Tactful opportunistic forwarding: What human routines and cooperation can improve?

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Rafael Lima Costa[1,2,3], Aline Carneiro Viana[3], Artur Ziviani[4], and Leobino Nascimento Sampaio[2]

[1] École Polytechnique/IPP, France
[2] Federal University of Bahia (UFBA), Brazil
rlimacosta@ufba.br, leobino@ufba.br
[3] Inria, France
aline.viana@inria.fr
[4] National Laboratory for Scientific Computing (LNCC), Brazil
ziviani@lncc.br

Abstract. Opportunistic D2D forwarding algorithms have leveraged human mobility characteristics to improve cost-effective content delivery. Most previous proposals focused on traditional or simplistic human-centered metrics to improve performance in scenarios such as cellular data offloading. Still, there is a need to approximate algorithm's metrics to inherent in-depth aspects of human mobility hidden into real datasets while leveraging more realistic scenarios interesting to mobile operators. This work proposes TOOTS, a novel *human-aware opportunistic D2D forwarding strategy* for cost-effective content delivery on cellular networks. TOOTS features a dissemination policy and a forwarding algorithm that *leverages wireless encounters patterns, temporal, spatial, geographic, and direction awareness* to improve cost-effectiveness delivery. These characteristics are extracted from NCCU and GRM datasets. We compare TOOTS with the most popular state-of-art social-aware algorithm, Bubble Rap, combined with three dissemination policies. Results from TOOTS show increased performance in terms of delivery rate, delivery latency, and overhead.

Keywords: Human-centered computing · social computing · network architectures · Device-to-Device (D2D) forwarding.

1 Introduction

The advent of 5G wireless networks will drive new business models in nearly every vertical industry. Device-to-Device (D2D) communication and opportunistic forwarding are considered enablers of 5G [1] and 6G [18] network communication and, consequently, of emerging applications. They represent a new paradigm to offload traffic from wireless communication networks, which have attracted multiple research initiatives involving user participation [13]. D2D opportunistic forwarding algorithms tackled cost-effective and timely delivery of data [5, 9]: that is, 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).

Previous research discussed opportunistic networks' deployment to deal with networking performance challenges, such as traffic growth (e.g., through data offloading). Most initiatives focused on proposing algorithms and evaluating their metrics, but they still lack more evaluations with real traces to show opportunistic gain in real-world applications (i.e., in scenarios with more realistic settings). These algorithms typically consider users encounters and individual mobility [5, 10, 9], points of interest (PoIs) [9], and time-evolving social ties between node pairs [8]. Apart from that, not much was done to approximate the evaluation metrics to broader inherent aspects of human mobility while targeting QoE and QoS [2]. There is thus a lack of initiatives beyond traditional techniques or limited human-mobility features to identify routines (spatiotemporal patterns), related consequences (e.g., wireless encounters), and movement decisions (e.g., motion direction) with more granularity and precision. This work focuses on metrics able to reflect human mobility features during periods of the day. Still, each population has particular habits that can change wireless contact dynamics [4]. Therefore, such metrics must be evaluated throughout different populations, while spatiotemporal aspects must fit each population's habits.

In this work, we combine features extracted from a real-world and a synthetic dataset and apply them into a novel Tactful Opportunistic cOmmunicaTion Strategy (TOOTS). This strategy features *a dissemination policy and a forwarding algorithm*. In the former, users' spatiotemporal properties and induced wireless encounters are leveraged to choose content-disseminating nodes that have shown previous encounter routine with destination nodes. The forwarding algorithm relies on nodes' popularity, displacement, network-cell (as PoIs) visiting and proximity, and displacement direction.

In [2], we presented and detailed the features of TOOTS, including mathematical formulations, and results from metrics characterizations using MACACO (a private European Dataset) [17]. In [2], we discussed mobility datasets handling and characterization. The same methodology is applied here with different datasets. Conversely, the word *tactful*, which is part of the strategy's name, means having or showing skill and sensitivity in handling with people. In [3], we discuss the Tactful Networking paradigm, whose goal is to add perceptive senses to wireless networks by assigning it with human-like capabilities of observation, interpretation, and reaction to daily-life features and associated entities. Our contributions with TOOTS are thus the following:

- The TOOTS design combining human-aware metrics in a more granular and precise way than state-of-art to improve networking and system performance;
- The comparison of the TOOTS effectiveness in each stage using a real-world and a synthetic dataset with state-of-art enhanced Epidemic and Store-wait-forward, and Bubble Rap alternatives;
- TOOTS reaches 100% delivery rate with respectively 28%, and 73% less delivery latency, and with 16%, and 27% less overhead in the real-world and synthetic datasets.
- The notion of going beyond traditional techniques when dealing with human-aware metrics to reach a superior system and networking performance. We also emphasize the need to evaluate such opportunistic strategies through more realistic scenarios and real datasets, incentivizing mobile network operators to deploy opportunistic networks more widely.

