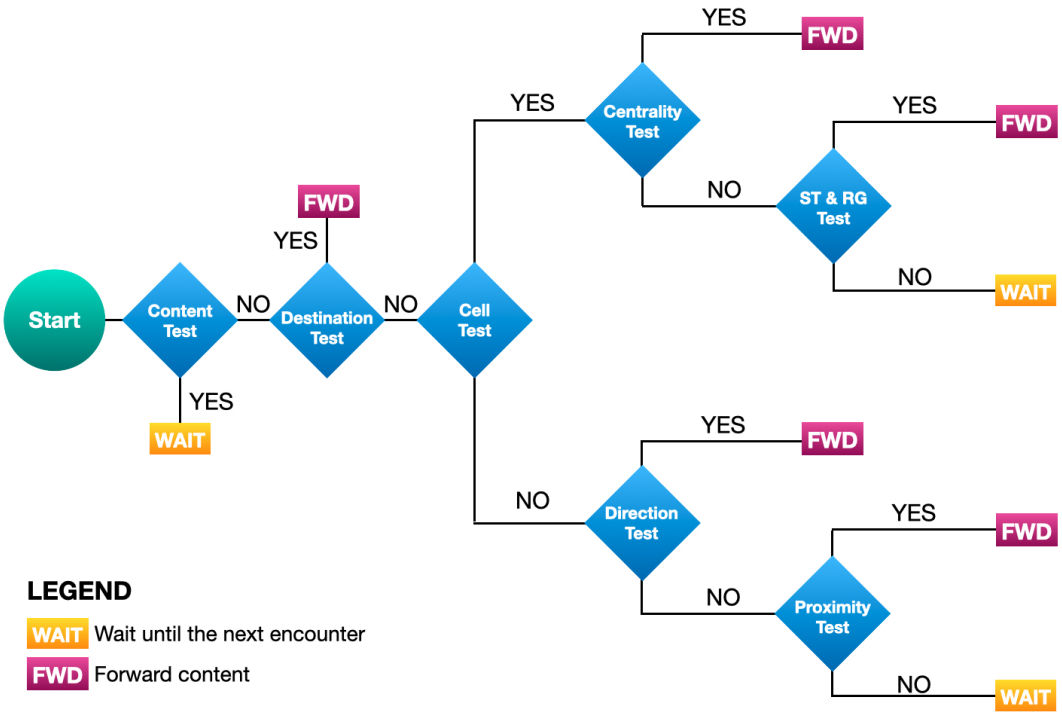


Figure 5.3: TOOTS forwarding flow diagram of the Algorithm 2.

5.5 2nd TOOTS Phase: Human-Aware Forwarding

After running the Alg. 1, the operator injects the content c to each chosen disseminator (i.e., transmits from MEC site to the node) node ($u \in D(c)$), which stores c in a local buffer. From this moment, when any node carrying c has an encounter, the Alg. 2 runs locally (i.e., in a distributed fashion) for deciding if the content is forwarded. As for facilitating the comprehension of the algorithm, we also present a flow diagram in Fig. 5.3. The algorithm lines and the flow diagram boxes will be mentioned in the explanations to follow.

The algorithm input is: a destination node d (i.e., $d \in C$), the content c, the present period p, the encountered node v, and the coordinates of d's cell, given by l. All metrics coefficients are stored locally by each node in a table divided by period p. The content c is transmitted from u to v, only if an algorithm's condition is satisfied.

First **(line 2)**, if v already carries c, u waits till the next encounter **(content test)**. Second **(line 4)**, if v is the destination (i.e., $v = d$), u transmits c **(destination test)**. The success of the transmission depends if there is an edge e between u and v, with enough persistence (i.e., that does not suffer disconnection caused by a topology change) until the amount of time t necessary to transfer c's full data.

As previously stated (Chap. 3), the geographic space of both datasets was divided into network cells. If **(line 6)** v is at the same cell **(cell test)** reported by the destination (given by l), the centrality degree from u and v in p are compared **(centrality test)**. If v's avg. CD is higher (line 7), c is forwarded, as v has a higher forwarding potential inside its cell, (i.e., v met more nodes). If the previous test is false, the algorithm tests **(line 9)** if $\Delta_{RG_p}(v) > \Delta_{RG_p}(u)$ and $\Delta_{ST_p^{cell}}(v) > \Delta_{ST_p^{cell}}(u)$ **(ST & RG test)**. If true, that means v has less "popularity"

Algorithm 2: HumanAwareForwarding

input : d, c, p, v, l
output: A forwarding Decision

```
1  begin
2      if c ∈ v then
3          exit(0)
4      else if v = d then
5          v ⟵ c
6      else if v.cell = l then
7          if Δ_{C_{D_p}}(v) > Δ_{C_{D_p}}(u) then
8              v ⟵ c
9          else if Δ_{R_{G_p}}(v) > Δ_{R_{G_p}}(u) and Δ_{ST_p^l}(v) > Δ_{ST_p^l}(u) then
10             v ⟵ c
11     else
12         if testDirection(v, l) then
13             v ⟵ c
14         else if Δ_{MP_p^l(v)} < Δ_{MP_p^l(u)} then
15             v ⟵ c
16     end
17 end
```

than u (i.e., lower avg. CD). On the other hand, v has a higher avg. RG which gives it the potential to do larger displacements inside the cell given by l. Furthermore, v's routine makes it stay longer inside l (v has higher avg. ST). Due to these intuitions, c is forwarded to v (line 10). When v is in a different cell than the one given by l, an instant mobility test **(line 12)** in relation to l is performed **(direction test)**. If v's predominant direction in the last 30 minutes was towards l (i.e., the line 12 test is true), c is forwarded, as v can potentially reach or get close to the domain of the cell given by l. Finally, if the direction test is not true, the Destination Proximity metric is used **(line 14)**. If v's avg. MP ($\Delta_{MP_p^l(v)}$) is smaller, c is forwarded **(proximity test)**, as that means v got closer (or visited) the cell given by l during the period p and due to human routines, this behavior is more likely to repeat.

5.6 Summary

In this chapter we introduced TOOTS, our tactful opportunistic communication strategy. First, we described the application scenario example in which we evaluate TOOTS hereafter. This scenario targets a more complete and realistic environment that could be of interest to mobile carriers. The scenario assumes a cellular operator with a MEC infrastructure that stores content frequently requested by the subscribers closer to the edge. The goal is to perform cost-effective content delivery through opportunistic D2D communication among the subscribers.

Following, we presented the formal definition for the problem of choosing disseminator nodes (TOOTS' 1st phase). We showed that the Content Dissemination (CD) problem is NP-Hard. CD's decision problem is similar to the minimum dominating set, which is NP-Complete. For such reasons, we proposed a policy for choosing disseminator nodes.

As a motivation to build the strategy, we evaluated the overhead and latency of the state-of-art Epidemic Forwarding within NCCU and GRM datasets. With 30 m contact range, epidemic delivered 100% of the contents in 2.6 and 3.6 hours (respectively on NCCU and GRM), but with 98.44%, and 99.62% network infection (i.e., overhead). The network was flooded, which is highly costly and not feasible in the real world. Epidemic also showed a 6.62 and 8.85 average hop count (respectively on NCCU and GRM), which gave the first insight into the dissemination policy: trying to take the contents closer to its consumers might reduce intermediary nodes, and so the overhead and delivery latency.

Finally, we presented TOOTS, including a tactful dissemination policy for choosing the disseminator nodes and a human-aware forwarding algorithm. The 1st phase (TDP Policy) chooses a set of disseminators for each content, relying on direct encounters with the consumers, the improved centrality degree metric, and our human-aware time division. The following facts justify these features:

- We choose users that had direct contacts with the consumers since they are most likely to repeat those interactions;
- Taking the content closer to its consumers (i.e., choosing disseminators that had direct encounters with the consumers) would increase the strategy's cost-effectiveness, i.e., increasing the delivery rate and decreasing the delivery delay and overhead;
- The improved centrality degree metric targets users with longer duration and earlier contacts (i.e., they happen earlier in the time windows). That also could lead us to improved performance since longer contacts can avoid forwarding interruptions and increase the delivery rate while earlier contacts can reduce the delivery delay.

TOOTS' 2nd phase relies on probabilistic spatiotemporal aspects, social information (i.e., wireless contacts), PoI awareness related to network cells, and individual mobility. These characteristics come from the metrics and features previously presented, discussed, and analyzed. We combined this 2nd phase in a forwarding algorithm that considers our insights from each metric targeting the increased performance.

Chapter 6

TOOTS Evaluations, Results, and Analysis

As previously stated, TOOTS is composed of two phases: a Tactful Dissemination Policy (TDP) and a Human-Aware Forwarding Algorithm. Our empirical evaluation is presented and performed through simulation analysis with the ONE simulator and the NCCU and GRM datasets. This chapter is organized as follows. We start presenting our evaluation setup where we use more realistic settings (e.g., content size, content time-to-live, and varying contact range) than most related work. Then, we analyze the results in terms of average delivery rate and latency from our TDP compared to state-of-art Store-wait-forward and Epidemic forwarding. Finally, we compare TOOTS with Bubble Rap (the most popular strategy in the context) enhanced with three dissemination policies: random-based (RDP), centrality-based (CDP), and tactful-based (TDP).

6.1 Evaluation Setup

As previously stated, the goal of the strategy is cost-effective content delivery through users' opportunistic communication. In our simulations, the contents range from 11-14 MB, an average size for 60 seconds YouTube 720P HD 30fps advertising videos. TOOTS uses seven days of users' mobility (extracted from NCCU and GRM datasets) during a learning phase. The contents are generated during one day, being one offloading task started every hour. The content delivery deadline is three days, which according to [29] is a reasonable time for delay-tolerant content. Each content has a set of random consumers with varying set sizes. The contents are injected into the network through the users. The first set of users carrying the content is called the Disseminator set. Upon having a contact (i.e., given by a specific communication range), they run an algorithm to make a forwarding decision. If the content is not fully transmitted during a contact, the forwarding is aborted. Every node in the simulation has an 802.11/11 Mbps network interface. We evaluate two communication ranges: 30 m (avg. for WiFi Direct) and 10 m (referred to as Bluetooth). This whole scenario is simulated with the Opportunistic Network Environment (ONE) Simulator through the NCCU and GRM datasets as mobility models. Each experiment case ran 30 times, and the confidence intervals appear when necessary. As previously stated in Sec 2.4, some state-of-art work focused a lot on performance, but their evaluations had non-realistic settings (e.g., a tiny content size possibly transferred through very short contact duration). Throughout the setup mentioned above, we make the evaluated algorithms front more challenges to be successful.

Comparison Strategies: We compare TOOTS 1st phase (Tactful Dissemination Policy) by combining it with state-of-art Store-wait-forward (a.k.a., direct delivery) and Epidemic Forwarding. The first works by trying to forward content to an encountered node only if this

one is the destination (i.e., the consumer). For such reason, the store-wait-forward has zero overhead. The latter always tries to forward the content to an encountered node that does not have it. As the name says, the latter has a high " network infection" potential (i.e., high overhead).

The entire strategy (i.e., tactful dissemination policy + human-aware forwarding algorithm) comparison performs with Bubble Rap, remarked as the most popular social-based forwarding algorithm in opportunistic delay-tolerant networks. Bubble Rap works by assigning a GlobalRank, and a LocalRank to each node. The GlobalRank accounts for node's popularity in the whole network, while the LocalRank measures the popularity into a community. Both centrality-related ranks are linked with the C-Window temporal approach, which accounts for nodes' popularity in the last time window of 24 hours. Bubble Rap also relies on social communities calculations, where each node is assigned to at least one community. According to these metrics, a content c stored in the buffer of a node u is transmitted by Bubble Rap to an encountered node v, when: v is the consumer (i.e., the destination d); v's GlobalRank is higher, or v belongs to the consumer's (d) community; v has higher LocalRank and belongs to the consumer's community.

Herein, Bubble Rap is combined with three policies for choosing disseminator nodes. These policies are used to inject the contents in the network whenever a content delivery process is started:

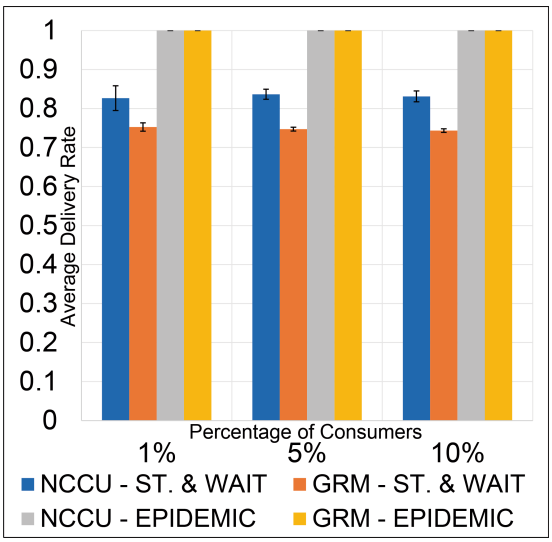
- **Random-Based Dissemination Policy (RDP)**: the origin nodes are randomly selected (i.e., it works like the traditional Bubble Rap trying to forward content to source-destination using intermediary nodes);
- **Centrality-Based Dissemination Policy (CDP)**: the origin is selected as the higher centrality node (i.e., the node which has more encounters);
- **Tactful-Based Dissemination Policy (TDP)**: our proposal detailed in Sec. 5.4. TDP node selection is based on direct encounters with the consumers, combined with higher C_{LID} metric coefficient.

Evaluation Metrics: In the 1st phase, we compare TOOTS' TDP with store-wait-forward and epidemic regarding delivery rate and delivery latency. Our goals here were: (i) to determine if the TDP increases the delivery rate and reduces the delay when combined with store-wait-forward; (ii) to discover if the TDP could reduce the delay and the average number of hops when combined with the epidemic. We skip the overhead measurements from the 1st phase since store-wait-forward represents the best case in terms of overhead (i.e., zero) and epidemic forwarding the worst case.

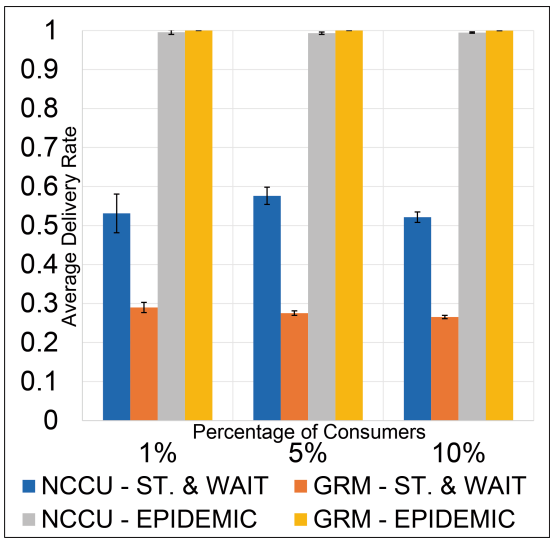
In the 2nd phase, the benchmark metrics are delivery rate, delivery latency, and network infection (i.e., overhead). Our goal in this phase was to determine if our whole strategy has more cost-effectiveness for delivering content in the scenario than Bubble Rap combined with different dissemination policies (including ours).

