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A Social-Aware Routing Protocol For Opportunistic Networks

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Abstract

This work proposes the Cultural Greedy Ant (CGrAnt) protocol to solve the problem of data delivery in opportunistic and intermittently connected networks referred to as Delay Tolerant Networks (DTNs). CGrAnt is a hybrid Swarm Intelligence-based forwarding protocol designed to address the dynamic and complex environment of DTNs. CGrAnt is based on: (1) Cultural Algorithms (CA) and Ant Colony Optimization (ACO) and (2) operational metrics that characterize the opportunistic social connectivity between wireless users. The most promising message forwarders are selected via a greedy transition rule based on local and global information captured from the DTN environment. Using simulations, we first analyze the influence of the ACO operators and CA knowledge on the CGrAnt performance. We then compare the performance of CGrAnt with the PROPHET and Epidemic protocols under varying networking parameters. The results show that CGrAnt achieves the highest delivery ratio (gains of 99.12% compared with PROPHET and 40.21% compared with Epidemic) and the lowest message replication (63.60% lower than PROPHET and 60.84% lower than Epidemic).

Keywords: cultural algorithms, ant colony, social analysis, forwarding protocol, intermittently connected networks.

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1 **1. Introduction**

2 The pervasiveness of computing devices and the emergence of new ap-
3 plications and cloud services are factors emphasizing the increasing need
4 for adaptive networking solutions. In most cases, this adaptation requires
5 the design of interdisciplinary approaches as those inspired by nature, so-
6 cial structures, games, and control systems. The approach presented in this
7 paper brings together solutions from different, yet complementary domains,
8 i.e., networking, artificial intelligence, and complex networks, and is aimed at
9 addressing the problem of efficient data delivery in intermittently connected
10 networks.

11 As mobile devices become increasingly powerful in terms of communi-
12 cation capabilities, the appearance of opportunistic and intermittently con-
13 nected networks referred to as Delay Tolerant Networks (DTNs) is becoming
14 a reality (Khabbaz et al., 2012; Chaintreau et al., 2007; Tournoux et al.,
15 2011). In such networks, contacts occur opportunistically in corporate en-
16 vironments such as conferences sites, urban areas, or university campuses.
17 Understanding node mobility is of fundamental importance in DTNs when
18 designing new communication protocols that consider opportunistic encoun-
19 ters among nodes. In fact, it is well known in the literature that the move-
20 ment of nodes in such networks is not random and is a manifestation of
21 their routine behavior and intentions (Gonzalez et al., 2008). Together with
22 contact-based interactions among nodes, this movement generates a mobile
23 social network. The analysis of such mobility patterns and the understanding
24 of how mobile nodes interact (i.e., wirelessly encounter) play a critical role
25 in the design of solutions for DTNs.

26 On the other hand, given that adaptation in nature is a permanent and
27 continuous process, we note that the dynamic and complex environment of
28 DTNs favors the application of Swarm Intelligence (SI) methods, including
29 approaches based on Ant Colony Optimization (ACO) (Dorigo et al., 1996)
30 and Cultural Algorithms (CAs) (Reynolds, 1994). In fact, the environment
31 of opportunistic DTNs presents certain features in the mobility patterns of
32 the network nodes that can be sufficiently explored by joining CA and ACO
33 (e.g., knowledge stored in the belief space can guide the swarms through new
34 or already constructed paths depending on the node behavior).

35 Motivated by those issues, this paper proposes the use of a Cultural

36 Greedy Ant routing protocol, known as CGrAnt, to identify the most promis-
37 ing social-aware forwarders in DTNs, while profiting from SI-based paradigms.
38 For this approach, the opportunistic and complex information (such as fre-
39 quency and duration, centrality metrics, or mobility features) with respect
40 to physical encounters between mobile nodes is gathered and favorable paths
41 along which to forward each message are determined, while limiting data
42 redundancy. Hence, the forwarding approach implemented by CGrAnt is
43 adaptive and designed to match forwarding decisions to different mobility
44 and operating conditions. Using a simulation environment, we evaluate the
45 performance of CGrAnt under varying parameters, i.e., movement models,
46 buffer sizes, message TTLs, simulation times, communication ranges, and
47 transmission rates. The results confirm the satisfactory behavior of our rout-
48 ing protocol in key performance metrics, such as: message delivery ratio,
49 message redundancy ratio, and message delivery delay.