The results mentioned above cope with [3], which talks about the need to have a more in-depth look into human characteristics to build tactful networking solutions. The remainder of this work is organized as follows. Sec. 2 discusses related work. Sec. 3 presents the mobility models (datasets) used and motivates the strategy design. Sec. 4 discusses TOOTS, including its architecture, features, and algorithms for content-dissemination and forwarding. Sec. 5 presents the experimentation results, analysis, and discussions. Sec. 6 concludes this paper and points out future work.

2 Related Work

Over the years, different works extracted user mobility metrics to assist routing algorithms and opportunistic forwarding strategies. Due to the dynamic human mobility, choosing the nodes to forward the content is challenging.

In [5], authors introduced Bubble Rap, a distributed forwarding algorithm for delay-tolerant networks. The algorithm exploits centrality and community detection; characteristics remarked as less volatile than user mobility. Bubble Rap outperformed other state-of-art algorithms and is used as a benchmark with recently published research [9, 14]. Despite its broad contributions, the major shortcomings relate to evaluations with small scenarios (available traces were below 100 nodes). Further, community detection algorithms are computationally expensive and require parameters calibration, which is not feasible in real-time D2D scenarios.

In [8], authors propose dLife, a forwarding algorithm relying on contacts duration and degree during daily hour periods. They capture the social behavior and interactions dynamism, resulting in improved delivery rate, cost, and latency. Like Bubble Rap, dLife was simulated through small traces. The evaluation setup and scenario are also a shortcoming (e.g., content size ranging from 1 to 100 kb).

In [10], authors introduced GROUPS-NET, an opportunistic algorithm that relies on social group meetings. GROUPS-NET requires a centralized computation of group-to-group paths whenever a given device wishes to send content to a destination. This requirement is challenging in larger populations. Furthermore, the algorithm is validated within two campus datasets, and other kinds of environments must be evaluated. In large-scale scenarios, they had a similar delivery ratio as Bubble Rap, but with reduced overhead.

In [9], the algorithm SAMPLER combines individual mobility, PoIs, and social-awareness for opportunistic routing. Despite showing improved delivery ratio, reduced overhead, and delivery latency, this work has a few shortcomings. The algorithm requires static relay points deployment and social community computations, which require parameters calibration. Second, there is a lack of details about the simulation scenario and parameters to turn possible reproducibility for comparison reasons. Finally, the evaluations need more realistic settings. For example, the authors considered any contact as enough to forward a message. Other parameters, such as message time-to-live and more realistic content-size, must be evaluated.

TOOTS positioning: From the related initiatives described herein, we consider that understanding human-behavior and context from mobility is important for networking solutions. Different from such studies, we use metrics with a more granular link with time. We focused on identifying different human activities during periods of the day. Through the dataset and our metrics analysis, we found that their coefficients vary according to the moment (period) observed [2]. Considered human-mobility features are routines (spatiotemporal patterns), related consequences (e.g., wireless encounters), and movement decisions (e.g., motion direction). Metrics and insights based on generic aspects might not apply to all populations, so datasets of different kinds, and more users need to be evaluated. Facets such as node density, proximity, transportation mode, and even cultural factors can change contact dynamics. Therefore, temporal aspects and other characteristics must be chosen accordingly.

3 Rationale

Datasets description: We use the real-world NCCU trace [16], which features the displacements (given by GPS coordinates) of 115 users on a campus (3764 m × 3420 m) throughout two weeks. Additionally, we adopted the synthetic GRM dataset, which captures social regularity by human mobility [11]. The GRM dataset has 1000 users displacements in a 1500 m x 1500 m area throughout two weeks and applies here to simulate a larger network (i.e., with more nodes).