6.2 Tactful Dissemination Policy Results and Analysis

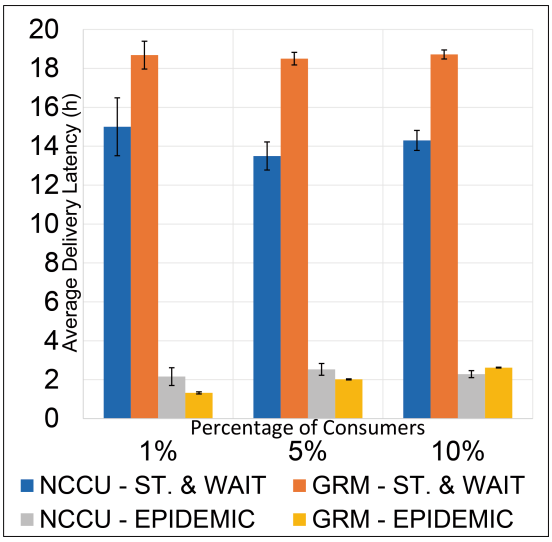
This sections presents the evaluation results of the TDP policy. For this, we combine the TDP with two state-of-art forwarding strategies: store-wait-forward (a.k.a., direct delivery), and



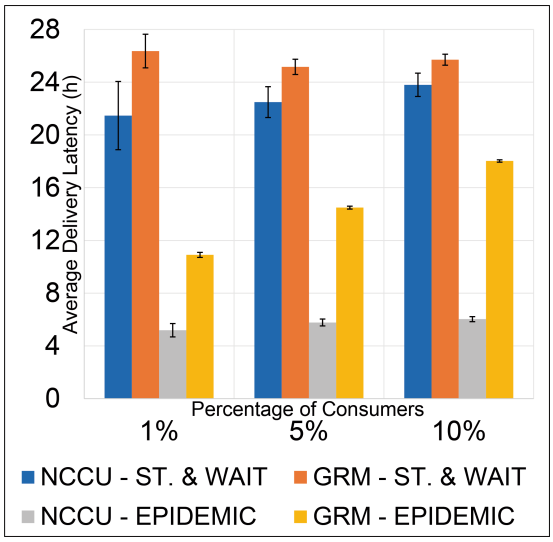
(a) Avg. delivery rate on NCCU and GRM datasets with 30 m communication range



(b) Avg. delivery rate on NCCU and GRM datasets with 10 m communication range



(c) Avg. delivery latency on NCCU and GRM datasets with 30 m communication range



(d) Avg. delivery latency on NCCU and GRM datasets with 10 m communication range

Figure 6.1: Tactful dissemination policy average delivery rate and delivery latency performance evaluation. TDP is combined with epidemic and store-and-wait forwarding in scenarios with varying amount of consumers and different communication range.

epidemic forwarding. In this combination, we use the TDP for electing the disseminator nodes, chosen as content sources, followed by running each forwarding strategy. The performance of the TDP-enhanced store-wait-forward and epidemic forwarding is shown in Fig. 6.1. As shown in Sec. 5.3, traditional epidemic with 30 m communication range had 98.44%, and 99.62% network infection (i.e., overhead) respectively on NCCU and GRM. Nevertheless, the TDP-enhanced epidemic might get decreased delivery latency with comparable delivery rate. Given the metrics applied in the TDP policy, the TDP-enhanced store-wait-forward has the potential

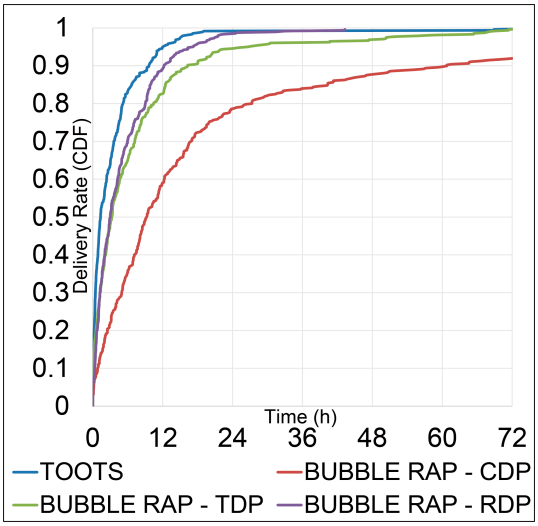
to increase the delivery rate while decreasing the delivery latency. Despite the success of the store-wait-forward algorithm depends on direct encounters with the consumers, the TDP content dissemination brings an improvement. Still, depending on dataset characteristics, and the social bonds between source and destination nodes, these improvements might take time or never happen.

In Fig. 6.1(a), the TDP-enhanced store-wait-forward show an improved average delivery rate of 82% and 75% respectively on NCCU and GRM, independent of the consumer set size evaluated (1%, 5%, and 10% of each dataset). This delivery rate improvement is explained by one of TDP insights, which is choosing nodes with direct encounters per period with the consumers. For instance, in comparison with the traditional store-wait-forward, the TDP-enhanced strategy's average delivery rate with 1% of consumer set size was 18% and 60% higher respectively on NCCU and GRM. In Fig. 6.1(a), the TDP-enhanced epidemic forwarding, as expected, reaches 100% average delivery rate regardless of the consumer set size and dataset. In comparison with the traditional Epidemic forwarding algorithm, the TDP-enhanced epidemic had decreased average hop count, which impacts also in the delivery latency (analysis to follow).

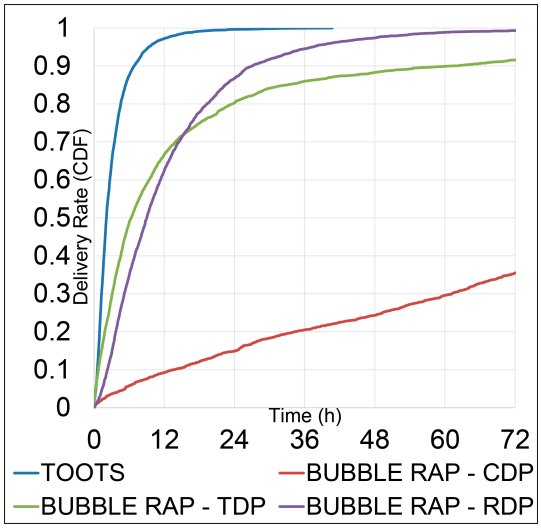
With more restricted contact-range (Fig. 6.1(b)), as expected, the performance of the content delivery task decreases on both datasets. Still, when compared with the traditional store-wait-forward, the TDP-enhanced has better performance in delivery rate and delivery latency. The plot also shows that the TDP-Enhanced Epidemic reaches 100% delivery rate in all scenarios on both datasets, which is an improvement in comparison with the traditional Epidemic. Furthermore, thanks to TDP-policy, the overhead on GRM with 1% of consumers was reduced in 50%. This is also explained by a characteristic of this dataset, which is having nodes with a lower number of encounters. The plot from Fig. 6.1(b) also shows that the contact range does not create an impact when the percentage of consumers varies up till 10% in those datasets.

Following in the evaluations, in Fig. 6.1(c), we plot the average delivery latency. The TDP-enhanced store-wait-forward, regardless of the size of consumers set, takes 13-15h to deliver the contents on NCCU, and 18h-19h on GRM. With that said, the TDP policy makes possible to deliver at least 75% of the delay-tolerant contents in an acceptable time [29], regardless of the dataset, and with zero overhead. In comparison with the traditional store-wait-forward, the TDP-enhanced strategy's average delivery latency with 1% of consumers was reduced 23% on NCCU and 48% on GRM. As previously stated, thanks to the TDP policy, the number of hops in epidemic forwarding decreased, and so the delivery delay (18.6% and 64.5% smaller respectively on NCCU and GRM with 1% of consumers). Still, the networking infection of epidemic forwarding makes this algorithm very costly or unfeasible in real scenarios.

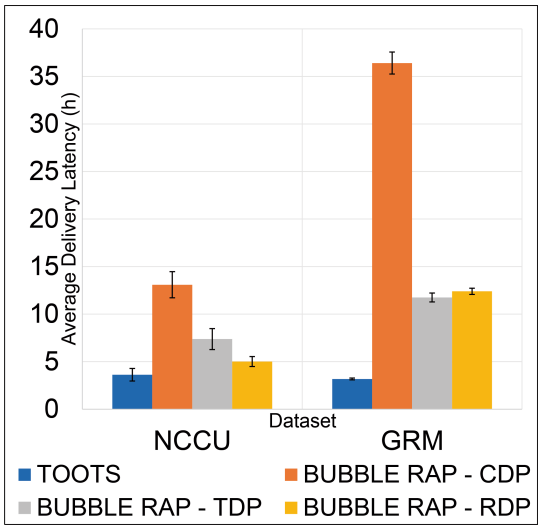
Again, with more restricted contact range (Fig. 6.1(d)), there are less contacts on both datasets, and so the delivery delay increases . Nevertheless, even in this scenario, thanks to TDP policy, most of the delay-tolerant contents still reach their consumers in an acceptable time. As Epidemic forwarding is unfeasible in realistic scenarios, and TDP-Enhanced store-wait-forward showed an average delivery rate of 55%, we look for a forwarding algorithm able to increase the delivery rate with as lower as possible overhead, and delivery latency.



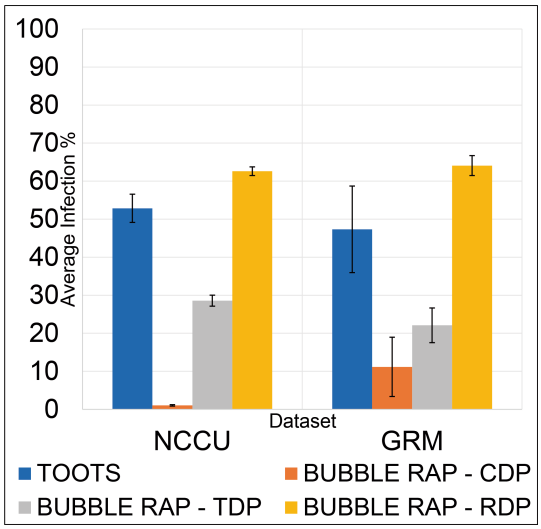
(a) Delivery rate on NCCU dataset with 30 m communication range



(b) Delivery rate on GRM dataset with 30 m communication range



(c) Avg. delivery latency on NCCU and GRM datasets with 30 m communication range



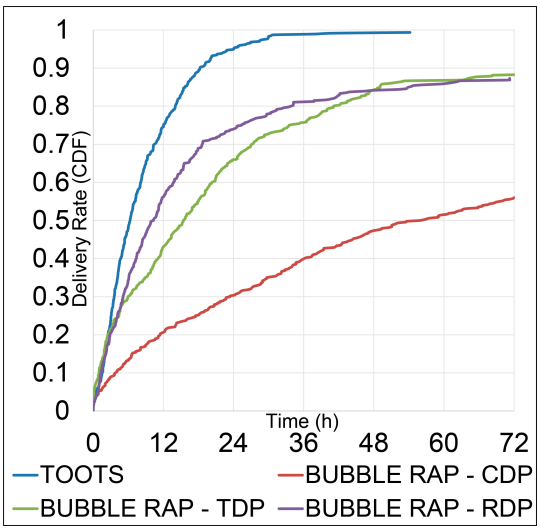
(d) Avg. infection % (overhead) on NCCU and GRM datasets with 30 m communication range

Figure 6.2: Delivery rate, delivery latency, and overhead performance comparison of TOOTS, Bubble Rap-CDP, Bubble Rap-TDP, and Bubble Rap-RDP on NCCU and GRM datasets with 30 m communication range.

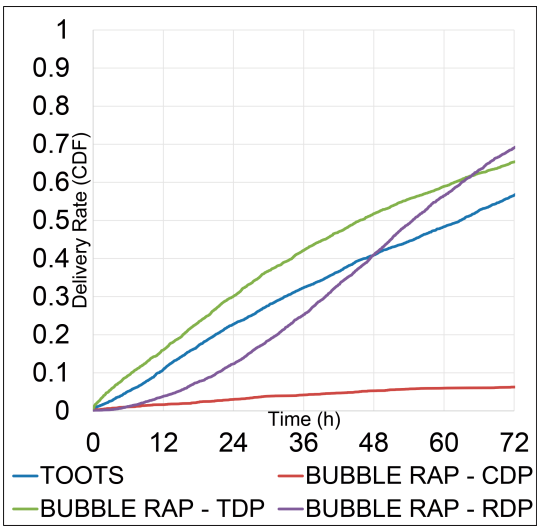
6.3 TOOTS Forwarding Results and Analysis

Finally, we present the evaluation of the full strategy in terms of delivery rate, delivery latency, and overhead within NCCU and GRM datasets. As with the state-of-art epidemic forwarding evaluation, the scenario has random consumers with the set size equal to 1% of dataset total nodes and varying communication range (10 m and 30 m). We compare TOOTS' performance with Bubble Rap.

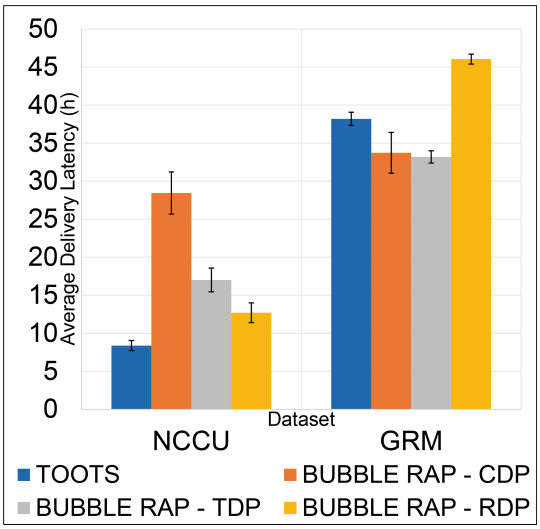
First, in Fig. 6.2(a) TOOTS and Bubble Rap are evaluated in terms of delivery rate through



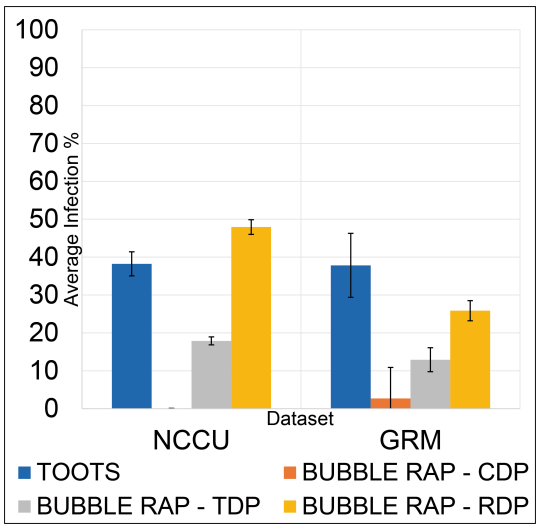
(a) Delivery rate on NCCU dataset with 10 m communication range



(b) Delivery rate on GRM dataset with 10 m communication range



(c) Avg. delivery latency on NCCU and GRM datasets with 10 m communication range



(d) Avg. infection % (overhead) on NCCU and GRM datasets with 10 m communication range

Figure 6.3: Delivery rate, delivery latency, and overhead performance comparison of TOOTS, Bubble Rap-CDP, Bubble Rap-TDP, and Bubble Rap-RDP on NCCU and GRM datasets with 10 m communication range.

the NCCU dataset with 30 m communication range. TOOTS reached 100% delivery ratio and was also the fastest strategy, with approx. 90% of the generated contents delivered in up to 9 hours. Even in the NCCU dataset which has a smaller number of nodes, those with high centrality degree, Bubble Rap-CDP failed to deliver approx. 10% of the contents. Adopting a CDP is not feasible in real-world, as this strategy originates a "bottleneck" tending to train the device resources of the most "popular" users. Despite reaching 100% delivery ratio, a higher overhead is expected in Bubble Rap-RDP (analysis to follow). Finally, Bubble Rap-TDP also delivered 100% of the contents, but in such experiments, this strategy took slightly more time

than TOOTS to deliver all contents.

Within the GRM dataset and 30 m communication range (Fig. 6.2(b)), TOOTS reaches 100% delivery rate, with approx. 97% of the contents in up to 12 hours. Bubble Rap-CDP delivery rate is even worst than in NCCU. This is explained by the fact GRM nodes' has much lower centrality degrees, and, by a communication bottleneck generated by higher node density, where nodes' interfaces are able to transmit only one content at once. As in the previous analysis, Bubble Rap-RDP reached 100% delivery ratio, but with a higher overhead expected (analysis to follow). Bubble Rap-TDP delivered approx. 94% of the contents. This can be explained by a characteristic of GRM: nodes with low centralitty degrees, which makes Bubble Rap-TDP need more time to reach 100% delivery rate.