50 The remainder of this paper is structured as follows. Section 2 provides
51 an overview of the principles that drive our approach and its application
52 environment. Section 3 describes the CGrAnt routing protocol in detail,
53 and Section 4 presents the simulation environment. Sections 5 and 6 in-
54 vestigate how the proposed operational metrics and components affect the
55 CGrAnt’s performance. Section 7 compares the performance of CGrAnt with
56 two known DTN forwarding protocols under varying networking parameters,
57 and finally, Section 8 summarizes the concluding remarks and future direc-
58 tions.

59 **2. Rationale and Background**

60 This section begins with an overview of the addressed problem. The main
61 innovations and contributions are further discussed, and the state-of-the-art
62 of forwarding in DTN environment is described, with particular attention
63 given to approaches based on SI.

64 *2.1. Problem overview*

65 In DTNs, a fully connected multi-hop path may not exist between a
66 sender and a receiver due to either mobility issues or varying conditions
67 of wireless communications, thus requiring the use of specific mechanisms to
68 ensure robustness in the data communication among nodes. The information
69 exchange must be performed in an opportunistic fashion through so-called
70 carry-and-forward routing techniques (Cerf et al., 2007). The nodes may

71 need to store messages from other nodes in their buffers for long periods of
72 time and carry these messages until a forwarding opportunity arises (Cerf
73 et al., 2007). Additionally, message replication may be necessary to increase
74 the probability of successfully delivered messages. However, certain problems
75 exist in a limited resource scenario: replications are undesirable because they
76 compete with valid data messages in the paths toward a destination, and the
77 storage of neighbors' data messages can be a problem due to limited buffer
78 sizes.

79 The problem of routing in DTNs can thus, be modeled as a multimodal
80 optimization problem attempting to find not just one solution but a set of
81 solutions (i.e., multiple paths between two nodes). The finite set of possible
82 solutions (i.e., paths formed by a sequence of nodes in which each node
83 permutation generates a new solution) characterizes the routing in DTNs as
84 a combinatorial problem. The problem can be also modeled as a dynamic
85 state because the search space characteristics and the location and value of
86 the solutions will change over time. The problem of routing in DTNs presents,
87 therefore, a complex challenge, with several aspects still unexplored by most
88 approaches described in the literature. Therefore, an updated consideration
89 of the DTN dynamics is necessary and can be accomplished by periodically
90 analyzing the neighbor information and selecting more than one path along
91 which to forward each message while limiting message redundancy. The
92 dynamicity and complex premises of DTNs characterize it as an environment
93 favorable for the application of SI algorithms, including ACO and CA (Dorigo
94 et al., 1996; Reynolds, 1994).

95 *2.2. CGrAnt in a Nutshell*

96 In view of the problem discussed in the previous session, we propose the
97 CGrAnt protocol as a solution to the problem of identifying a set of good
98 nodes along which to route each message in DTNs. To increase the reliability
99 in such dynamic networks, choosing the best path for routing of messages
100 should not be the main goal of a routing protocol. Indeed, it is equally
101 important to maintain a diversity of paths and avoid convergence to only
102 one or a few solutions.

103 CGrAnt can be defined as a hybrid SI system based on (1) CA and ACO
104 and (2) operational metrics that characterize the opportunistic social connec-
105 tivity between nodes. To adapt to the large topology variations encountered
106 by a DTN and to reduce latency in message delivery, the following modifi-
107 cations are incorporated into CGrAnt that differentiate it from traditional

108 SI-based protocols. (1) The SI control messages named Forward Ants (FAs),
109 responsible for the path construction, are encapsulated into the data mes-
110 sages. (2) The number of FAs created and forwarded is dynamically defined
111 according to the knowledge stored in the nodes. (3) CGrAnt adopts a greedy
112 ACO transition rule that is similar to the deterministic transition rule pro-
113 posed in the Ant Colony System (ACS) (Dorigo and Gambardella, 1997).
114 Nevertheless, instead of using both probabilistic and deterministic rules as
115 in ACS, CGrAnt uses only the greedy transition rule, which considers the
116 heuristic function and/or pheromone concentration, to forward messages to
117 the most promising node(s), and/or to exploit previously found good solu-
118 tions. The search space exploration is still provided by the DTNs dynamics.
119 (4) Instead of using time-based pheromone evaporation, CGrAnt performs
120 an event-driven evaporation, which only occurs if a node detects that a new
121 path toward a destination has been found. Thus, allowing redundant paths
122 becomes more important than converging to the best path. (5) Because
123 there is no central element in DTNs, the knowledge stored in the CA belief
124 space is distributed among network nodes. (6) The information exchanged
125 between the belief and population spaces always occurs in a distributed man-
126 ner intermediated by the CGrAnt operational metrics. The ACO and CA
127 modifications seem more adapted to intermittently connected networks such
128 as DTNs, yet a subset may allow CGrAnt to operate in different dynamic
129 scenarios.