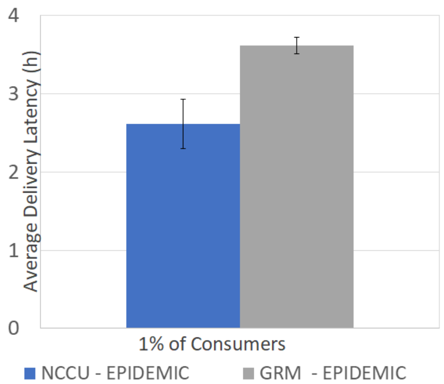


Fig. 1. Epidemic Forwarding Average Delivery Latency Performance Evaluation.

Overhead and Latency evaluation: In Fig. 1, we evaluate the Epidemic forwarding with a consumer set size equal to 1% of each dataset number of nodes. Note that 1% represents a limited number of consumers, which puts the Epidemic strategy in a challenging scenario. Depending on the strategy's kind and the datasets' characteristics, this can result in lower bound results for dissemination strategies, which will also be used in the TOOTS evaluation hereafter. Although mostly evaluated in the literature, we illustrate here the performance constraints related to the Epidemic forwarding algorithm using the two mentioned datasets. The Epidemic algorithm always tries forwarding a content to an encountered node that does not have it. In an opportunistic scenario, Epidemic forwarding is known as having smaller delays and a higher delivery ratio; however bringing a heavy network overhead burden. Source and destination nodes were chosen randomly with a content generation per hour during one full day. The experiments were carried 30 times, and so the confidence intervals are presented.

The Epidemic algorithm delivers the contents with an average latency of 2.6 and 3.6 hours, respectively, for NCCU and GRM. On those experiments, the delivery-rate was 100%, but with 98.44%, and 99.62% average network "infection" (overhead). The latter means that most network nodes became forwarders. For reaching such a delivery rate and small delivery latency, the network was flooded, which is not feasible in the real-world and is highly costly. Furthermore, one of the Epidemic Forwarding characteristics is a higher average of hops (i.e., intermediary nodes) for delivering the message. For example, in these experiments, there are 6.62 and 8.85 average hops respectively for content-delivery on NCCU and GRM. This characteristic brought an insight and motivation for our strategy, which is taking the content closer to the destination and try reducing the number of hops and so possibly the delay and overhead by combining rational dissemination with intelligent forwarding decisions. In the next section, we introduce TOOTS.

4 TOOTS Architecture and Strategy Description

TOOTS architecture: Fig. 2 describes the architecture for TOOTS. It features a mobile network owned by a cellular operator with an infrastructure of mobile edge computing (MEC) [7]. In this MEC site, the operator stores contents commonly requested by its subscribers. The operator's goal is to offload content through opportunistic D2D communication, assuming the users are willing to cooperate through incentives (e.g., data plan savings). We assume the operator controls the offloading process, while the forwarding decisions happen in the user devices based on locally calculated metrics. TOOTS learns from users' mobility for seven days. Upon having a set of user requests for a given content, the operator runs our Tactful Dissemination Policy (TDP) (Sec. 4.1) to choose the disseminator nodes. In Fig. 2, we see two different contents offloading through the chosen disseminators. Subsequently, an algorithm (Sec. 4.2) runs locally (in the node) for taking a forwarding decision.

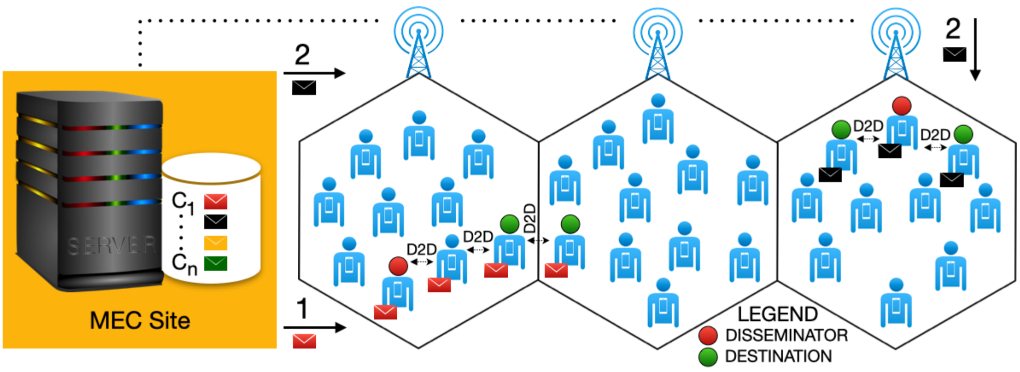


Fig. 2. TOOTS Architecture.