In Fig. 6.2(c), the strategies are evaluated in terms of delivery latency, considering a 30 m communication range. On both datasets, TOOTS had the lower average delivery latency, followed by Bubble Rap-RDP, and Bubble Rap-TDP respectively on NCCU and GRM. Reminding that only TOOTS and Bubble Rap-RDP delivered 100% of the contents in up to 72h. On GRM, Bubble Rap-CDP had a much higher average delivery latency, as this strategy struggles with the bottlenecks on fewer nodes with higher centrality, and by a characteristic from this dataset showed in Chap. 3: from the time the contents are generated till their time-to-live (i.e., end of the simulation), over 90% of the nodes has less than 0.4 centrality degree, which are low coefficients.

In Fig. 6.2(d) we evaluate the overhead of each strategy. Bubble Rap-CDP appears with the smaller overhead both on NCCU and GRM datasets with 30 m communication range. On NCCU, this is explained by the existence of higher centrality degree nodes, which makes possible for the disseminator nodes to find the destination directly for most of the generated contents. Still, as previously discussed, there is a bottleneck, lowering Bubble Rap-CDP's delivery rate in comparison with other strategies. As expected, Bubble Rap-RDP had the worst-case in terms of overhead. In comparison with Bubble Rap-TDP, the latter performs with 53% less overhead on NCCU, and 65% less on GRM. Nevertheless, we remark that the TDP-enhanced Bubble Rap needs more time to reach 100% delivery rate on GRM, when there is a 72 h deadline. Applying other larger real-world datasets will be interesting when evaluating this strategy. TOOTS was the fastest strategy, it reached 100% delivery rate, and had 10% and 17% less overhead than Bubble Rap-RDP respectively on NCCU and GRM.

Finally, from Fig. 6.3(a) to Fig. 6.3(d) we evaluate how imposing a more restrict contact range (10 m) affects the strategies' performance in terms of delivery rate, delivery latency, and overhead on both datasets. In Fig. 6.3(a) we see that TOOTS is the fastest, and the only strategy that reaches 100% delivery rate on the real-world NCCU dataset. Bubble Rap-TDP and Bubble Rap-RDP reach close to 90% delivery rate and require more time, which could be more than the acceptable for delay-tolerant content. Bubble Rap-CDP fronts an even worst bottleneck, as there are less contacts and their duration are also reduced. When the dataset is the GRM (Fig. 6.3(b)), we see that the reduced contact range impacts in lower performance of the algorithms. The delivery rate ranges from 56% (TOOTS) to 68% (Bubble Rap-RDP). On the other hand, Bubble Rap-TDP reaches a very similar delivery rate (65%), with less average latency. This reduced performance on GRM dataset is justified by the already very low CD nodes which are even more reduced when the lower contact range is applied. With that said, the efficiency of opportunistic forwarding algorithms and their deployment in realistic scenarios depend on characteristics of the populations in terms of contacts, and also the technology used for D2D communication. D2D technologies with higher transmission capacity and higher

contact range can compensate certain contact restrictions imposed by the populations, or their mobility context. Fig. 6.3(c) certifies TOOTS as the strategy with the smaller delay on NCCU dataset. On GRM, thanks to the TDP policy, there is 28% less delivery delay with Bubble Rap. From the overhead analysis (Fig. 6.3(d)) we learn that on NCCU, with 10 m contact range, TOOTS had less forwarding decisions (i.e., imposed by less contacts) and so transmitted less contents. The TDP policy also assists Bubble Rap to reduce the overhead within both datasets. We conclude that on the real world dataset, 10 m communication range was enough for TOOTS to deliver 100% of the contents in an acceptable time (i.e., avg. 9h), and with less overhead than Bubble Rap-RDP (which had over 10% less delivery rate)

6.4 Summary

In this chapter we presented the TOOTS' evaluation in its two steps. In the 1st phase, our proposed Tactful Dissemination Policy (TDP) was evaluated through its combination with two state-of-art algorithms named Store & Wait and Epidemic Forwarding. Among the main outcomes of this phase results, are:

- TDP-enchanced store-wait-forward showed an improved average delivery rate of 82% and 75% respectively on NCCU and GRM, independent of the consumer set size evaluated (1%, 5%, and 10% of each dataset);
- In comparison with the traditional store-wait-forward, the TDP-enhanced strategy's average delivery rate with 1% of consumer set size was 18% and 60% higher respectively on NCCU and GRM;
- The TDP-Enhanced Epidemic reaches 100% delivery ratio in all scenarios on both NCCU and GRM, which is an improvement in comparison with the traditional Epidemic Forwarding;
- In comparison with the traditional store-wait-forward, the TDP-enhanced strategy's average delivery latency with 1% of consumers was reduced 23% on NCCU and 48% on GRM;
- Thanks to the TDP policy, the number of hops in epidemic forwarding decreased, and so the delivery delay (18.6% and 64.5% smaller respectively on NCCU and GRM with 1% of consumers).
- TDP policy was able to increase performance in terms of delivery rate, delivery latency, and overhead. We look for a forwarding algorithm able to reach even superior performance.

Finally, TOOTS (i.e., the full proposal) was compared with traditional Bubble Rap and enhanced versions of the latter with TDP, CDP (Centrality-based Dissemination Policy), and RDP (Random-based Dissemination Policy). As stated previously, Bubble Rap is the most popular social-aware forwarding algorithm, still used as a benchmark with recent research [14, 208]. Among the main outcomes of the full proposal results, are:

- On NCCU dataset and 30 m communication range, TOOTS reached 100% delivery ratio and was also the fastest strategy, with approx. 90% of the generated contents delivered

in up to 9 hours. In delay-tolerant scenarios, the deadline is usually referred to as 72 hours;

- Within the GRM dataset and 30 m communication range, TOOTS reached 100% delivery rate, with approx. 97% of the contents delivered in up to 12 hours;
- On both datasets, with 30 m communication range, TOOTS had the lower average delivery latency, followed by Bubble Rap-RDP, and Bubble Rap-TDP respectively on NCCU and GRM;
- A Centrality-based dissemination policy is not suitable for real-world scenarios, since it creates bottlenecks and tends to drain user device resources;
- TOOTS had 10% and 17% less overhead than BubbleRap-RDP respectively on NCCU and GRM with 30 m communication range. Furthermore, TDP policy was able to reduce significantly the overhead on the Bubble Rap-TDP enhanced;
- Restricted contact range reduced the performance of all algorithms in both datasets;
- With restricted contact-range (i.e., 10 m), TOOTS was the fastest, and the only strategy by far that reached 100% delivery rate on the real-world NCCU dataset;
- With restricted contact-range (i.e., 10 m), when the dataset was the GRM, the delivery rate ranged from 56% (TOOTS) to 68% (Bubble Rap-RDP). On the other hand, thanks to TDP policy, Bubble Rap-TDP reached a very similar delivery rate (65%) to Bubble Rap-RDP, with reduced delivery latency. This reduced performance is justified by a characteristic of the dataset, which already had low CD nodes, as they were even more reduced by restricting the contact range;
- Within NCCU dataset, 10 m communication range was enough for TOOTS to reach 100% delivery rate, being the faster strategy (i.e., avg. 9h delivery latency), and with less overhead than Bubble Rap-RDP (which had over 10% less delivery rate than TOOTS).
- The results of TOOTS' evaluation correlates better with the real-world dataset NCCU. That copes with the insights behind building TOOTS, which relies on human-aware aspects which are not totally present on GRM.

Chapter 7

Conclusion and Outlook

The following sections conclude this thesis. We start by summarizing the challenges and how we treated each one individually to reach the contributions. Following, we present further discussions and deliberate over out-of-scope subjects. Finally, we outline the limitations of this work, future research, and concluding remarks.

7.1 Summary of this Thesis

The main goal of this thesis was to build an opportunistic D2D communication strategy that leverages human characteristics to perform cost-effective content delivery in a mobile network scenario. Within such goal, our first research question arose:

Which lessons can we take from state-of-art opportunistic communication strategies when dealing with the human aspect? State-of-art opportunistic communication strategies and algorithms tackled cost-effective content delivery. Most of such proposals considered characteristics such as user encounters due to individual mobility, points of interest (PoIs), and time-evolving social ties between node pairs. Despite their contributions, in most cases, there was a gap between evaluation metrics and broader inherent aspects of human mobility. From such state-of-art, we learned some traditional techniques and human mobility features. According to open challenges in the field, it became necessary to identify other human traits and peculiarities hidden in the mobility datasets with more detail and precision. We then started to dig into other possible characteristics targeting a tactful opportunistic communication strategy for delivering content with improved performance. Naturally, the following research question was the following:

What human characteristics and peculiarities can we learn from mobility datasets to improve our strategy's performance? From the insights obtained from the state-of-art review, the study and proposal of the tactful networking paradigm, and the study and characterization of MACACO, NCCU, and GRM datasets, we identified characteristics that could lead to the strategy's improved performance. The first aspect was related to human routines. We thought that our strategy's features would need to be more precise than state-of-art. With that said, we thought that analyzing human activities in different periods of the day would bring different results reflecting heterogeneity in metrics/features coefficients. This idea was applied in all other characteristics later proposed as strategy's metrics. We added proximity and time of stay (both in terms of PoI) and direction awareness as other characteristics to offer insightful results to our strategy. Additionally, we analyzed traditional metrics related to user social aspects and displacements but in a different way than state-of-art and with other purposes (previously explained). After putting together this set of human characteristics, the next step linked to the following research question, i.e.,

How can we translate the identified peculiarities and characteristics into mobility metrics, and how can we combine those to reach superior performance in our strategy?

The characteristics mentioned above became metrics and features of our tactful opportunistic communication strategy:

- Human-Aware time approach - we divided the time in different windows to capture human activities and mobility throughout six periods of the day. All the other metrics calculations rely on this time approach, which is justified because humans are most likely to show repetitiveness in their mobility (e.g., encounters, displacements, PoI visiting) due to their routines.

- Radius of Gyration - we applied this traditional mobility metric differently from state-of-art. Herein, this metric selects more mobile nodes inside a network cell to take the content to a farther area.

- Centrality Degree - to measure users' encounters, also applied herein differently (with metric coefficients per periods of the day). The Centrality Degree identifies nodes with higher forwarding potential.

- Sojourn Time - applied to provide quantitative information about the permanence (i.e., time spent) on the network cells. We use this metric for identifying users that spend more time on the same cell as a consumer.

- Destination Proximity - used a PoI abstraction to find how close a given user reached towards a consumer's network cell.

- Geographic Direction AWareness - instant mobility metric to discover if a given node was moving towards a cell in the last 30 minutes.

All presented metrics featured their mathematical formulations (except the last, which relates to instant mobility). We also analyzed and discussed the metrics and features within the three datasets. Later on, we combined those metrics based on our human-aware insights to build a two-phases strategy, including a Tactful Dissemination Policy (TDP) (1st phase) and a Human-aware Forwarding algorithm (2nd phase).

In the first phase, the TDP selects disseminator nodes based on two metrics: users' direct encounters per period of the day and the local improved centrality degree metric (which considers encounters duration and earliness) per period. The reason and intuition behind these metrics were:

- Direct encounters with consumers - to start the content delivery process with the content closer to its consumer. As the users are most likely to repeat their encounters due to their routines, this could lead us to improved delivery rate, smaller delivery latency, and less overhead;

- Local improved centrality degree ($\Delta_{C_{LID_p}}(u)$) - this metric considers not only the amount of contacts (i.e., user "popularity"), but their duration and earliness. These two aspects are important, as the metric gives higher coefficients to contacts that occurred earlier in the time window and with longer duration. These could lead us to avoid wasting

device resources with unfinished content transmissions (i.e., interrupted by short-duration contacts) and reducing delay by choosing nodes that might repeat earlier contacts. The first characteristic could also lead to an improved delivery ratio since the user device interface can transmit only to a single user at a time. So if we choose proper longer contacts for transmitting, potentially we increase the delivery rate.

In the second phase, upon contact, the human-aware forwarding algorithm runs locally at the node that holds the content to make a forwarding decision. Intuitions and insights behind such algorithm are in Chap. 5. The TDP policy and the human-aware forwarding algorithm are the core of our Tactful Opportunistic Communication Strategy (TOOTS).

TOOTS was evaluated in a mobile network scenario to perform cost-effective opportunistic content delivery. We compared TOOTS' effectiveness on its two phases with different state-of-art algorithms. The 1st phase with enhanced Store-wait-forward and Epidemic algorithms. The 2nd phase (i.e., TOOTS entire strategy) with Bubble Rap through real and synthetic traces. Bubble Rap is the most popular algorithm in such context and appears as a benchmark with recent work. TOOTS improved the performance of a content delivery scenario in terms of delivery rate, delivery latency, and overhead. TOOTS' results correlate better with the real-world dataset NCCU. With that said, there is a need for larger real mobility datasets with available social behavior from the users. TOOTS' quantitative evaluation results are summarized in the introduction, detailed, and summarized on Chap. 6, so we skip from repeating those here.

As for reaching the main goal of this thesis, we also had to investigate human aspects technical details applied in state-of-art networking solutions. From such investigation, another research question (cf. 1) arose.

How was the human aspect applied in state-of-art networking research to improve QoS, QoE, and bring innovative solutions? We addressed this question by surveying the human aspect in networking. The starting point was the User-Centric Networks paradigm [12] evolution, according to [228], one of the most important concepts for future networking. User-centric was one of the first paradigms in computer networking to bring attention to user characteristics and featuring functionalities straight directed to satisfying user goals. We found that, over the years, the user and the human perspectives attracted attention. At first, users were seen as mere consumers of networking services of applications. This vision started to appear obsolete as the human aspects took part in the solutions for achieving superior network/system performance and helping providers offer QoS/QoE.

Based on the view acquired from surveying the human aspect in networking, we found that many proposed solutions' metrics or insights still lacked a broader human-aware vision. Additionally, opportunistic D2D communication, a paradigm often combined with user-centric goals, appeared as an enabler of recent technologies and future networking standards such as 5G/6G. For such reason, we decided to investigate this subject further for proposing our solution in this context. From these notions, we came with another research question (cf. 1).

Which human characteristics can we use to leverage networking research for improving system performance and user experience? In particular, opportunistic D2D algorithms? The broader human-aware vision that we acquired through the survey culminated into a conceptual contribution, the Tactful Networking perspective, introduced in

Chap 2. We named Tactful Networking as the paradigm that groups different concepts from broader human-behavior research, not restricted to the computer networks field, but from other areas of knowledge, such as philosophy and psychology. Among the human characteristics to shape human-aware networking services are mobility, routines, personality traits, temperament traits, humor, character traits, sharing wills, age, and socioeconomic status. Complementing the Tactful Networking discussions, we shared insights on how human-aware data can leverage network concepts, technologies, and communication models (5G, IoT, Vehicular Networks, Ultra-dense networks, Information-centric Networks, SDN, and NFV). These discussions identify several open research opportunities concerning the tactful networking paradigm. Other contributions of this thesis include discussions of a framework with best practices for extracting human data from datasets and a case study.

Resuming, we divide the contribution of this thesis into two branches. The first features the technical contributions: (i) Datasets analysis; (ii) TOOTS metrics; (iii) TOOTS dissemination policy; (iv) TOOTS human-aware forwarding algorithm; (v) TOOTS evaluations. The second branch features the conceptual contributions, which are: (i) Human aspect survey; (ii) Tactful networking paradigm; (iii) Tactful networking applications in mobile communications; (iv) Framework for extracting human data; (v) Future directions (discussed to follow in Sec 7.3).