130 *2.3. Related work*

131 We go through the related work in the area, discussing the most repre-
132 sentative results on both DTN forwarding protocol and swarm intelligence
133 methods.

134 *2.3.1. DTN Forwarding protocols*

135 The most common solutions in the literature take a controlled flooding ap-
136 proach. For instance, epidemic routing provides an optimal solution in terms
137 of message delivery and latency, when no buffer constraint is present (Vahdat
138 and Becker, 2000). In Epidemic routing, a node buffers a message and passes
139 it on to all encountered nodes that have not received it before. No good
140 message forwarders prediction is performed. To limit resource utilization, a
141 hop-count field can be set in each message. Epidemic routing is simple and
142 provides high reliability and adaptability, but it might generate too many

143 redundant messages, wasting communication and battery resources. To re-
144 duce this overhead, the Spray and Wait approach (Spyropoulos et al., 2005)
145 sprays messages over different contacts and then wait for these contacts to
146 eventually deliver the message to the destination.

147 Predicted-based approaches try to reduce the message overhead by se-
148 lecting a few good relays. In this context and more related to CGrAnt,
149 several approaches estimate a delivery likelihood based on the frequency or
150 similarities of meeting with contacts like PROPHET (Lindgren et al., 2003),
151 Delegation Forwarding (Erramilli et al., 2008), and Spray and Focus (Spy-
152 ropoulos et al., 2007). In particular, in PROPHET, vectors are exchanged
153 that indicate the predictability of each node in delivering their messages. This
154 predictability increases every time two nodes come into contact and reduces
155 if they fail to meet frequently. When a node A establishes a contact with
156 a node B , a message will be sent to B if its message delivery's prediction
157 is higher as compared to A . The delivery predictability also has a transi-
158 tive property. All these approaches, however, might be too conservative and
159 lose good forwarding opportunities in environments with scarce connectivity.
160 Most importantly, the majority of the approaches assume infinite buffers and
161 bandwidth.

162 Other approaches study the effect of social networking on data forward-
163 ing. BubbleRap (Hui et al., 2008) and SimBet (Daly and Haahr, 2007) use
164 information about social community structures and popularity within a com-
165 munity to choose good relays. (Zhang et al., 2012) introduce four social-aware
166 data diffusion schemes based on the social relationship and data similarity
167 of the contacts.

168 Differing from such protocols, CGrAnt conducts local and global searches
169 and gathers relevant information from the DTN nodes. CGrAnt can thus
170 analyze the utility of each node as a message forwarder and limit message
171 replications.

172 *2.3.2. Swarm intelligence methods*

173 Though ACO has been extensively used in network environments, espe-
174 cially in MANETs (Liu and Feng, 2005; Rosati et al., 2008), routing in DTNs
175 is challenging and few ACO protocols have been proposed. DAR (Rosati
176 et al., 2008) does not consider local information from neighboring nodes and
177 uses only the pheromone global information, which is not always available
178 in DTNs. ABMF (La and Ranjan, 2009) only aims to estimate the extra
179 capacity of each node as a message forwarder depending on its buffer dy-

180 namics. ACRP (Zhang et al., 2010b) uses the Epidemic protocol to flood
181 the network with control messages associated with Forward Ants (FAs) and
182 Backward Ants (BAs). None of the mentioned approaches consider the fol-
183 lowing important aspects of sparse and opportunistic networks: (i) analyzing
184 social metrics of nodes, including their degree and betweenness centralities
185 to aid select message forwarders; (ii) preventing the loss of previously found
186 good paths caused by pheromone evaporation processes that are periodically
187 performed (i.e., based on time, as in ABMF and ACRP) or the overuse of
188 those paths due to the absence of an evaporation process (as in DAR); and
189 (iii) dynamically limiting the number of control and data messages forwarded
190 in the network.