TOOTS metrics: TOOTS combines a novel temporal approach described below with other insights into a Tactful Dissemination Policy (TDP)(Sec. 4.1); the other metrics herein described are combined into a forwarding algorithm (Sec. 4.2). Following, we resume these metrics, which are detailed (including mathematical formulations) and evaluated in [2]. We discuss the intuitions behind the use of each metric in the descriptions of the algorithms.

– **Temporal Approach**: We divided the day into six non-uniform periods, with different durations. This decision is justified by associating the periods to the instants the population travels and has longer confinements (e.g., the period from 06:00 to 09:59 accounts for most individuals' home-to-work displacement, while from 10:00 to 13:59 there is more confinement at work and smaller displacements on lunchtime). With this temporal division, the intention is to extract decision factors increasingly accurate and closer to the real human routines. In [2], we show metrics coefficients heterogeneity per period in MACACO Dataset. The same phenomenon was observed here with NCCU and GRM, which reinforces our intuition.

- **Social Awareness Centrality Degree ($C_{D_p}(u)$)**: Measures the social bonds of a user u in a period of the day p, that is, his number of encounters given a certain communication range. Someone with a higher degree is more "popular" (i.e., has further encounters).
- **Coverage Area Radius of Gyration ($R_{G_p}(u)$)**: Quantifies in meters a user (u) individual mobility related to a center of mass, calculated from his movements in a period p.
- **Sojourn Time ($ST_p^c(u)$)**: Quantifies in hours a user's u stay in a network cell c in a period p. We divided [2] the limited geographic space from each dataset into cells (original local operators' cells were too large) and calculated users' stay.
- **Destination Proximity as Geographical Awareness ($MP_p^c(u)$)**: through a geodesic formula we calculate the maximum proximity a node u reached towards a cell c in a period p.
- **Geographic Direction Awareness**: analyzes the last 30 minutes of node mobility to determine if his displacement is towards a given cell.

4.1 1st TOOTS phase: TDP Policy

Herein, we detail our Tactful-Based Dissemination Policy (TDP). TDP (Alg. 1) chooses nodes based on their social behavior according to each time window. The intuition behind this is to start the offloading process with the content closer to their consumers. Following, we show how we apply the predictive regularity of user routines for choosing content disseminators. From the dynamic contact graph $G_t = (V, E_p)$, where V is the set of users (mobile nodes), and E_p is the set of edges found at the period p of the week k. We assume that there is a logically centralized operator entity that, at the end of a week k, receives the following information from each one of its nodes $u \in V$:

- **(a)**: $\sigma(u)_p$ - the set of users v encountered by u in each period p.
- **(b)**: $\Delta_{C_{LID_p}}(u)$ - the average local improved centrality degree metric [15] for a user u in a period p. This metric accounts for the number of contacts (i.e., encounters), considering their duration and earliness. With that said, higher coefficients belong to nodes with more contacts that had longer durations and happened earlier in a time window (i.e., in a period p).

Algorithm 1: SelectDisseminators

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

During the week $k+1$, upon having a set of consumers $C(c) \in V$ interested in a content c, Alg. 1 runs for choosing disseminator nodes. We justify the use of $\sigma(u)_p$ obtained at the week k by the fact that the policy tries to select nodes that had direct contact with the consumers, and due to their routines, they are most likely to repeat those interactions [12]. We prioritize the direct contacts, i.e., higher proximity as they are most likely to repeat, possibly minimizing the spending of network and user device resources. Further, the C_{LID} measures neighbourhood coverage capabilities through contacts and is used to identify the nodes' popularity in the network, giving importance to their contacts' duration and earliness. We use this metric because, in an opportunistic communication scenario, a contact that can transmit a message (i.e., the encounter lasts enough to send the data) earlier in the time window might decrease the total delivery latency. Furthermore, depending on the content size, choosing short contacts can waste node resources without proper message transmission.

Alg. 1 selects a set of disseminators $D(c)$ for offloading a content c on period p. $D(c)$ starts empty as the algorithm runs when there is a set of Consumers C requisitions for a content c. The policy selects (line 4) the user with the higher coefficient for the direct contacts with Consumers $(\sigma_p(u) \cap C)$, normalized by C's size, summed with the $\Delta_{C_{LID_p}}(u)$ (u's average C_{LID} in p). The Consumers covered by u are then removed (line 6). In this way, we guarantee a next user u with similar coefficient for direct contacts do not get selected. Alg. 1 loops (line 3) until the consumer set is not fully covered ($C \neq \emptyset$). The policy assumes there are no isolated users in the traces. In Sec. 5, we evaluate the performance of the proposed dissemination policy with different sizes of consumer set (1%, 5%, and 10% of each dataset size).