In the next section, we bring further discussions and out-of-scope subjects.

7.2 Further Discussions and Out of Scope Subjects

Following, through Q&A, we bring some further discussions about out-of-scope subjects of this thesis. We reassure that the focus of this work is the whole process for building a tactful opportunistic communication strategy for cost-effective content delivery in cellular networks. This process included surveying state-of-art and other goals already mentioned.

Q1: What is the difference between tactful networking solutions and what companies such as Google are doing regarding collecting information about the users from their mobile devices to shape novel solutions?

A1: Many technology companies collect user data from their mobile devices, and that relates to the Tactful Networking concept, particularly as data analytics is one of its key enablers. What Google does converges with Tactful Networking: We need to steer and adapt to user behavior and context to fulfill users' expectations while fostering innovative applications and services. That leads to a win-win situation. The user will have better QoE when accessing an operator network closer to his/her requirements (thus bringing the user the feeling of accessing services personally designed to her; one of the future considerations envisaged in 6G). Meanwhile, an operator can maximize profit by managing resources with lower cost and offering new services based on user-behavior understanding. In the last years the broader human-aware vision is helping to solve many networking challenges. Understanding more about human behavior can potentially boost solutions.

Q2: In section 2.1, several human-aware networking solutions are presented. Are they also considered tactful?

A2: Such related contributions pave the way and converge to what we denominate Tactful Networking. Tactful Networking is a perspective closer to individual aspects. It considers attributes that could link to performance and decouples the human factor from the networking system point of view, targeting a more personalized network service. Some of the attributes discussed in Sec. 2.1 are part of the Tactful Networking paradigm. These attributes, notions, and insights gathered from a broader view of the human perspective in networking were essential to develop TOOTS while targeting improved performance. Every human being is unique, so learning from these individuals makes it possible to develop suitable or personal solutions and applications.

Q3: Does TOOTS works in other scenarios besides the one presented?

A3: Yes. The proposed scenario only illustrates an application of the strategy to deliver content opportunistically through user empowerment. As previously stated, state-of-art works discussed more simplified scenarios or characteristics more distant to the real world. TOOTS can work or adapt to other opportunistic communication scenarios where the target is cost-effective content delivery from given sources to its destinations. It does not matter if the source is the mobile operator or a mobile node in the network that generates content for other users. TOOTS can assist scenarios where timely delivery is not the main concern, such as smartphone system updates, video advertisements, or scheduled on-demand content. The strategy shows that by using peculiar characteristics from human behavior, the content delivery system reaches superior performance in delivery rate, delivery latency, and overhead.

Q4: The strategy proposed herein relies on sensitive mobility data from users to achieve its goals. How does it work with the privacy of users?

A4: Privacy is a concern in Tactful Networking solutions since they rely on human-aware data. We assume the users' willingness to share their movement patterns (i.e., which is already very common). Other similar strategies discussed herein rely on the same kind of assumption. According to authors, such as [15], D2D and opportunistic communication enabled by AI will be one of the pieces of 6G. In [4] we discussed privacy as an essential element of Tactful Networking. Privacy techniques must protect the users, but in a way that does not harm innovation. Despite its importance, discussing privacy issues was out of the scope of this work. We assumed that implementing such ideas in the real world would need proper ways to protect their users' sensitive information (e.g., location coordinates). Several works propose mechanisms to guarantee privacy and anonymity in opportunistic networks [229, 230, 231]. These mechanisms are not trivial and sometimes require complex cryptography solutions and anonymization. Among the techniques used are generating pseudo node identifiers, onion routing [231], and public or symmetric key cryptography systems. Without privacy and trust mechanisms, it is hard to believe in massive real-world implementations of opportunistic D2D solutions. In TOOTS' proposed evaluation scenario, an idea would be to have a trustable entity to receive the nodes' required information to choose the disseminators set and generate pseudo-ID to the consumers (i.e., destination nodes) of a content. Cryptography mechanisms can also be studied to guarantee privacy and anonymity.

Q5: Mobile user devices have restricted or limited resources, such as storage, battery, and processing. Does TOOTS consider any such restrictions?

A5: These are definitely important concerns to consider in future work regarding TOOTS or other opportunistic strategies. Likewise, state-of-art did not focus on such limitations when building their strategies or algorithms, but more on strategy's performance itself. Some previous work relies on metrics that would not be feasible in the real world. In some examples, a specific set of "popular" users from a population would have their resources drained fast if they were cooperating to the opportunistic network goal. Such constraints are among the reasons why opportunistic D2D communication was not fully implemented in previous mobile network standards. The advent of smartphones and big data opens new opportunities to improve the performance of such content delivery solutions.

Q6: This work assumes that the users are willing to cooperate to deliver the content opportunistically. The incentive and reputation mechanisms play a crucial role in this kind of opportunistic environment, given the uncertainty, user selfishness, and other issues. For an operator to give incentives, such as the ones mentioned (i.e., data plan savings, bill discounts, access to paid content), they would concede to obtain some gains. What is the business model in this case?

A6: We discussed an evaluation scenario that links D2D with recent technologies (i.e., "hot topics" such as MEC). According to state-of-art research, D2D will be a MEC enabler in 5G/6G. We remark that the strategy can work in different scenarios where the intention is to deliver content opportunistically. There is a need to discuss other more realistic D2D scenarios to incentivize mobile carriers to invest in D2D solutions since they already have access to user data. The business model here would work with an operator making some concessions (i.e., incentives to its participating users), for obtaining gains. Among those, detouring a certain amount of traffic from its legacy network, increasing the network capillarity given by users' mobility, and offering connectivity in challenging situations (e.g., disasters, crowded places). Still, offloading benefits would have to be measured, and different types of contents with larger sizes also require evaluation. Building and applying incentive mechanisms are out of the scope of this thesis, so we assume that the users are willing to cooperate in the presented scenario.

In the following section, we discuss limitations of the presented work and future research directions for works based on the two branches of contributions of this thesis.

7.3 Limitations and Future Research Directions

7.3.1 A Tactful Opportunistic Communication Strategy

Along with this thesis, we discussed limitations or assumptions necessary for the tactful opportunistic communication strategy to increase the cost-effectiveness of a content delivery scenario. Among these limitations, there are several issues that we identified and can lead to future work. We describe and discuss those topics below:

Datasets and larger scenario evaluations: TOOTS and other state-of-art strategies need larger scales evaluations (i.e., in networks with more nodes). Previous solutions already showed

scalability issues. Despite the increased availability of real datasets in the last years, there is still a lack of those covering larger populations (e.g., whole metropolitan areas). These datasets will be essential for identifying possible insights for future strategies.

Metrics x Performance: There is a need to evaluate the correlation of each metric individually with the performance of the entire strategy. With that said, this knowledge can bring even more improved performance. As discussed throughout the thesis, TOOTS relies on different inherent human aspects. Not surprisingly, the presented strategy's results are more correlated with the real-world dataset used (NCCU). In this dataset, the human-aware time approach made it possible to calculate the metrics to reflect the users' routines with more granularity, possibly leading to better strategy performance. Other time-division approaches must be investigated through insights obtained from the study of other kinds of populations.

Proposing and analyzing new metrics: Apart from the metrics proposed, there is a multitude of possibilities when it comes to the tactful networking paradigm. Therefore, identifying and applying other metrics based on peculiar aspects of human mobility or behavior open new possibilities. Metrics can help to improve the overall performance of the strategy and tasks such as routing (e.g., relying on user interests and depending on the application types).

Overhead constraints: An important evaluation in the context of TOOTS would be to study the relation between overhead and opportunistic gain. For example, which are the cost x benefits for using the opportunistic strategy in an application scenario where data offloading is the main goal? Are the costs added to the network (i.e., to the nodes) reasonable for the amount of data offloaded? Using overhead thresholds could apply for studying such opportunistic gain;

Energy efficiency: Despite the increased capacity of mobile devices in the last years, energy (i.e., battery) is still a concern. TOOTS and most previous work did not study energy constraints within the algorithms. That is one of the critical issues when it comes to opportunistic networks. Energy efficiency in opportunistic communication links directly to tasks that consume many resources. Among those, the collection of mobility information (e.g., GPS), the forwarding and storage of messages, other networks and devices lookup, and the routing aspect (often adapted from conventional network algorithms). In TOOTS, we applied some metrics that might avoid wasting some resources (e.g., selecting contacts with longer durations to avoid forwarding interruptions), but the energy efficiency must be studied. In all cases, information from the human context can help predict situations and optimize energy consumption. For example, the knowledge of a user's meeting dynamics to forward messages to other devices that are more likely to take them to their final destination (reducing overhead). Nevertheless, the lookup and handover can happen at specific times, based on mobility prediction. The collection of user mobility information can also link to their routine habits, reducing the sampling frequency of the GPS, which tends to drain the battery of a mobile device quickly. Energy efficiency is paramount for the adoption of opportunistic communication strategies.

Incentive and Reputation mechanisms: Opportunistic communication works in a scenario where each individual has a device with limited resources, among those, bandwidth,

battery, storage, and memory. Because of these limitations, incentivizing collaboration is necessary since the success of these communication types is directly proportional to the adhesion of users. Previous work cited in Chap. 2 summarize proposed benefits such as financial and reciprocity. However, incentives can work more naturally by "imitating" social and human behavior. We do know that humans tend to cooperate when there is something in common. For example, social interactions and meeting dynamics can help to create incentive mechanisms between users who naturally share similarities in their daily lives. The same is true for reputation systems since users who have characteristics in common tend not to act greedy with their peers (in the peer-to-peer world, the well-known leechers). We assumed that the users in our scenario are willing to collaborate, but for real-world adoption of opportunistic forwarding, incentive and reputation mechanisms are necessary.

Security, privacy, and trust: The turnover of users connected to a mobile network and a large amount of information that travels through it also poses challenges related to the security and privacy of users' data. Authentication and authorization mechanisms to ensure that malicious individuals do not interfere are also necessary for this context. In the case of reliability management, the notion of interactions on mobile social networks has already been used [1]. Networks and circles of trust can be formed opportunistically from groups of people with a common interest, such as students in a classroom. Reliability can be propagated directly or indirectly among users. All of this must be done with concern for users' privacy, preventing their personal information from being used maliciously. Within our strategy (TOOTS), we assume there are mechanisms providing security, privacy, and trust, but there is a lack of building or adapting suitable mechanisms for industry implementations.

Simulation scenarios and parameters: Future work will need to evaluate TOOTS and other state-of-art proposals' effectiveness through varying contact ranges, bandwidth, increasing content size, and the number of days for the algorithm's learning phase. Furthermore, opportunistic strategies will need evaluations throughout modern D2D technologies specifications (i.e., wider communication range) and modern life scenarios (e.g., autonomous vehicles). As shown in this thesis, population characteristics, technological capabilities (e.g., contact range, bandwidth), and other aspects can impact the strategy's effectiveness.

7.3.2 Tactful Networking Paradigm

There are multiple issues from the human, networking, and computing systems perspectives for such a paradigm to progress. First, there is a need for changing modeling practices of network solutions. In addition to the focus on network performance and metrics, it is necessary to apply big data analytics related to human context and behavior information and to bring knowledge about human behavior combining ideas and methods from different areas such as machine learning, pervasive AI, HCI, stochastic modeling, psychology, sociology, computer networks, data science, and statistics. Throughout time, correlating this data will help analyze routines, build enhanced incentive mechanisms, and predict situations and behavior. This kind of information will apply to orchestrate better how the network shall behave from the operation point-of-view.

Second, emerging new applications, more people connected through more powerful smart-devices, cloud services massification, among others, bring data traffic raise and challenges to

network core and edge. The wireless communications technologies available will deal with improved capabilities user equipment that will accelerate the proliferation of performance-hungry applications. Such challenges call for having a new architectural paradigm for the current Internet. Here, intelligence should come from centralized computing facilities to distributed and in-network computation. The envisaged scenario is to have network intelligence pushed at the edge, much closer to UEs. Learning, reasoning, and decision making will provide distributed autonomy, replacing the classical centralized structures: Integrating collective intelligence in the network is essential. The natural Internet upgrade into a "network of subnetworks" is a new trend, where "local" evolution is the key principle to enhance situational awareness and adaptation of edge networks.

With the advent of smart devices and the big data era, multifaceted user information will bring novel opportunities. Therefore, future work will need to focus on identifying other human characteristics (e.g., personality traits) for proposing even more precise metrics to reflect human routines. Future Opportunistic D2D communication works will need to discuss envisaged scenarios with realistic challenges on crowded (i.e., metropolitan) areas and rural areas to motivate a more widespread adoption of human-centered technologies by the mobile carriers and industry.

Despite the traffic increase in the past few years, communication protocols remain limited. In many cases, they rely on strategies developed in the past, where the present scenario was not envisaged, much less the future. There is still a limited understanding of the characteristics that protocols must consider, including the traffic carried aspects and its generation context. Thus, intelligent protocols will be required to transport the requested information at the lowest possible cost to the network while simultaneously providing quality of service and experience for users [182].

Even with a vast literature available, there are still gaps in predicting human behavior under the influence of psychological, social, and demographic factors, among others, that should impact prediction models [232]. Quantitative studies are needed to uncover an expected degree or precision of these learning and predictions, which more suitable techniques to predict an individual's behavior, and how factors such as those above interfere with accuracy. Previous prediction methods require an extensive data history and high regularity of events. This fact reinforces the need to make datasets available and makes urgent the design of prediction techniques providing high accuracy while based on limited datasets.

Understanding the human decision-making process is also necessary, as the decisions we take can reflect in extracted human traits increasingly used as input to develop networking solutions. According to [143], "a group of individuals, no matter how highly organized it may be at any given instant, tends toward greater disorder or randomization, called entropy". Therefore, investigating and detecting what causes entropy, when, and why it happens in human decision-making is essential for future Tactful Networking solutions. The amount of individual entropy can also link to personality traits, which influence other human traits like mobility patterns, interactions, and social activities. Nevertheless, according to [143], Intrinsic Information Theory (IIT) is helpful to understand the conscious state of mind in decision-making. Consciousness is led by aspects such as spatial and temporal boundaries, information, and individual perspectives. Establishing this relationship with decision-making is essential, as we call for future network design to consider human behavioral aspects. Our behavior and individual characteristics directly impact how we demand network resources and what kind of resources are requested.

The Tactful Networking paradigm will also be a cornerstone for envisaged 6G that will empower our cities to be smart and fully connected with many services and devices. 6G will also be boosted by Deep Learning from Artificial Intelligence (AI), relying on data mining from network aspects and user devices and behavior to provide context-aware service-enabled communications. A human-aware AI layer will enable more intelligent network services deployment and empower applications such as autonomous driving and connected vehicles, haptic communications, augmented reality, smart healthcare, and smart homes. Concerning 6G challenges, the study of human aspects can bring insights to the future edge and cloud computing, higher networking densification (with even smaller cells to reduce latency and increase capacity), and dynamic topology environments.

Finally, whenever human user data is being collected, stored, or analyzed, suitable privacy-preserving mechanisms must be provided. Future Tactful Networking solutions must find the balance between privacy and user satisfaction, and among privacy and protocols, services, and application utility. These solutions or services must keep in mind that there will be no privacy implementation in real life if users are cut from their typical applications, services, or likes. Distributed management inherently disperses valuable information and facilitates the use of private-owned data management systems [233]. Therefore, distributed edge servers are much less likely to become the target of security attacks, reducing information leakage.

7.4 Concluding Remarks

The contributions of this thesis are ten-fold, divided in technical or conceptual. Among these contributions we highlight: (i) the full process for building a tactful opportunistic strategy for cost-effective content delivery in mobile networks, and (ii) the tactful networking paradigm as a cornerstone for future networking solutions. Our results showed that through this research direction which involves the human as part of the solution, it is possible to improve performance. We addressed multiple challenges and conclude that our technical and conceptual contributions and the shared intuitions have the potential to serve as a lead to a multitude of work in the networking domain when it comes to human-aware big data, and also to the specific field of opportunistic forwarding.