191 (Ma et al., 2008; Zhang et al., 2010a) use CA for performing routing in
192 a static topology with service quality constraints. They, however, operate in
193 a static environment and do not analyze the dynamics of the contacts in a
194 social network to determine opportunities. Moreover, they search for a single
195 optimal path with a set of constraints and use Situational and Normative
196 knowledge only to increase the convergence speed. Finally, they use a single
197 and centralized belief space.

198 Considering these issues, we proposed a first version of the SI-based
199 routing protocol for DTNs that used only ACO (Vendramin et al., 2012b).
200 Guided by pheromone concentration, heuristic functions, and social metrics,
201 the Greedy Ant (GrAnt) protocol performed better than the well-known
202 DTN routing protocols (Vendramin et al., 2012b).

203 CGrAnt encompasses CA and ACO metaheuristics and can be considered
204 as an extension of our previous method (Vendramin et al., 2012b). CGrAnt
205 improves the learning process and the gathering, during evolution, of high-
206 level information to be stored in the CA belief space.

207 **3. The CGrAnt Routing Protocol**

208 As previously mentioned, the CGrAnt routing protocol is based on CA
209 and ACO meta-heuristics. CA is comprised of two spaces: (1) **Belief Space**,
210 which represents the knowledge (i.e., set of information) gathered during the
211 search for a set of paths and (2) **Population Space**, which is composed
212 of individuals (i.e., ants) looking for solutions (i.e., forwarding paths) in an
213 ACO framework.

214 In DTN, due to the lack of central element capable of storing and publish-
215 ing all gathered information, the CGrAnt components are distributed among

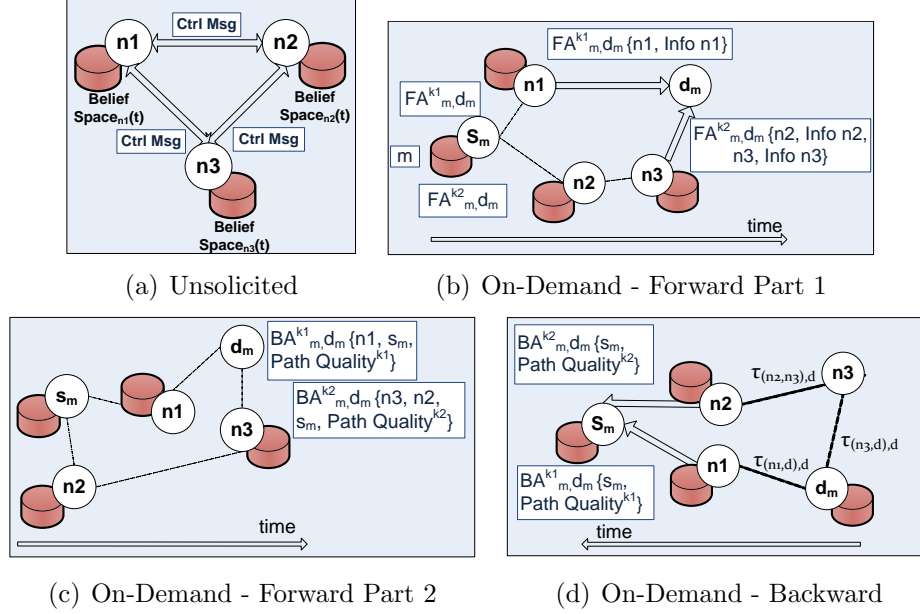


Figure 1: Operation Modes of the CGrAnt Protocol.

216 different belief spaces, each stored in a network node; each node knows only
 217 a subset of the population space. The exchange of information between the
 218 belief and population spaces always occurs in a distributed manner.

219 CGrAnt operates in two modes: **unsolicited** and **on-demand** (Fig-
 220 ure 1). In the **unsolicited mode** (Figure 1(a)), control messages (Ctrl Msg)
 221 are always exchanged among neighboring nodes to update the information
 222 stored in each belief space. If it is necessary to establish a data session be-
 223 tween the source of a data message m (s_m) and its destination (d_m), CGrAnt
 224 switches to the **on-demand mode** (Figures 1(b)- 1(d)). In each node that
 225 contains a data message m to be forwarded, one or more Forward Ants (FA)
 226 k , are forwarded toward d_m along with m via one or more neighboring nodes.
 227 During the path construction, an ant k collects information (Info) on each
 228 node n that composes the path toward d_m . The node n can be either a
 229 node i that contains a buffered message m to be forwarded or a neighboring
 230 node j . A subset of this information is used by CGrAnt for the belief space
 231 update of each node. The other part is carried by the FA until it reaches
 232 d_m (Figure 1(b)). In d_m , the quality of the constructed path is calculated
 233 based on the information gathered by the FA. A Backward Ant (BA) is sub-