4.2 2nd TOOTS phase: Human-Aware Forwarding

After the disseminator set $D(c)$ for a content c is chosen, the operator sends the content to each node $u \in D(c)$, for storing in its local buffer. From this moment, upon an encounter, any node carrying c runs Alg. 2 to decide on the next forwarding neighbor. The input is: the destination node d (that is, $d \in C$), the content c, the period p, the encountered node v, and l as the coordinates of d's cell. Each node stores the metrics coefficients locally by period p during the whole simulation, and a node u transmits c to v only if a certain algorithm condition is satisfied. First (line 2), if v already has c, u waits for the next encounter. Second (line 4), if $v = d$, (v is the destination), c is transmitted. The content is successfully sent if the edge e between u and v is persistent enough (there is no topology change causing a disconnection) until the time t necessary to transfer c.

Algorithm 2: HumanAwareForwarding

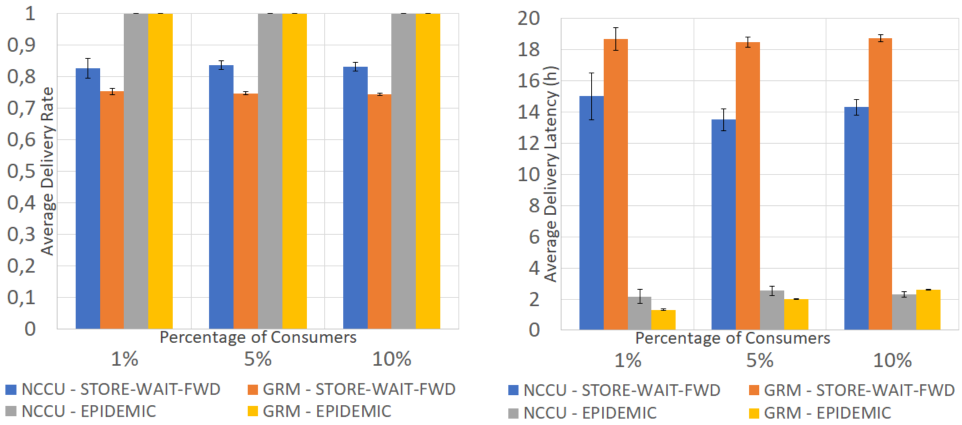
input : d, c, p, v, l
output: A forwarding Decision
1 **begin**
2   **if** $c \in v$ **then**
3   exit(0)
4   **else if** $v = d$ **then**
5     $v \longleftarrow c$
6   **else if** $v.cell = l$ **then**
7   **if** $\Delta_{C_{D_p}}(v) > \Delta_{C_{D_p}}(u)$ **then**
8       $v \longleftarrow c$
9   **else if** $\Delta_{RG_p}(v) > \Delta_{RG_p}(u)$ *and* $\Delta_{ST^l_p}(v) > \Delta_{ST^l_p}(u)$ **then**
10       $v \longleftarrow c$
11   **else**
12   **if** $testDirection(v, l)$ **then**
13       $v \longleftarrow c$
14   **else if** $\Delta_{MP^l_p(v)} < \Delta_{MP^l_p(u)}$ **then**
15       $v \longleftarrow c$
16   **end**
17 **end**

As explained in Sec. 4, the geographic space was divided into cells. If v is at l (line 6), the nodes avg. centrality degree in the period p are compared. If v has a higher avg. CD, it means v met more nodes in p, so c is forwarded to v, given his higher capacity of dissemination inside that cell. In the contrary case (line 9), if $\Delta_{RG_p}(v) > \Delta_{RG_p}(u)$ and $\Delta_{ST^{cell}_p}(v) > \Delta_{ST^{cell}_p}(u)$, v is less "popular" (lower $\Delta_{C_{D_p}}$) than u. Nevertheless, v can potentially cover a larger area inside the cell l (given his higher RG) and routinely stays longer in l (given his higher avg. ST). Hence, c is then forwarded to v (line 10). If v is not in l, his recent mobility in relation to l is checked. If the direction test is true (line 12), i.e., v moves towards the aim and has the potential to reach or to get closer to l, c is sent to v. Finally, if the direction test is false, the avg. destination proximity is checked. If $\Delta_{MP^l_p(v)} < \Delta_{MP^l_p(u)}$, c is forwarded to v, meaning that node v got closer (or visited) l during p and it is more likely to repeat this behavior.