Bibliography

[1] R. Costa, L. Sampaio, A. Ziviani, and A. Viana, "Humanos no ciclo de comunicação: facilitadores das redes de próxima geração," in *Livro de Minicursos do XXXVI Simpósio Brasileiro de Redes de Computadores e Sistemas Distribuídos (SBRC) 2018*, (Campos do Jordão, SP), may 2018. (Cited on pages ix, 3, 6, 19 and 80.)

[2] R. L. Costa, A. Carneiro Viana, A. Ziviani, and L. N. Sampaio, "Towards human-aware d2d communication," in *2020 16th International Conference on Distributed Computing in Sensor Systems (DCOSS)*, pp. 173–180, 2020. (Cited on pages ix, 2, 3, 6, 20 and 26.)

[3] R. Costa, A. Viana, A. Ziviani, and L. Sampaio, "Extração e análise de dados como suporte a estratégias de comunicação d2d cientes do humano," in *Proceedings of the Brazilian Symposium on Computer Networks and Distributed Systems (SBRC)*, pp. 449–462, 12 2020. (Cited on pages ix, 1, 3, 7 and 32.)

[4] R. L. Costa, A. C. Viana, A. Ziviani, and L. N. Sampaio, "Tactful networking: Humans in the communication loop," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 5, no. 1, pp. 92–107, 2021. (Cited on pages ix, 1, 3, 4, 7, 9, 13, 19, 20, 32, 34, 44, 51 and 77.)

[5] R. L. Costa, A. C. Viana, A. Ziviani, and L. N. Sampaio, "Tactful opportunistic forwarding: What human routines and cooperation can improve?," in *Advanced Information Networking and Applications* (L. Barolli, I. Woungang, and T. Enokido, eds.), (Cham), pp. 638–652, Springer International Publishing, 2021. (Cited on pages ix, 3 and 7.)

[6] B. Raad and B. Mlacic, *Big Five Factor Model, Theory and Structure*, pp. 559–566. US: Elsevier, 12 2015. (Cited on pages xiii, 14, 16 and 17.)

[7] "Ericsson mobility report." [Online]. Available: https://www.ericsson.com/4adc87/assets/local/mobility-report/documents/2020/november-2020-ericsson-mobility-report.pdf, 2020. (Cited on page 1.)

[8] Cisco, "Visual networking index: Global mobile data traffic forecast update, 2017–2022 white paper." https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white-paper-c11-738429.html, 2019. Accessed: 2019-07-30. (Cited on page 1.)

[9] Cisco, "Annual internet report (2018–2023)." [Online]. Available: https://www.cisco.com/c/en/us/solutions/executive-perspectives/annual-internet-report/, 2020. (Cited on pages 1, 4 and 12.)

[10] I. F. Akyildiz, S. Nie, S.-C. Lin, and M. Chandrasekaran, "5g roadmap: 10 key enabling technologies," *Computer Networks*, vol. 106, no. Supplement C, pp. 17 – 48, 2016. (Cited on pages 1, 4, 11, 19 and 20.)

[11] M. Lauridsen, L. C. Gimenez, I. Rodriguez, T. B. Sorensen, and P. Mogensen, "From lte to 5g for connected mobility," *IEEE ComMag*, vol. 55, pp. 156–162, Mar. 2017. (Cited on pages 1 and 19.)

[12] R. Sofia and P. Mendes, "User-provided networks: consumer as provider," *IEEE ComMag*, vol. 46, pp. 86–91, Dec. 2008. (Cited on pages 1, 10 and 75.)

[13] R.-G. Cheng, N.-S. Chen, Y.-F. Chou, and Z. Becvar, "Offloading multiple mobile data contents through opportunistic device-to-device communications," *Wireless Personal Commun.*, vol. 84, pp. 1963–1979, Oct 2015. (Cited on pages 1, 2, 35 and 42.)

[14] I. O. Nunes, C. Celes, I. Nunes, P. O. S. Vaz de Melo, and A. A. F. Loureiro, "Combining spatial and social awareness in d2d opportunistic routing," *IEEE Communications Magazine*, vol. 56, pp. 128–135, Jan 2018. (Cited on pages 1, 2, 12, 17, 24, 25, 33, 35, 37, 39, 41, 42, 44, 45, 46 and 70.)

[15] S. Zhang, J. Liu, H. Guo, M. Qi, and N. Kato, "Envisioning device-to-device communications in 6g," *IEEE Network*, vol. 34, no. 3, pp. 86–91, 2020. (Cited on pages 1, 3, 4, 22 and 77.)

[16] M. Conti, C. Boldrini, S. S. Kanhere, E. Mingozzi, E. Pagani, P. M. Ruiz, and M. Younis, "From manet to people-centric networking: Milestones and open research challenges," *Comput. Commun.*, vol. 71, no. Supplement C, pp. 1 – 21, 2015. (Cited on page 1.)

[17] R. Schoenen, G. Bulu, A. Mirtaheri, T. Beitelmal, and H. Yanikomeroglu, "First survey results of quantified user behavior in user-in-the-loop scenarios for sustainable wireless networks," in *Proc. IEEE VTC Fall*, pp. 1–5, IEEE, Sep. 2012. (Cited on page 1.)

[18] L. Duan, L. Huang, C. Langbort, A. Pozdnukhov, J. Walrand, and L. Zhang, "Human-in-the-loop mobile networks: A survey of recent advancements," *IEEE Journal on Selected Areas in Communications*, vol. 35, pp. 813–831, April 2017. (Cited on pages 1 and 11.)

[19] A. Junior and R. Sofia, "Energy-efficient routing in user-centric environments," in *Proc. IEEE/ACM Greencom/CPSCom*, pp. 436–441, IEEE, Dec 2010. (Cited on page 1.)

[20] Z. Wang, R. Schoenen, H. Yanikomeroglu, and M. St-Hilaire, "Load balancing in cellular networks with user-in-the-loop: A spatial traffic shaping approach," in *Proc. IEEE ICC*, pp. 2638–2643, Jun. 2015. (Cited on pages 1 and 11.)

[21] P. Hui, J. Crowcroft, and E. Yoneki, "Bubble rap: Social-based forwarding in delay-tolerant networks," *IEEE TMC*, vol. 10, pp. 1576–1589, Nov 2011. (Cited on pages 1, 2, 17, 24, 35, 40, 41, 42, 44 and 46.)

[22] I. O. Nunes, P. O. S. V. de Melo, and A. A. F. Loureiro, "Leveraging d2d multihop communication through social group meeting awareness," *IEEE Wireless Communications*, vol. 23, no. 4, pp. 12–19, 2016. (Cited on pages 1, 2, 11, 14, 17, 24, 25, 35, 42 and 46.)

[23] Q. Yan, W. Chen, B. Bai, and H. V. Poor, "Multicast-pushing with human-in-the-loop: Where social networks meet wireless communications," in *Proc. IEEE ICC*, pp. 1–6, May 2017. (Cited on pages 1 and 11.)

[24] D. Wang, Y. Lan, T. Zhao, Z. Yin, and X. Wang, "On the design of computation offloading in cache-aided d2d multicast networks," *IEEE Access*, vol. 6, pp. 63426–63441, 2018. (Cited on pages 1 and 12.)

[25] T. H. Silva, A. C. Viana, F. Benevenuto, L. Villas, J. Salles, A. Loureiro, and D. Quercia, "Urban computing leveraging location-based social network data: A survey," *ACM Comput. Surv.*, vol. 52, pp. 17:1–17:39, Feb. 2019. (Cited on pages 1, 12, 14 and 18.)

[26] H. Zhang, W. Huang, and Y. Liu, "Handover probability analysis of anchor-based multi-connectivity in 5g user-centric network," *IEEE Wireless Commun. Letters*, vol. 8, pp. 396–399, Apr. 2019. (Cited on pages 1 and 12.)

[27] W. Moreira, P. Mendes, and S. Sargento, "Opportunistic routing based on daily routines," in *IEEE WoWMoM*, pp. 1–6, 2012. (Cited on pages 2, 24, 35 and 42.)

[28] P. Mendes, W. Moreira, and S. Sargento, "Social-aware opportunistic routing protocol based on user's interactions and interests," *Ad Hoc Networks*, vol. 129, 10 2013. (Cited on pages 2, 25, 35 and 42.)

[29] K. Thilakarathna, A. C. Viana, A. Seneviratne, and H. Petander, "Design and analysis of an efficient friend-to-friend content dissemination system," *IEEE Transactions on Mobile Computing*, vol. 16, no. 3, pp. 702–715, 2017. (Cited on pages 2, 24, 35, 46, 55, 57, 63 and 66.)

[30] T. Tsai and H. Chan, "Nccu trace: social-network-aware mobility trace," *IEEE Communications Magazine*, vol. 53, no. 10, pp. 144–149, 2015. (Cited on pages 2 and 30.)

[31] S. Kosta, A. Mei, and J. Stefa, "Large-scale synthetic social mobile networks with swim," *IEEE Transactions on Mobile Computing*, vol. 13, no. 1, pp. 116–129, 2014. (Cited on page 2.)

[32] I. O. Nunes, C. Celes, M. D. Silva, P. O. Vaz de Melo, and A. A. Loureiro, "Grm: Group regularity mobility model," in *Proc. ACM MSWiM*, pp. 85–89, 2017. (Cited on pages 2 and 30.)

[33] CHIST-ERA, "MACACO android application (MACACOApp)." `http://macaco.inria.fr/macacoapp/`, Dec. 2015. (Cited on pages 3 and 30.)

[34] A. Cuttone, S. Lehmann, and M. C. González, "Understanding predictability and exploration in human mobility," *EPJ Data Science*, vol. 7, p. 2, Jan 2018. (Cited on page 3.)

[35] I. O. Nunes, C. Celes, I. Nunes, P. O. S. V. de Melo, and A. A. F. Loureiro, "Combining spatial and social awareness in d2d opportunistic routing," *IEEE Communications Magazine*, vol. 56, pp. 128–135, Jan 2018. (Cited on pages 3 and 46.)

[36] K. Jaffrès-Runser, G. Jakllari, T. Peng, and V. Nitu, "Crowdsensing mobile content and context data: Lessons learned in the wild," in *Proc. IEEE PERCOM Workshops*, pp. 311–315, Mar. 2017. (Cited on page 4.)

[37] R. D. Oliveira, M. Cherubini, and N. Oliver, "Influence of personality on satisfaction with mobile phone services," *ACM Trans. Comput.-Hum. Interact.*, vol. 20, pp. 10:1–10:23, May 2013. (Cited on pages 4 and 14.)

[38] Q. Yan, W. Chen, and H. V. Poor, "Big data driven wireless communications: A human-in-the-loop pushing technique for 5g systems," *IEEE Wireless Commun.*, vol. 25, pp. 64–69, Feb. 2018. (Cited on page 4.)

[39] P. K. Mishra, A. K. Mishra, and S. Tripathi, "Relay selection scheme for dynamic network scenario in multi-hop d2d communication," in *IEEE ICCCS*, pp. 538–542, 2019. (Cited on page 4.)

[40] M. Waqas, Y. Niu, Y. Li, M. Ahmed, D. Jin, S. Chen, and Z. Han, "A comprehensive survey on mobility-aware d2d communications: Principles, practice and challenges," *IEEE Communications Surveys Tutorials*, vol. 22, no. 3, pp. 1863–1886, 2020. (Cited on page 4.)

[41] W. Lee, M. Kim, and D.-H. Cho, "Transmit power control using deep neural network for underlay device-to-device communication," *IEEE Wireless Communications Letters*, vol. 8, no. 1, pp. 141–144, 2019. (Cited on page 4.)

[42] A. Markhasin, A. Zolotuev, and V. Belenky, "The 5g ubiquitous directional communication technologies of public e-health for rural and remote areas," in *2019 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON)*, pp. 1002–1006, 2019. (Cited on page 4.)

[43] S. Sharma, N. Gupta, and V. A. Bohara, "Insights from the measurement results for adaptive and cooperative d2d communication framework," in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, 2018. (Cited on page 4.)

[44] R. Bolla, R. Rapuzzi, and M. Repetto, "Handling mobility over the network," in *Proc. ACM CFI*, pp. 16–19, 2009. (Cited on page 10.)

[45] S. Vihavainen, A. Oulasvirta, and R. Sarvas, "I can't lie anymore!: The implications of location automation for mobile social applications," in *Proc. IEEE MobiQuitous*, pp. 1–10, Jul. 2009. (Cited on page 10.)

[46] G. Biczók, L. Toka, A. Vidacs, and T. A. Trinh, "On incentives in global wireless communities," in *Proc. ACM U-NET Workshop*, pp. 1–6, 2009. (Cited on page 10.)

[47] A. Mislove, B. Viswanath, K. P. Gummadi, and P. Druschel, "You are who you know: Inferring user profiles in online social networks," in *Proc. ACM WSDM*, pp. 251–260, 2010. (Cited on page 10.)

[48] P. Olmo Vaz de Melo, A. Carneiro Viana, M. Fiore, K. Jaffrès-Runser, F. Le Mouël, A. A. F. Loureiro, L. Addepalli, and G. Chen, "RECAST: Telling Apart Social and Random Relationships in Dynamic Networks," *Performance Evaluation*, vol. 87, pp. 1–1, Mar. 2015. (Cited on pages 10, 14, 17 and 33.)

[49] T. Hossmann, T. Spyropoulos, and F. Legendre, "Know thy neighbor: Towards optimal mapping of contacts to social graphs for dtn routing," in *Proc. IEEE INFOCOM*, pp. 1–9, Mar. 2010. (Cited on page 10.)

[50] M. Balman, E. Chaniotakisy, A. Shoshani, and A. Sim, "A flexible reservation algorithm for advance network provisioning," in *Proc. ACM/IEEE SC*, pp. 1–11, Nov. 2010. (Cited on page 10.)

[51] A. Sehgal and R. Agrawal, "Qos based network selection scheme for 4g systems," *IEEE Trans. on Consumer Elect.*, vol. 56, pp. 560–565, May 2010. (Cited on page 10.)

[52] J. Antoniou, V. Papadopoulou, V. Vassiliou, and A. Pitsillides, "Cooperative user–network interactions in next generation communication networks," *Comput. Netw.*, vol. 54, no. 13, pp. 2239 – 2255, 2010. (Cited on page 10.)

[53] A. G. Ribeiro, R. Sofia, and A. Zúquete, "Improving mobile networks based on social mobility modeling," in *Proc IEEE ICNP*, pp. 289–291, Oct 2011. (Cited on page 10.)

[54] J. Cho, A. Swami, and I. Chen, "A survey on trust management for mobile ad hoc networks," *IEEE Commun. Surveys Tutorials*, vol. 13, no. 4, pp. 562–583, 2011. (Cited on page 10.)

[55] D. Christin, A. Reinhardt, S. S. Kanhere, and M. Hollick, "A survey on privacy in mobile participatory sensing applications," *Journal of Systems and Software*, vol. 84, no. 11, pp. 1928 – 1946, 2011. (Cited on page 10.)

[56] E. Ibarrola, J. Xiao, F. Liberal, and A. Ferro, "Internet qos regulation in future networks: a user-centric approach," *IEEE ComMag*, vol. 49, pp. 148–155, Oct 2011. (Cited on page 10.)

[57] A. Jimenez-Molina and I.-Y. Ko, "Spontaneous task composition in urban computing environments based on social, spatial, and temporal aspects," *Engineering Appl. of Artif. Intelligence*, vol. 24, no. 8, pp. 1446 – 1460, 2011. (Cited on page 10.)