234 sequently created with the information obtained by the corresponding FA
 235 (Figure 1(c)), the FA is deleted, and the BA is sent back through the reverse
 236 path followed by the FA. In its path toward the source (s_m) of the FA, the
 237 BA updates the ACO pheromone concentration operator (τ) in each link be-
 238 tween the nodes that compose the reverse path (Figure 1(d)) according to the
 239 constructed path quality. At each visited node, its identification is removed
 240 from the BA’s record. In subsequent message forwarding, the ACO operators
 241 (Pheromone Concentration and Heuristic Function) and the CA belief space
 242 (along with other CGrAnt components) dictate the routing decision in each
 243 node and infer the best forwarders for each message.

244 The next sections describe the CGrAnt routing protocol in detail. Sec-
 245 tions 3.1 to 3.3 describe the components used by CGrAnt that influence the
 246 search for paths. Sections 3.4 and 3.5 describe the routing phases of CGrAnt,
 247 which determine the route(s) a message must follow to reach its destination.

248 3.1. Metrics and Indicators

249 The communication between the belief and population spaces is mediated
 250 by specific metrics and indicators. The metrics incorporated into CGrAnt are
 251 classified as **basic** (obtained directly from the population space or nodes) or
 252 **composite** (obtained from manipulating basic metrics). The basic metrics
 253 are classified into **local** (associated with each node and its neighboring nodes)
 254 and **global** (associated with complete paths constructed by ants) categories.
 255 Figure 2 illustrates the metrics and their relationships with the belief space
 256 stored in each node. The Situational and History knowledge influence the
 257 population space and the population space update the global metrics.

258 Table 1 provides a brief description of the metrics and variables used
 259 throughout this paper.

260 The **Local Basic Metrics** used by CGrAnt include the following:

- 261 • **Frequency of Encounters** ($FE_{n,d}$) between a pair of nodes n and d ;
- 262 • **Duration of an Encounter** ($DE_{n,d}$) between n and d ;
- 263 • **Average Pause Time** (\overline{PT}_n) in the places visited by n ;
- 264 • **Average Movement Speed** (\overline{MS}_n) of a node n ;
- 265 • **Degree Centrality** (DC_n) of a node n (Freeman, 1979). As n encoun-
 266 ters more nodes in the network and increments its degree centrality, it
 267 has more opportunities to choose the best message forwarders;

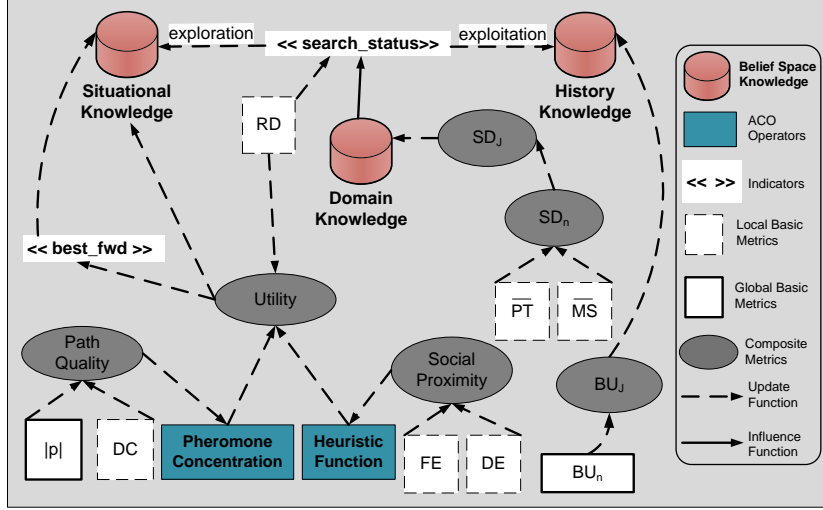


Figure 2: Belief Space of a Node.

268 • **Relationship Degree** ($RD_{i,m}$) of a node i with respect to each of its
 269 data messages m . $RD_{i,m}$ defines i as the source (s_m) or an intermediate
 270 node of m .