5 Experimentation Results and Analysis

As stated previously, the operator's goal is to offload content through opportunistic communication. The contents consist of 60 seconds advertising videos with the average size of a YouTube 720P HD 30fps video, ranging from 11-14 MB. TOOTS learns from users mobility for seven days; one day is for content generation, with an offloading task started by the operator every hour, and three days are the delivery deadline [15]. The consumers of each content are chosen randomly, with different consumer set sizes. The operator injects the contents on the network through their subscribers, who run a forwarding algorithm upon each contact. Every node has an 802.11/11 Mbps network interface. The communication range evaluated is 30 m (avg. for WiFi Direct). This scenario simulation is through the Opportunistic Network Environment (ONE) Simulator [6], with NCCU and GRM imported as mobility models. Each experiment was carried 30 times. The confidence intervals are calculated when necessary.

5.1 TDP Results and Analysis



(a) Average Delivery Rate (b) Average Delivery Latency

Fig. 3. Tactful Dissemination Policy Average Delivery Rate and Average Delivery Latency Performance Evaluation.

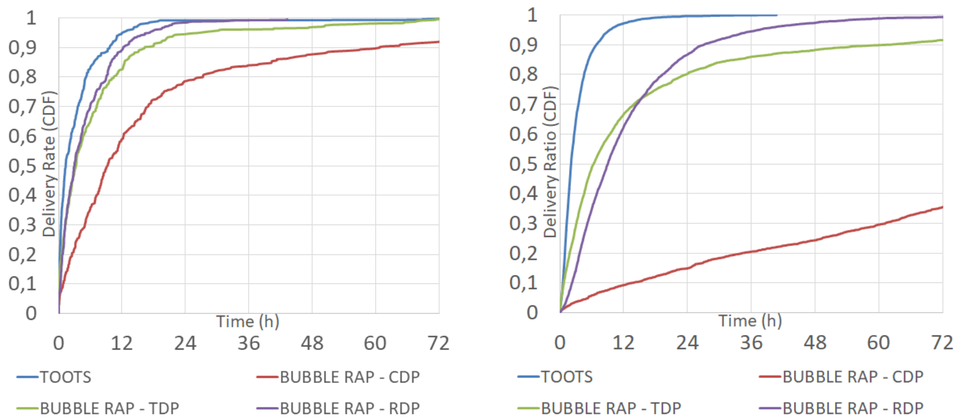
This section evaluates the TDP policy only. For this, we modify two literature forwarding strategies, named store-wait-forward (a.k.a., direct delivery) and epidemic forwarding. This modification consists of using the dissemination-nodes given by the TDP policy as the starting content sources, executing then each of the literature strategies. Fig. 3 plots the performance of the TDP-enhanced store-wait-forward and epidemic forwarding. The store-wait-forward transmits the message only if the encountered node is the destination (consumer). In both traditional and TDP-enhanced versions, the store-wait-forward has zero overhead. Traditional epidemic had 98.44%, and 99.62% overhead, as shown in Sec. 3. On the other hand, the TDP-enhanced epidemic might get a comparable delivery rate and decreased delay. TDP-enhanced store-wait-forwarding has a potentially higher delivery rate and decreased delivery latency, as its success, though still depending on direct encounters, is improved by the TDP's initial content dissemination. Improvements might still take time (or never happen) depending on the source and destination social bonds.

Fig. 3(a) reveals that combined with store-wait-forward, TDP induces an average delivery rate of 82% on NCCU and 75% on GRM, regardless of the number of consumers evaluated (1%, 5%, and

10%). TDP enhancement assures choosing nodes with past direct encounters with the consumers, which favors the delivery rate increase. Compared with the traditional store-wait-forward, the TDP-enhanced average delivery rate with 1% of consumers was 18% higher on NCCU and 60% higher on GRM. In Fig. 3(a), as expected, the TDP-enhanced epidemic forwarding reaches 100% average delivery rate in all scenarios. Besides, the TDP enhancement favors the decrease of the average hop count of the traditional Epidemic forwarding.