[58] Y. Lu, M. Motani, and W.-C. Wong, "The user-context module: A new perspective on future internet design," *Procedia Comput. Science*, vol. 5, pp. 280 – 287, 2011. (Cited on page 10.)

[59] A. Tudzarov and T. Janevski, "Functional architecture for 5g mobile networks," *Int. Journal of Adv. Science and Technol.*, vol. 3, 08 2011. (Cited on page 10.)

[60] R. Sofia, P. Mendes, M. Damásio, S. Henriques, F. Giglietto, E. Giambitto, and A. Bogliolo, "Moving towards a socially-driven internet architectural design," *Proc. ACM SIGCOMM*, vol. 42, 07 2012. (Cited on page 10.)

[61] E. Palomar, A. Alcaide, A. Ribagorda, and Y. Zhang, "The peer's dilemma: A general framework to examine cooperation in pure peer-to-peer systems," *Comput. Netw.*, vol. 56, no. 17, pp. 3756 – 3766, 2012. (Cited on page 10.)

[62] S. Zarifzadeh, N. Yazdani, and A. Nayyeri, "Energy-efficient topology control in wireless ad hoc networks with selfish nodes," *Comput. Netw.*, vol. 56, no. 2, pp. 902 – 914, 2012. (Cited on page 10.)

[63] M. Yildiz, M. A. Khan, F. Sivrikaya, and S. Albayrak, "Cooperation incentives based load balancing in ucn: A probabilistic approach," in *Proc. IEEE GLOBECOM*, pp. 2746–2752, Dec 2012. (Cited on page 10.)

[64] C. Huang, G. M. Lee, and N. Crespi, "A semantic enhanced service exposure model for a converged service environment," *IEEE ComMag*, vol. 50, pp. 32–40, Mar. 2012. (Cited on page 10.)

[65] H. Tuncer, S. Mishra, and N. Shenoy, "A survey of identity and handoff management approaches for the future internet," *Comput. Commun.*, vol. 36, no. 1, pp. 63 – 79, 2012. (Cited on page 10.)

[66] Y. Najaflou, B. Jedari, F. Xia, L. T. Yang, and M. S. Obaidat, "Safety challenges and solutions in mobile social networks," *IEEE Systems Journal*, vol. 9, pp. 834–854, Sep. 2013. (Cited on page 11.)

[67] M. Yildiz and M. A. Khan, "Mobility behavior modeling in ucn," in *Proc. IEEE WCNC*, pp. 2184–2189, Apr. 2013. (Cited on page 11.)

[68] P. Bellavista, R. Montanari, and S. K. Das, "Mobile social networking middleware: A survey," *Pervasive and Mobile Comput.*, vol. 9, no. 4, pp. 437 – 453, 2013. (Cited on page 11.)

[69] M. Amani, A. Aijaz, N. Uddin, and A. H. Aghvami, "On mobile data offloading policies in heterogeneous wireless networks," in *Proc. IEEE VTC Spring*, pp. 1–5, Jun. 2013. (Cited on page 11.)

[70] M. Conti, M. Mordacchini, and A. Passarella, "Design and performance evaluation of data dissemination systems for opportunistic networks based on cognitive heuristics," *ACM Trans. Auton. Adapt. Syst.*, vol. 8, pp. 12:1–12:32, Sept. 2013. (Cited on page 11.)

[71] J. Wu, M. Xiao, and L. Huang, "Homing spread: Community home-based multi-copy routing in mobile social networks," in *Proc. IEEE INFOCOM*, pp. 2319–2327, Apr. 2013. (Cited on page 11.)

[72] Y. Zhu, B. Xu, X. Shi, and Y. Wang, "A survey of social-based routing in delay tolerant networks: Positive and negative social effects," *IEEE Commun. Surveys Tutorials*, vol. 15, pp. 387–401, First 2013. (Cited on pages 11 and 17.)

[73] G. Aloi, M. D. Felice, V. Loscrì, P. Pace, and G. Ruggeri, "Spontaneous smartphone networks as a user-centric solution for the future internet," *IEEE ComMag*, vol. 52, pp. 26–33, Dec. 2014. (Cited on page 11.)

[74] T. Jamal and P. Mendes, "Cooperative relaying in user-centric networking under interference conditions," *IEEE ComMag*, vol. 52, pp. 18–24, Dec. 2014. (Cited on page 11.)

[75] M. N. Tehrani, M. Uysal, and H. Yanikomeroglu, "Device-to-device communication in 5g cellular networks: challenges, solutions, and future directions," *IEEE ComMag*, vol. 52, pp. 86–92, May 2014. (Cited on page 11.)

[76] B. Bangerter, S. Talwar, R. Arefi, and K. Stewart, "Networks and devices for the 5g era," *IEEE ComMag*, vol. 52, pp. 90–96, Feb. 2014. (Cited on page 11.)

[77] C. I, C. Rowell, S. Han, Z. Xu, G. Li, and Z. Pan, "Toward green and soft: a 5g perspective," *IEEE ComMag*, vol. 52, pp. 66–73, Feb. 2014. (Cited on page 11.)

[78] A. Ferragut and F. Paganini, "Network resource allocation for users with multiple connections: Fairness and stability," *IEEE/ACM Trans. on Netw.*, vol. 22, pp. 349–362, Apr. 2014. (Cited on page 11.)

[79] X. Xing, T. Jing, W. Zhou, X. Cheng, Y. Huo, and H. Liu, "Routing in user-centric networks," *IEEE ComMag*, vol. 52, pp. 44–51, Sep. 2014. (Cited on page 11.)

[80] P. A. Frangoudis and G. C. Polyzos, "Security and performance challenges for user-centric wireless networking," *IEEE ComMag*, vol. 52, pp. 48–55, Dec. 2014. (Cited on page 11.)

[81] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "Incentive mechanisms for user-provided networks," *IEEE ComMag*, vol. 52, pp. 20–27, Sep. 2014. (Cited on page 11.)

[82] G. Lee, H. Kim, Y. Cho, and S. Lee, "Qoe-aware scheduling for sigmoid optimization in wireless networks," *IEEE Commun. Letters*, vol. 18, pp. 1995–1998, Nov 2014. (Cited on page 11.)

[83] M. Katsarakis, G. Fortetsanakis, P. Charonyktakis, A. Kostopoulos, and M. Papadopouli, "On user-centric tools for qoe-based recommendation and real-time analysis of large-scale markets," *IEEE ComMag*, vol. 52, pp. 37–43, Sep. 2014. (Cited on page 11.)

[84] M. Conti and S. Giordano, "Mobile ad hoc networking: milestones, challenges, and new research directions," *IEEE ComMag*, vol. 52, pp. 85–96, Jan. 2014. (Cited on page 11.)

[85] M. Eslami, O. Karimi, and T. Khodadadi, "A survey on wireless mesh networks: Architecture, specifications and challenges," in *Proc. IEEE ICSGRC*, pp. 219–222, Aug 2014. (Cited on page 11.)

[86] R. Schoenen and H. Yanikomeroglu, "User-in-the-loop: spatial and temporal demand shaping for sustainable wireless networks," *IEEE ComMag*, vol. 52, pp. 196–203, Feb. 2014. (Cited on page 11.)

[87] D. S. Nunes, P. Zhang, and J. Sá Silva, "A survey on human-in-the-loop applications towards an internet of all," *IEEE Commun. Surveys Tutorials*, vol. 17, pp. 944–965, Secondquarter 2015. (Cited on page 11.)

[88] D. Syrivelis, G. Iosifidis, D. Delimpasis, K. Chounos, T. Korakis, and L. Tassiulas, "Bits and coins: Supporting collaborative consumption of mobile internet," in *Proc. IEEE INFOCOM*, pp. 2146–2154, Apr. 2015. (Cited on page 11.)

[89] P. Castagno, R. Gaeta, M. Grangetto, and M. Sereno, "Device-to-device content distribution in cellular networks: A user-centric collaborative strategy," in *Proc. IEEE GLOBECOM*, pp. 1–6, Dec 2015. (Cited on page 11.)

[90] P. Ameigeiras, J. J. Ramos-munoz, L. Schumacher, J. Prados-Garzon, J. Navarro-Ortiz, and J. M. Lopez-soler, "Link-level access cloud architecture design based on sdn for 5g networks," *IEEE Network*, vol. 29, pp. 24–31, Mar. 2015. (Cited on page 11.)

[91] F. Rebecchi, M. Dias de Amorim, V. Conan, A. Passarella, R. Bruno, and M. Conti, "Data offloading techniques in cellular networks: A survey," *IEEE Commun. Surveys Tutorials*, vol. 17, no. 2, pp. 580–603, 2015. (Cited on pages 11, 14 and 17.)

[92] D. Montero, M. Yannuzzi, A. Shaw, L. Jacquin, A. Pastor, R. Serral-Gracia, A. Lioy, F. Risso, C. Basile, R. Sassu, M. Nemirovsky, F. Ciaccia, M. Georgiades, S. Charalambides, J. Kuusijarvi, and F. Bosco, "Virtualized security at the network edge: a user-centric approach," *IEEE ComMag*, vol. 53, pp. 176–186, Apr. 2015. (Cited on page 11.)

[93] H. Mousa, S. B. Mokhtar, O. Hasan, O. Younes, M. Hadhoud, and L. Brunie, "Trust management and reputation systems in mobile participatory sensing applications: A survey," *Comput. Netw.*, vol. 90, pp. 49 – 73, 2015. (Cited on page 11.)

[94] X. Hu, T. H. S. Chu, V. C. M. Leung, E. C. . Ngai, P. Kruchten, and H. C. B. Chan, "A survey on mobile social networks: Applications, platforms, system architectures, and future research directions," *IEEE Commun. Surveys Tutorials*, vol. 17, no. 3, pp. 1557–1581, 2015. (Cited on page 11.)

[95] X. Wang, X. Li, and V. C. M. Leung, "Tasa: traffic offloading by tag-assisted social-aware opportunistic sharing in mobile social networks," in *The 21st IEEE International Workshop on Local and Metropolitan Area Networks*, pp. 1–6, April 2015. (Cited on page 11.)

[96] F. Delmastro, V. Arnaboldi, and M. Conti, "People-centric computing and communications in smart cities," *IEEE ComMag*, vol. 54, pp. 122–128, Jul. 2016. (Cited on page 11.)

[97] M. Kamel, W. Hamouda, and A. Youssef, "Ultra-dense networks: A survey," *IEEE Commun. Surveys Tutorials*, vol. 18, no. 4, pp. 2522–2545, 2016. (Cited on page 11.)

[98] J. Park, S. Y. Jung, S. Kim, M. Bennis, and M. Debbah, "User-centric mobility management in ultra-dense cellular networks under spatio-temporal dynamics," in *Proc. IEEE GLOBECOM*, pp. 1–6, Dec 2016. (Cited on page 11.)

[99] V. Arnaboldi, M. Conti, M. La Gala, A. Passarella, and F. Pezzoni, "Ego network structure in online social networks and its impact on information diffusion," *Comput. Commun.*, vol. 76, pp. 26–41, Feb. 2016. (Cited on page 11.)

[100] P. Charonyktakis, M. Plakia, I. Tsamardinos, and M. Papadopouli, "On user-centric modular qoe prediction for voip based on machine-learning algorithms," *IEEE Trans. on Mobile Comput.*, vol. 15, pp. 1443–1456, Jun. 2016. (Cited on page 11.)

[101] S. CC, V. Raychoudhury, G. Marfia, and A. Singla, "A survey of routing and data dissemination in delay tolerant networks," *J. Netw. Comput. Appl.*, vol. 67, pp. 128–146, May 2016. (Cited on page 11.)

[102] K. I. Pedersen, M. Niparko, J. Steiner, J. Oszmianski, L. Mudolo, and S. R. Khosravirad, "System level analysis of dynamic user-centric scheduling for a flexible 5g design," in *Proc. IEEE GLOBECOM*, pp. 1–6, Dec 2016. (Cited on page 11.)

[103] P. Gandotra, R. K. Jha, and S. Jain, "A survey on device-to-device (d2d) communication: Architecture and security issues," *Journal of Network and Computer Applications*, vol. 78, no. Supplement C, pp. 9 – 29, 2017. (Cited on page 11.)

[104] M. Kamel, W. Hamouda, and A. Youssef, "Performance analysis of multiple association in ultra-dense networks," *IEEE Trans. on Commun.*, vol. 65, pp. 3818–3831, Sep. 2017. (Cited on page 11.)

[105] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, "A survey on mobile edge networks: Convergence of computing, caching and communications," *IEEE Access*, vol. 5, pp. 6757–6779, 2017. (Cited on page 11.)

[106] S. Barmpounakis, A. Kaloxylos, P. Spapis, and N. Alonistioti, "Context-aware, user-driven, network-controlled rat selection for 5g networks," *Comput. Netw.*, vol. 113, pp. 124–147, Feb. 2017. (Cited on page 12.)

[107] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "Efficient and fair collaborative mobile internet access," *IEEE/ACM Transactions on Networking*, vol. 25, pp. 1386–1400, June 2017. (Cited on page 12.)

[108] J. Ma, J. Wang, and P. Fan, "A cooperation-based caching scheme for heterogeneous networks," *IEEE Access*, vol. 5, pp. 15013–15020, 2017. (Cited on page 12.)

[109] N. Cruz and H. Miranda, "Recurring contacts between groups of devices: Analysis and application," *IEEE Trans. on Mobile Comput.*, vol. 17, pp. 1666–1679, Jul. 2018. (Cited on page 12.)

[110] Y. Meng, C. Jiang, H. H. Chen, and Y. Ren, "Cooperative device-to-device communications: Social networking perspectives," *IEEE Network*, vol. 31, pp. 38–44, May 2017. (Cited on pages 12 and 17.)

[111] D. Tsolkas, E. Liotou, N. Passas, and L. Merakos, "A survey on parametric qoe estimation for popular services," *Journal of Netw. and Comput. Appl.*, vol. 77, 01 2017. (Cited on page 12.)

[112] T. Qiu, N. Chen, K. Li, M. Atiquzzaman, and W. Zhao, "How can heterogeneous internet of things build our future: A survey," *IEEE Communications Surveys Tutorials*, vol. PP, no. 99, pp. 1–1, 2018. (Cited on page 12.)

[113] Q. Yan, W. Chen, and H. V. Poor, "Big data driven wireless communications: A human-in-the-loop pushing technique for 5g systems," *IEEE Wireless Commun.*, vol. 25, pp. 64–69, Feb. 2018. (Cited on page 12.)

[114] E. K. Wang, Y. Li, Y. Ye, S. M. Yiu, and L. C. K. Hui, "A dynamic trust framework for opportunistic mobile social networks," *IEEE Transactions on Network and Service Management*, vol. 15, pp. 319–329, March 2018. (Cited on page 12.)

[115] J. Yan, D. Wu, H. Wang, and R. Wang, "User centric content sharing based on d2d cellular networks," *IEEE Trans. on Vehicular Technol.*, vol. 67, pp. 11208–11218, Nov 2018. (Cited on page 12.)

[116] A. Aijaz, "Toward human-in-the-loop mobile networks: A radio resource allocation perspective on haptic communications," *IEEE Trans. on Wireless Commun.*, vol. 17, pp. 4493–4508, Jul. 2018. (Cited on page 12.)

[117] G. Zhang, F. Ke, Y. Peng, C. Zhang, and H. Zhang, "User access and resource allocation in full-duplex user-centric ultra-dense heterogeneous networks," in *Proc. IEEE GLOBECOM*, pp. 1–6, Dec 2018. (Cited on page 12.)

[118] S. Zhang, P. He, K. Suto, P. Yang, L. Zhao, and X. Shen, "Cooperative edge caching in user-centric clustered mobile networks," *IEEE Trans. on Mobile Comput.*, vol. 17, pp. 1791–1805, Aug 2018. (Cited on page 12.)