In Fig. 3(b), we evaluate the average delivery latency. We see that regardless of the size of consumers set, the contents take on average 13h-15h to be delivered with TDP-enhanced store-wait-forward on NCCU and 18h-19h on GRM, respectively. Thanks to the TDP policy, most of the delay-tolerant content is forwarded in an acceptable time [15]. Compared with the traditional store-wait-forward with 1% of consumers, TDP-enhanced reduced the average delivery latency by 23% on NCCU and 48% on GRM. As expected, when the forwarding is the enhanced epidemic, the average delay is smaller (18.6% less on NCCU and 64.5% less on GRM with 1% of consumers), but with comparable networking infection (overhead), which is unfeasible or very costly in real scenarios. From these findings above, we look for a forwarding algorithm able to increase the delivery rate with as lower as possible overhead and delivery latency.

5.2 TOOTS forwarding Results and Analysis



(a) NCCU - Delivery Rate (b) GRM - Delivery Rate

Fig. 4. Delivery Rate Performance Comparison of TOOTS, Bubble Rap-CDP, Bubble Rap-TDP, and Bubble Rap-RDP on NCCU and GRM datasets.

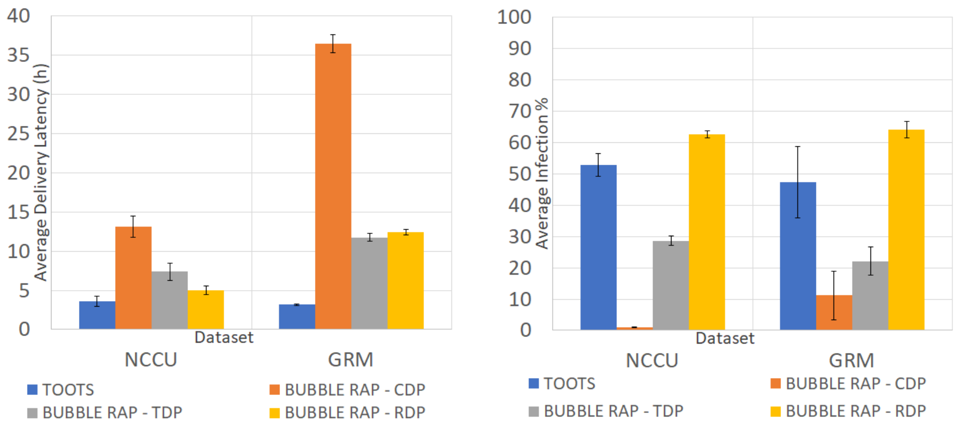
Finally, TOOTS (i.e., the full strategy) is evaluated in terms of delivery rate, delivery latency, and overhead within NCCU and GRM datasets. The chosen scenario is with random consumer sets with a size equal to 1% of dataset nodes (as used for the epidemic performance evaluation). TOOTS's performance is compared with Bubble Rap, the most popular social-based forwarding algorithm for delay-tolerant content. In Bubble Rap, each node gets a GlobalRank, and a LocalRank. The first measures the popularity in the whole network, while the second stores the popularity inside a community. Both centrality ranks are calculated with the C-Window technique, which measures nodes' popularity as the average number of unique nodes encountered throughout a time window of fixed length from the last 24 hours. Furthermore, Bubble Rap identifies social communities, and each node must belong to at least one. Given these metrics, the forwarding strategy transmits a content c carried by u to v when: v is the destination node (d); v has higher GlobakRank or belongs to d's community; v belongs to d's community and has higher LocalRank.

We combine Bubble Rap with three dissemination policies responsible for injecting the contents into the network upon the start of the offloading process by the operator:

- **Random-Based Dissemination Policy (RDP)**: selects origin nodes randomly (i.e., working like the traditional Bubble Rap);
- **Centrality-Based Dissemination Policy (CDP)**: selects the higher centrality node as the origin;
- **Tactful-Based Dissemination Policy (TDP)**: proposed in Sec. 4.1. Selects the nodes with more direct encounters and higher C_{LID}.

In Fig. 4(a), we evaluate the delivery rate for both TOOTS and Bubble Rap on NCCU trace. TOOTS achieved a 100% delivery ratio and had the fastest delivery (90% of the contents delivered in up to 9 hours). Bubble Rap-CDP failed in delivering all contents, even in the NCCU's smaller population, which has overall high centrality degree nodes. Furthermore, using a CDP in the real-world is not feasible, as it creates a bottleneck and tends to drain the most "popular" users' devices resources. Bubble Rap-RDP reaches 100% of delivery ratio but is expected to show higher overhead (analysis to follow). Finally, Bubble Rap-TDP reaches a 100% delivery ratio but takes slightly more time to forward all contents successfully than TOOTS.