[119] Y. Yang, X. Deng, D. He, Y. You, and R. Song, "Machine learning inspired codeword selection for dual connectivity in 5g user-centric ultra-dense networks," *IEEE Trans. on Vehicular Technol.*, vol. 68, pp. 8284–8288, Aug 2019. (Cited on page 12.)

[120] A. S. Shafigh, S. Glisic, E. Hossain, B. Lorenzo, and L. A. DaSilva, "User-centric distributed spectrum sharing in dynamic network architectures," *IEEE/ACM Trans. on Netw.*, vol. 27, pp. 15–28, Feb 2019. (Cited on page 12.)

[121] S. Zaidi, O. Ben Smida, S. Affes, U. Vilaipornsawai, L. Zhang, and P. Zhu, "User-centric base-station wireless access virtualization for future 5g networks," *IEEE Trans. on Commun.*, vol. 67, pp. 5190–5202, Jul. 2019. (Cited on page 12.)

[122] W. Saad, M. Bennis, and M. Chen, "A vision of 6g wireless systems: Applications, trends, technologies, and open research problems," *IEEE Network*, vol. 34, no. 3, pp. 134–142, 2020. (Cited on pages 12 and 22.)

[123] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y. A. Zhang, "The roadmap to 6g: Ai empowered wireless networks," *IEEE Communications Magazine*, vol. 57, no. 8, pp. 84–90, 2019. (Cited on pages 12 and 22.)

[124] K. Antonakoglou, X. Xu, E. Steinbach, T. Mahmoodi, and M. Dohler, "Toward haptic communications over the 5g tactile internet," *IEEE Commun. Surveys & Tutorials*, vol. 20, no. 4, pp. 3034–3059, 2018. (Cited on page 13.)

[125] A. Aijaz and M. Sooriyabandara, "The tactile internet for industries: A review," *Proc. of the IEEE*, vol. 107, no. 2, pp. 414–435, 2019. (Cited on page 13.)

[126] K. Thilakarathna, S. Seneviratne, K. Gupta, M. A. Kaafar, and A. Seneviratne, "A deep dive into location-based communities in social discovery networks," *Computer Communications*, vol. 100, 11 2016. (Cited on pages 14, 18 and 33.)

[127] C. Comito, D. Falcone, and D. Talia, "Mining human mobility patterns from social geotagged data," *Pervasive and Mobile Comput.*, vol. 33, pp. 91 – 107, 2016. (Cited on pages 14 and 33.)

[128] E. M. R. Oliveira, A. C. Viana, C. Sarraute, J. Brea, and I. Alvarez-Hamelin, "On the regularity of human mobility," *Pervasive and Mobile Computing*, vol. 33, no. Supplement C, pp. 73 – 90, 2016. (Cited on pages 14, 15, 16, 17, 24, 44, 45 and 58.)

[129] V. F. Mota, F. D. Cunha, D. F. Macedo, J. M. Nogueira, and A. A. Loureiro, "Protocols, mobility models and tools in opportunistic networks: A survey," *Comput. Commun.*, vol. 48, pp. 5 – 19, 2014. Opportunistic networks. (Cited on page 14.)

[130] D. Koll, J. Li, and X. Fu, "The good left undone: Advances and challenges in decentralizing online social networks," *Comput. Commun.*, vol. 108, pp. 36 – 51, 2017. (Cited on page 14.)

[131] G. Zyba, G. M. Voelker, S. Ioannidis, and C. Diot, "Dissemination in opportunistic mobile ad-hoc networks: The power of the crowd," in *Proc. IEEE INFOCOM*, pp. 1179–1187, Apr. 2011. (Cited on page 14.)

[132] M. C. González, C. A. Hidalgo, and A.-L. Barabási, "Understanding individual human mobility patterns," *Nature*, vol. 453, pp. 779–782, June 2008. (Cited on pages 14, 16 and 17.)

[133] G. Chen, S. Hoteit, A. C. Carneiro Viana, M. Fiore, and C. Sarraute, "Enriching sparse mobility information in Call Detail Records," *Computer Communications*, vol. 122, pp. 44–58, 2018. (Cited on pages 14, 17, 24 and 32.)

[134] C. Song, Z. Qu, N. Blumm, and A.-L. Barabasi, "Limits of predictability in human mobility," *Science*, vol. 327, pp. 1018–1021, Feb. 2010. (Cited on pages 14, 16, 17, 24, 32 and 44.)

[135] B. A. A. Nunes, M. A. S. Santos, B. T. de Oliveira, C. B. Margi, K. Obraczka, and T. Turletti, "Software-defined-networking-enabled capacity sharing in user-centric networks," *IEEE ComMag*, vol. 52, pp. 28–36, Sep. 2014. (Cited on page 14.)

[136] I. F. Akyildiz, P. Wang, and S.-C. Lin, "Softair: A software defined networking architecture for 5g wireless systems," *Comput. Netw.*, vol. 85, pp. 1 – 18, 2015. (Cited on page 14.)

[137] M. J. Chorley, R. M. Whitaker, and S. M. Allen, "Personality and location-based social networks," *Comput. in Human Behavior*, vol. 46, pp. 45–56, 2015. (Cited on pages 14 and 16.)

[138] J. Staiano, F. Pianesi, B. Lepri, N. Sebe, N. Aharony, and A. Pentland, "Friends don't lie," in *Proc. ACM UbiComp*, 2012. (Cited on page 14.)

[139] A. Paudel, B. R. Bajracharya, M. Ghimire, N. Bhattarai, and D. S. Baral, "Using personality traits information from social media for music recommendation," in *Proc. IEEE ICCCS*, pp. 116–121, Oct 2018. (Cited on page 14.)

[140] H. Ning, S. Dhelim, and N. Aung, "Personet: Friend recommendation system based on big-five personality traits and hybrid filtering," *IEEE Trans. on Comput. Social Systems*, vol. 6, pp. 394–402, Jun. 2019. (Cited on page 14.)

[141] L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan, "Group formation in large social networks: membership, growth, and evolution," in *Proc. ACM SIGKDD*, pp. 44–54, 2006. (Cited on pages 14 and 18.)

[142] M. Buchanan, "Behavioural Science: Secret signals," *Nature*, vol. 457, pp. 528–530, Jan. 2009. (Cited on pages 14 and 18.)

[143] J. Rodger, "Quantumis: A qualia consciousness awareness and information theory quale approach to reducing strategic decision-making entropy," *Entropy*, vol. 21, p. 125, 01 2019. (Cited on pages 15 and 81.)

[144] C. M. Schneider, V. Belik, and M. C. G. Thomas Couronné, Zbigniew Smoreda, "Unravelling daily human mobility motifs journal of the royal society interface," *Journal of The Royal Society Interface*, vol. 10, no. 84, p. 1, 2013. (Cited on page 16.)

[145] Y.-A. Montjoye, C. Hidalgo, M. Verleysen, and V. Blondel, "Unique in the crowd: The privacy bounds of human mobility," *Scientific reports*, vol. 3, p. 1376, 03 2013. (Cited on pages 16 and 32.)

[146] A. Cuttone, S. Lehmann, and M. C. González, "Understanding predictability and exploration in human mobility," *EPJ Data Science*, vol. 7, p. 2, Jan 2018. (Cited on pages 16 and 17.)

[147] Y.-A. de Montjoye, J. Quoidbach, F. Robic, and A. S. Pentland, "Predicting personality using novel mobile phone-based metrics," in *Social Comput., Behavioral-Cultural Modeling and Prediction*, no. 1 in 1, pp. 48–55, 2013. (Cited on page 16.)

[148] B. Mønsted, A. Mollgaard, and J. Mathiesen, "Phone-based metric as a predictor for basic personality traits," *Journal of Research in Personality*, vol. 74, pp. 16–22, 2018. (Cited on page 16.)

[149] F. Alam, E. A. Stepanov, and G. Riccardi, "Personality traits recognition on social network-Facebook," in *Proc. ICWSM*, 2013. (Cited on page 16.)

[150] L. Alessandretti, P. Sapiezynski, V. Sekara, S. Lehmann, and A. Baronchelli, "Evidence for a conserved quantity in human mobility," *Nature Human Behaviour*, vol. 1, no. 1, pp. 1–1, 2018. (Cited on page 16.)

[151] S. Park, A. Matic, K. Garg, and N. Oliver, "When simpler data does not imply less information: A study of user profiling scenarios with constrained view of mobile HTTP(S) traffic," *ACM Trans. Web*, vol. 12, no. 2, pp. 9:1–9:23, 2018. (Cited on page 16.)

[152] M. Ficek and L. Kencl, "Inter-call mobility model: A spatio-temporal refinement of call data records using a gaussian mixture model," in *Proc. IEEE INFOCOM*, pp. 469–477, 2012. (Cited on page 17.)

[153] E. Cho, S. A. Myers, and J. Leskovec, "Friendship and mobility: user movement in location-based social networks," in *Proc. ACM SIGKDD*, pp. 1082–1090, 2011. (Cited on page 18.)

[154] J. Leskovec, L. Backstrom, R. Kumar, and A. Tomkins, "Microscopic evolution of social networks," in *Proc. ACM SIGKDD*, pp. 462–470, 2008. (Cited on page 18.)

[155] P. Erdös and A. Rényi, "On the evolution of random graphs," *Publ. Math. Inst. Hung. Acad. Sci.*, vol. 7, p. 17, 1960. (Cited on page 18.)

[156] D. Naboulsi, M. Fiore, S. Ribot, and R. Stanica, "Large-scale Mobile Traffic Analysis: a Survey," *IEEE Communications Surveys & Tutorials*, vol. PP, no. 99, pp. 1–1, 2015. (Cited on pages 18 and 32.)

[157] R. Becker, R. Caceres, K. Hanson, J. Loh, S. Urbanek, A. Varshavsky, and C. Volinsky, "A tale of one city: Using cellular network data for urban planning," *IEEE Pervasive Comput.*, vol. 10, pp. 18–26, Apr. 2011. (Cited on page 18.)

[158] H. T. Marques-Neto, F. H. Z. Xavier, W. Z. Xavier, C. H. S. Malab, A. Ziviani, L. M. Silveira, and J. M. Almeida, "Understanding human mobility and workload dynamics due to different large-scale events using mobile phone data," *Journal of Netw. and Systems Management*, vol. 26, pp. 1079–1100, Oct 2018. (Cited on page 18.)

[159] R. Keralapura, A. Nucci, Z.-L. Zhang, and L. Gao, "Profiling users in a 3g network using hourglass co-clustering," in *Proc. ACM MobiCom*, pp. 341–352, 2010. (Cited on page 18.)

[160] A. Vaccari, L. Liu, A. Biderman, C. Ratti, F. Pereira, J. Oliveirinha, and A. Gerber, "A holistic framework for the study of urban traces and the profiling of urban processes and dynamics," in *Proc. IEEE ITSC*, pp. 1–6, Oct 2009. (Cited on page 18.)

[161] E. Mucelli Rezende Oliveira, A. Carneiro Viana, K. P. Naveen, and C. Sarraute, "Mobile Data Traffic Modeling: Revealing Temporal Facets," *Comput. Netw.*, vol. 112, pp. 176–193, Jan. 2017. (Cited on pages 18 and 19.)

[162] A. Mehrotra, A. Nguyen, J. Blumenstock, and V. Mohan, "Differences in phone use between men and women: Quantitative evidence from rwanda," in *Proc. ACM ICTD*, pp. 297–306, 2012. (Cited on page 19.)

[163] I. Trestian, S. Ranjan, A. Kuzmanovic, and A. Nucci, "Measuring serendipity: Connecting people, locations and interests in a mobile 3g network," in *Proc. ACM SIGCOMM*, pp. 267–279, 2009. (Cited on page 19.)

[164] U. Paul, A. P. Subramanian, M. M. Buddhikot, and S. R. Das, "Understanding traffic dynamics in cellular data networks," in *Proc. IEEE INFOCOM*, pp. 882–890, Apr. 2011. (Cited on page 19.)

[165] H. H. Jo, M. Karsai, J. Karikoski, and K. Kaski, "Spatiotemporal correlations of handset-based service usages," *EPJ Data Science*, vol. 1, pp. 1–18, 2012. (Cited on page 19.)

[166] G. Chen, S. Hoteit, A. C. Viana, M. Fiore, and C. Sarraute, "The spatiotemporal interplay of regularity and randomness in cellular data traffic," in *Proc. IEEE LCN*, pp. 187–190, Oct 2017. (Cited on page 19.)

[167] F. Z. Yousaf, M. Bredel, S. Schaller, and F. Schneider, "Nfv and sdn—key technology enablers for 5g networks," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 11, pp. 2468–2478, 2017. (Cited on page 19.)

[168] S. P. Shah, B. J. Pattan, N. Gupta, N. D. Tangudu, and S. Chitturi, "Service enabler layer for 5g verticals," in *2020 IEEE 3rd 5G World Forum (5GWF)*, pp. 269–274, 2020. (Cited on page 19.)

[169] D. Kozioł, F. S. Moya, L. Yu, V. V. Phan, and S. Xu, "Qos and service continuity in 3gpp d2d for iot and wearables," in *2017 IEEE Conference on Standards for Communications and Networking (CSCN)*, pp. 233–239, Sept 2017. (Cited on page 20.)

[170] T. Bakhshi, "Securing wireless software defined networks: Appraising threats, defenses research challenges," in *2018 International Conference on Advancements in Computational Sciences (ICACS)*, pp. 1–6, 2018. (Cited on page 20.)

[171] S. Tayeb, S. Latifi, and Y. Kim, "A survey on iot communication and computation frameworks: An industrial perspective," in *2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 1–6, Jan 2017. (Cited on page 20.)

[172] H. Hejazi, H. Rajab, T. Cinkler, and L. Lengyel, "Survey of platforms for massive iot," in *2018 IEEE International Conference on Future IoT Technologies (Future IoT)*, pp. 1–8, Jan 2018. (Cited on page 20.)

[173] P. Barnaghi and A. Sheth, "On searching the internet of things: Requirements and challenges," *IEEE Intelligent Systems*, vol. 31, pp. 71–75, Nov 2016. (Cited on page 20.)

[174] K. Routh and T. Pal, "A survey on technological, business and societal aspects of internet of things by q3, 2017," in *2018 3rd International Conference On Internet of Things: Smart Innovation and Usages (IoT-SIU)*, pp. 1–4, 2018. (Cited on page 20.)

[175] Z. Wang, L. Sun, M. Zhang, H. Pang, E. Tian, and W. Zhu, "Propagation- and mobility-aware d2d social content replication," *IEEE Transactions on Mobile Computing*, vol. 16, pp. 1107–1120, April 2017. (Cited on page 21.)

[176] H. A. M. Name, F. O. Oladipo, and E. Ariwa, "User mobility and resource scheduling and management in fog computing to support iot devices," in *2017 Seventh International Conference on Innovative Computing Technology (INTECH)*, pp. 191–196, Aug 2017. (Cited on page 21.)

[177] V. Petrov, K. Mikhaylov, D. Moltchanov, S. Andreev, G. Fodor, J. Torsner, H. Yanikomeroglu, M. Juntti, and Y. Koucheryavy, "When iot keeps people in the loop: A path towards a new global utility," *IEEE Communications Magazine*, vol. 57, no. 1, pp. 114–121, 2019. (Cited on page 21.)

[178] S. Glass, I. Mahgoub, and M. Rathod, "Leveraging manet-based cooperative cache discovery techniques in vanets: A survey and analysis," *IEEE Communications Surveys Tutorials*, vol. 19, no. 4, pp. 2640–2661, 2017. (Cited on page 21.)

[179] Z. MacHardy, A. Khan, K. Obana, and S. Iwashina, "V2x access technologies: Regulation, research, and remaining challenges," *IEEE Communications Surveys & Tutorials*, 2018. Aceito para publicação. (Cited on page 21.)