In the GRM trace (Fig. 4(b)), TOOTS delivers 100% of the contents, with an average of 97% in up to 12 hours. Bubble Rap-CDP shows an even worst delivery performance than in NCCU. That happens due to (i) communication bottlenecks, as there is a higher node density, and each node interface can transmit only one content at a time, and (ii) the fact that the GRM dataset has overall nodes with much lower centrality degrees. Bubble Rap-RDP delivers 100% but is also expected to show higher overhead (analysis to follow). Bubble Rap-TDP reaches close to 94% delivery ratio. This result can also be explained by GRM's lower centrality degrees (explanation to follow), calling for more time needed to reach 100% delivery ratio in Bubble Rap-TDP.



(a) Avg. Delivery Latency (b) Avg. Infection % (Overhead)

Fig. 5. Delivery Latency and Overhead Performance Comparison of TOOTS, Bubble Rap-CDP, Bubble Rap-TDP, and Bubble Rap-RDP on NCCU and GRM datasets.

In Fig. 5(a), we evaluate the delivery latency. TOOTS has the lower average delivery latency on both datasets, followed by Bubble Rap-RDP on NCCU and Bubble Rap-TDP on GRM. We remind that on GRM, only TOOTS and Bubble Rap-RDP reached 100% delivery rate in up to 72h. On GRM, Bubble Rap-CDP shows a much higher average latency, justified by the bottlenecks on the fewer higher centrality nodes, and by a dataset characteristic: from the content-generation time till the end of the simulation, over 90% of the nodes has low centrality degrees (up till 0.4). These dataset characterization results were not plotted as we focus on the full strategy proposal and its results.

Finally, in Fig. 5(b), we find the Bubble Rap-CDP with the smaller overhead on both datasets. On NCCU, this happens as the higher centrality degree node can find the destination directly for most of the contents generated. On the other hand, still, a bottleneck arises. Despite the lower overhead, Bubble Rap-CDP has a shallow delivery rate compared with the other proposals. The time windows used by Bubble Rap here also might be a reason for the slower delivery performance.

Bubble Rap-RDP presents the worst-case in terms of overhead. Compared with Bubble Rap-TDP, there is respectively 53% and 65% less overhead on NCCU and GRM. On the other hand, we must remember this combination does not deliver 100% of the contents on GRM when the deadline is up to 72h. Using other real datasets with larger populations would be interesting to evaluate this strategy. TOOTS is the fastest strategy able to deliver 100% of the contents on both datasets. Its overhead is respectively 10% and 17% smaller than Bubble Rap-RDP.

6 Conclusion and Future Work

Despite remarked as an enabler of future networking generations since 4G/LTE, opportunistic communications have not been widely deployed by cellular operators. In this work, we discussed a more realistic application scenario and introduced a human-aware opportunistic communication strategy named TOOTS. Compared to Bubble RAP and in both datasets (i.e., NCCU and GRM), TOOTS shows increased delivery performance and reduced delivery delay and overhead. Besides, TOOTS does not rely on complex communities calculation requiring parameter calibration. These characteristics make Bubble Rap challenging to be implemented in real-world scenarios.

Aiming for even better performance, future work related to TOOTS must focus on evaluating the involved decision factors individually. In particular, in the real dataset NCCU, TOOTS showed a better correlation with the leveraged human characteristics. The time-window proposal also made it possible to calculate more precise metrics reflecting the routine-based human mobility behavior at different daily periods.

There is still a lack of datasets with larger populations to be evaluated for real-world data offloading applications. We found that a dissemination strategy to inject the contents into the network is valuable in a scenario such as the one presented. Further, research must also evaluate the presented algorithm and other similar proposals regarding different contact-range, available bandwidth, variable content-size, and node energy constraints.

When it comes to human-aware metrics in the big data era, there is also a multitude of possibilities. Thus, future research shall invest efforts in proposing different metrics to identify human routines and social aspects. Finally, different application scenarios must be discussed so we can have a clearer idea of what opportunistic D2D communication will be able to do or enhance. Showing opportunistic gains in more realistic scenarios and innovative applications can motivate cellular network operators to invest more efforts in the context of human-centered networks.

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