[180] G. Luo, Q. Yuan, H. Zhou, N. Cheng, Z. Liu, F. Yang, and X. S. Shen, "Cooperative vehicular content distribution in edge computing assisted 5g-vanet," *China Communications*, vol. 15, no. 7, pp. 1–17, 2018. (Cited on page 21.)

[181] D. López-Pérez, M. Ding, H. Claussen, and A. H. Jafari, "Towards 1 gbps/ue in cellular systems: Understanding ultra-dense small cell deployments," *IEEE Communications Surveys & Tutorials*, vol. 17, pp. 2078–2101, Fourthquarter 2015. (Cited on page 22.)

[182] W. Yu, H. Xu, H. Zhang, D. Griffith, and N. Golmie, "Ultra-dense networks: Survey of state of the art and future directions," in *2016 25th International Conference on Computer Communication and Networks (ICCCN)*, pp. 1–10, Aug 2016. (Cited on pages 22 and 81.)

[183] M. A. Adedoyin and O. E. Falowo, "Combination of ultra-dense networks and other 5g enabling technologies: A survey," *IEEE Access*, vol. 8, pp. 22893–22932, 2020. (Cited on page 22.)

[184] A. C. S. Araújo, L. N. Sampaio, and A. Ziviani, "BEEP: Balancing energy, redundancy, and performance in fat-tree data center networks," *IEEE Internet Computing*, vol. 21, no. 4, pp. 44–53, 2017. (Cited on page 22.)

[185] G. Xylomenos, C. N. Ververidis, V. A. Siris, N. Fotiou, C. Tsilopoulos, X. Vasilakos, K. V. Katsaros, and G. C. Polyzos, "A survey of information-centric networking research," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 2, pp. 1024–1049, 2014. (Cited on page 22.)

[186] L. Zhang, A. Afanasyev, J. Burke, V. Jacobson, P. Crowley, C. Papadopoulos, L. Wang, B. Zhang, *et al.*, "Named data networking," *ACM SIGCOMM Computer Communication Review*, vol. 44, no. 3, pp. 66–73, 2014. (Cited on page 22.)

[187] S. Arshad, M. A. Azam, M. H. Rehmani, and J. Loo, "Recent advances in information-centric networking-based internet of things (icn-iot)," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2128–2158, 2019. (Cited on pages 22 and 23.)

[188] M. B. Lehmann, M. P. Barcellos, and A. Mauthe, "Providing producer mobility support in NDN through proactive data replication," in *NOMS 2016 - 2016 IEEE/IFIP Network Operations and Management Symposium*, pp. 383–391, IEEE, apr 2016. (Cited on page 22.)

[189] F. R. C. Araújo and L. N. Sampaio, "Mobilidade em NDN: Consumidores versus Produtores," in *XIII Workshop de Redes P2P, Dinâmicas, Sociais e Orientadas a Conteúdo (WP2P+)*, (Belém, PA), pp. 8–13, SBC, may 2017. (Cited on page 22.)

[190] G. Panwar, R. Tourani, T. Mick, A. Mtibaa, and S. Misra, "DICE: Dynamic Multi-RAT Selection in the ICN-enabled Wireless Edge," in *Proceedings of the Workshop on Mobility in the Evolving Internet Architecture*, MobiArch '17, (New York, NY, USA), pp. 31–36, ACM, 2017. (Cited on page 22.)

[191] R. A. Rehman and B. Kim, "LOMCF: Forwarding and Caching in Named Data Networking Based MANETs," *IEEE Transactions on Vehicular Technology*, vol. 66, pp. 9350–9364, Oct 2017. (Cited on page 22.)

[192] O. Hahm, E. Baccelli, T. C. Schmidt, M. Wählisch, C. Adjih, and L. Massoulié, "Low-power Internet of Things with NDN & Cooperative Caching," in *Proceedings of the 4th ACM Conference on Information-Centric Networking*, ICN '17, (New York, NY, USA), pp. 98–108, ACM, 2017. (Cited on page 22.)

[193] Z. Chen and M. Kountouris, "Cache-enabled Small Cell Networks with Local User Interest Correlation," in *IEEE 16th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, pp. 680–684, 2015. (Cited on page 22.)

[194] S. E. Hajri and M. Assaad, "Caching Improvement Using Adaptive User Clustering," *arXiv preprint arXiv:1605.09602*, 2016. (Cited on page 22.)

[195] A. Ioannou and S. Weber, "A survey of caching policies and forwarding mechanisms in information-centric networking," *IEEE Commun. Surveys Tutorials*, vol. PP, no. 99, pp. 1–1, 2016. (Cited on page 22.)

[196] V. B. C. da Silva, M. E. M. Campista, and L. H. M. K. Costa, "Trac: A trajectory-aware content distribution strategy for vehicular networks," *Vehicular Communications*, vol. 5, pp. 18 – 34, 2016. (Cited on page 23.)

[197] N. Anerousis, P. Chemouil, A. A. Lazar, N. Mihai, and S. B. Weinstein, "The origin and evolution of open programmable networks and sdn," *IEEE Communications Surveys Tutorials*, pp. 1–1, 2021. (Cited on page 23.)

[198] A. A. Gebremariam, M. Usman, and M. Qaraqe, "Applications of artificial intelligence and machine learning in the area of sdn and nfv: A survey," in *2019 16th International Multi-Conference on Systems, Signals Devices (SSD)*, pp. 545–549, 2019. (Cited on page 23.)

[199] T. Das, V. Sridharan, and M. Gurusamy, "A survey on controller placement in sdn," *IEEE Communications Surveys Tutorials*, vol. 22, no. 1, pp. 472–503, 2020. (Cited on page 23.)

[200] O. S. Al-Heety, Z. Zakaria, M. Ismail, M. M. Shakir, S. Alani, and H. Alsariera, "A comprehensive survey: Benefits, services, recent works, challenges, security, and use cases for sdn-vanet," *IEEE Access*, vol. 8, pp. 91028–91047, 2020. (Cited on page 23.)

[201] I. Benkacem, T. Taleb, M. Bagaa, and H. Flinck, "Performance benchmark of transcoding as a virtual network function in cdn as a service slicing," in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, April 2018. (Cited on page 23.)

[202] H. Wang, S. Zeng, Y. Li, and D. Jin, "Predictability and prediction of human mobility based on application-collected location data," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2020. (Cited on pages 24, 44 and 45.)

[203] M. J. Williams, R. M. Whitaker, and S. M. Allen, "There and back again: Detecting regularity in human encounter communities," *IEEE Transactions on Mobile Computing*, vol. 16, no. 6, pp. 1744–1757, 2017. (Cited on page 24.)

[204] M. C. Gonzalez, C. Hidalgo, and A.-L. Barabasi, "Understanding individual human mobility patterns," *Nature*, vol. 453, pp. 779–82, 07 2008. (Cited on pages 24, 32 and 44.)

[205] P. O. V. de Melo, A. C. Viana, M. Fiore, K. Jaffrès-Runser, F. L. Mouël, A. A. Loureiro, L. Addepalli, and C. Guangshuo, "Recast: Telling apart social and random relationships in dynamic networks," *Performance Evaluation*, vol. 87, pp. 19 – 36, 2015. (Cited on pages 24 and 44.)

[206] J. Guo, S. Zhang, J. Zhu, and R. Ni, "Measuring the gap between the maximum predictability and prediction accuracy of human mobility," *IEEE Access*, vol. 8, pp. 131859–131869, 2020. (Cited on page 24.)

[207] A. Lindgren, A. Doria, and O. Schelén, "Probabilistic routing in intermittently connected networks," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 7, p. 19–20, July 2003. (Cited on page 24.)

[208] J. Tao, H. Wu, S. Shi, J. Hu, and Y. Gao, "Contacts-aware opportunistic forwarding in mobile social networks: A community perspective," in *IEEE WCNC*, pp. 1–6, 2018. (Cited on pages 24 and 70.)

[209] P. Hui, A. Chaintreau, J. Scott, R. Gass, J. Crowcroft, and C. Diot, "Pocket switched networks and human mobility in conference environments," in *Proceedings of the 2005 ACM SIGCOMM Workshop on Delay-Tolerant Networking*, WDTN '05, (New York, NY, USA), p. 244–251, Association for Computing Machinery, 2005. (Cited on page 24.)

[210] T. Henderson, D. Kotz, and I. Abyzov, "The changing usage of a mature campus-wide wireless network," *Computer Networks*, vol. 52, no. 14, pp. 2690–2712, 2008. (Cited on page 25.)

[211] N. Eagle and A. (Sandy) Pentland, "Reality mining: Sensing complex social systems," *Personal Ubiquitous Comput.*, vol. 10, pp. 255–268, Mar. 2006. (Cited on page 30.)

[212] Y. Zheng, L. Zhang, X. Xie, and W.-Y. Ma, "Mining interesting locations and travel sequences from gps trajectories," in *Proc. of the WWWW*, WWW '09, pp. 791–800, ACM, 2009. (Cited on page 30.)

[213] R. Ganti, F. Ye, and H. Lei, "Mobile crowdsensing: Current state and future challenges," *IEEE Communications Magazine*, vol. 49, pp. 32–39, Nov. 2011. (Cited on page 32.)

[214] L. R. Goldberg, "A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models," *I. Mervielde, I. Deary, F. De Fruyt and F. Ostendorf, Eds., Personality Psychology in Europe, Tilburg University Press, Tilburg*, pp. 7–28, 1999. (Cited on page 32.)

[215] G. Ranjan, H. Zang, Z.-L. Zhang, and J. Bolot, "Are call detail records biased for sampling human mobility?," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 16, p. 33, Dec. 2012. (Cited on page 32.)

[216] A. G. Miklas, K. K. Gollu, K. K. W. Chan, S. Saroiu, K. P. Gummadi, and E. De Lara, "Exploiting social interactions in mobile systems," in *Proceedings of the UbiComp '07*, (Berlin, Heidelberg), pp. 409–428, Springer-Verlag, 2007. (Cited on page 33.)

[217] M. V. Barbera, A. C. Viana, M. D. de Amorim, and J. Stefa, "Data offloading in social mobile networks through vip delegation," *Ad Hoc Networks*, vol. 19, pp. 92 – 110, 2014. (Cited on page 33.)

[218] E. G. Caldarola and A. M. Rinaldi., "Big data visualization tools: A survey - the new paradigms, methodologies and tools for large data sets visualization," in *Proceedings of the 6th International Conference on Data Science, Technology and Applications - Volume 1: KomIS,*, (NY), pp. 296–305, INSTICC, SciTePress, 2017. (Cited on page 33.)

[219] A. Khan, J. A. Doucette, R. Cohen, and D. J. Lizotte, "Integrating machine learning into a medical decision support system to address the problem of missing patient data," in *2012 11th International Conference on Machine Learning and Applications*, vol. 1, (NY), pp. 454–457, IEEE Press, Dec 2012. (Cited on page 33.)

[220] P. Andruszkiewicz and H. Rybinski, "Data acquisition and information extraction for scientific knowledge base building," in *2018 IEEE 12th International Conference on Semantic Computing (ICSC)*, (NY), pp. 256–259, IEEE Press, Jan 2018. (Cited on page 33.)

[221] Zhifei Mao, Jing Ma, Yuming Jiang, and Bin Yao, "Performance evaluation of wifi direct for data dissemination in mobile social networks," in *2017 IEEE Symposium on Computers and Communications (ISCC)*, pp. 1213–1218, 2017. (Cited on page 39.)

[222] Eeti, A. Singh, and H. Cherifi, "Centrality-based opinion modeling on temporal networks," *IEEE Access*, vol. 8, pp. 1945–1961, 2020. (Cited on page 46.)

[223] M. Salehi and E. Hossain, "Stochastic geometry analysis of sojourn time in multi-tier cellular networks," *IEEE Transactions on Wireless Communications*, pp. 1–1, 2020. (Cited on page 47.)

[224] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Communications Surveys Tutorials*, vol. 19, no. 4, pp. 2322–2358, 2017. (Cited on page 53.)

[225] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, "A survey on mobile edge networks: Convergence of computing, caching and communications," *IEEE Access*, vol. 5, pp. 6757–6779, 2017. (Cited on page 53.)

[226] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Communications Surveys Tutorials*, vol. 19, pp. 2322–2358, Fourthquarter 2017. (Cited on page 53.)

[227] A. Keränen, J. Ott, and T. Kärkkäinen, "The one simulator for dtn protocol evaluation," in *Proc. ICST*, Simutools '09, 2009. (Cited on page 56.)

[228] A. Aldini and A. Bogliolo, *User-Centric Networking: Future Perspectives*. Springer Publishing Company, Incorporated, 1st ed., 2016. (Cited on page 75.)

[229] D. Chen, G. Navarro-Arribas, C. Pérez-Solà, and J. Borrell, "Message anonymity on predictable opportunistic networks," *Journal of Ambient Intelligence and Humanized Computing*, 07 2019. (Cited on page 77.)

[230] Q. Jiang, K. Deng, Z. Lei, and C. Liu, "A privacy-preserving protocol for utility-based routing in dtns," *Information*, vol. 10, p. 128, 04 2019. (Cited on page 77.)

[231] S. Bakiras, E. Troja, X. Xu, and J. F. Naves, "Secure and anonymous communications over delay tolerant networks," *IEEE Access*, vol. 8, pp. 88158–88169, 2020. (Cited on page 77.)

[232] V. S. Subrahmanian and S. Kumar, "Predicting human behavior: The next frontiers," *Science*, vol. 355, no. 6324, pp. 489–489, 2017. (Cited on page 81.)

[233] R. Ladjel, N. Anciaux, P. Pucheral, and G. Scerri, "Trustworthy distributed computations on personal data using trusted execution environments," in *IEEE TrustCom/BigDataSE*, pp. 381–388, 2019. (Cited on page 82.)

ECOLE DOCTORALE

Titre : La mise en réseau tactique en tant que pierre angulaire de la communication D2D opportuniste tenant compte de l'humain

Mots clés : informatique centrée sur l'humain, informatique sociale, architectures de réseau mobile, transfert d'appareil à appareil (D2D), prédiction de mobilité

Résumé : Parmi les défis du réseau mobile, il y a la croissance du trafic de données, un nombre croissant d'appareils connectés, des limitations de spectre et des mises à jour d'infrastructure coûteuses. Dans ce contexte, la communication D2D opportuniste apparaît comme une solution tout en favorisant des innovations. Cette thèse guide le lecteur tout au long du processus de construction d'une nouvelle stratégie de coopération opportuniste tactique (TOOTS). La proposition consiste à: apprendre les meilleures pratiques de pointe sur l'aspect humain; obtenir des informations pour améliorer les performances de la stratégie; utiliser, proposer et analyser des métriques sensibles aux humains; combiner des métriques et des aperçus dans la stratégie visant une performance améliorée dans un scénario mobile plus réaliste; et enfin, évaluer la stratégie à travers ses forces et ses faiblesses. Nous montrons que TOOTS a amélioré les performances d'un scénario opportuniste en suivant ce processus.

Title : Tactful Networking as a cornerstone for Opportunistic Human-Aware D2D Communication

Keywords : Human-centered computing, social computing , network architectures, Device-to-Device (D2D) forwarding, mobility prediction

Abstract : Among mobile network challenges, there is data traffic growth, an increasing number of connected devices, spectrum limitations, and costly infrastructure updates. In this context, opportunistic D2D communication appears as a solution while fostering innovative applications and services. This thesis guides the reader through the whole process for building a novel Tactful Opportunistic COmmunicaTion Strategy (TOOTS). The proposal consists of: learning human-aspect state-of-art best practices; achieving insights to improve strategy's performance; using, proposing, and analyzing human-aware metrics; combining metrics and insights into the strategy targeting an improved performance in a more realistic mobile scenario; and finally, evaluating the strategy through its strengths and shortcomings. We show that TOOTS improved the performance of an opportunistic scenario in terms of overhead, delivery rate, and latency through following this process.

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