271 The **Global Basic Metrics** of CGrAnt include:

- 272 • **Number of Hops** ($|p|$) in a complete path p . If there are few hops in a
 273 path, fewer resources are consumed, and less interference is generated;
- 274 • **Betweenness Utility of a node** ($BU_{n,d}$) n relative to a destination
 275 node d . To obtain a high betweenness utility relative to d , a node
 276 n must appear with a high frequency in paths between any source
 277 node and d . Each time a node n receives a BA indicating that n is a
 278 component of a complete path (global solution) to d , its betweenness
 279 utility is updated, $BU_{n,d}(t) = BU_{n,d}(t - 1) + 1$.

280 The **Composite Metrics** of CGrAnt include the following:

- 281 • **Social Proximity** ($SP_{n,d}$) between n and d is directly associated with
 282 the ACO local operator **Heuristic Function** (η) and is defined as
 283 $SP_{n,d} = FE_{n,d} \times DE_{n,d}$;

- 284 • **Path Quality** ($Q_{p_{s_m, d_m}^k}$), which measures the quality of a path p con-
 285 structed by an FA k between nodes s_m and d_m . It encompasses the
 286 number of hops ($|p|$) and the average degree centrality of nodes n (DC_n)
 287 that compose a path to d_m :

$$Q_{p_{s_m, d_m}^k}(t) = \frac{\sum_{\forall n \in p_{s_m, d_m}^k} DC_n(t)}{|p_{s_m, d_m}^k|} + \frac{1}{|p_{s_m, d_m}^k|} \quad (1)$$

288 The Path Quality metric is directly associated with the ACO global
 289 operator **Pheromone Concentration** (τ);

- 290 • **Utility** of a node n in relation to d ($U_{n,d}$), which describes how well
 291 n can perform as a message forwarder to d . The $U_{n,d}$ is subsequently
 292 determined according to the basic metric $RD_{i,m}$:

$$U_{n,d}(t) = \begin{cases} \eta_{n,d}(t) & \text{if } RD_{i,m} = s_m \\ \eta_{n,d}(t) + \tau_{(i,y),d}(t) & \text{otherwise,} \end{cases} \quad (2)$$

293 The $U_{n,d}(t)$ can thus consider only local or both local and global in-
 294 formation. The local information $\eta_{n,d}(t)$ is the heuristic function of
 295 ACO measured by $SP_{n,d}$, and the global information $\tau_{(i,y),d}(t)$ is the
 296 pheromone concentration on each link (i, y) belonging to a path to d ,
 297 and y is defined as:

$$y = \begin{cases} d_m & \text{if } n = i \\ j & \text{if } n = j, \end{cases} \quad (3)$$

- 298 • **Stagnation Degree** (SD_n) of a node n , which allows the identifica-
 299 tion of the most mobile nodes in a dynamic scenario (e.g., buses or
 300 vehicles) and consequently, adapts CGrAnt to heterogeneous network-
 301 ing encounters on the fly. For this, SD_n considers the node average
 302 pause time (\overline{PT}_n) and average movement speed (\overline{MS}_n):

$$SD_n(t) = \left(\frac{\overline{PT}_n}{\overline{MS}_n} \right) \quad (4)$$

- 303 • **Stagnation Degree of the social network** (SD_j^i) of a node i , which
 304 is based on the SD_n metric:

$$SD_j^i(t) = \frac{1}{|J|} \sum_{j \in J} SD_j(t), \quad (5)$$

305 where J is the set of nodes encountered by node i ;

306 • **Betweenness Utility of the social network** ($BU_{J,d}^i$) of a node i
 307 in relation to d , which considers the basic metric $BU_{n,d}$. The $BU_{J,d}^i$
 308 is initialized differently depending on the origin of the BA that announces
 309 to i that a complete path to d has been constructed:

$$BU_{J,d}^i(0) = \begin{cases} BU_{i,d}(t) & \text{if BA came from } d \\ BU_{j,d}(t) & \text{if BA came from } j \end{cases} \quad (6)$$

310 The $BU_{J,d}^i$ metric is updated with $BU_{i,d}$ whenever i receives a BA.
 311 When the BA comes from a neighboring node j (not from d), $BU_{J,d}^i$
 312 is also updated with $BU_{j,d}$:

$$BU_{J,d}^i(t) = \begin{cases} Z & \text{if BA came from } d \\ \frac{1}{2}(Z + BU_{j,d}(t)) & \text{if BA came from } j, \end{cases} \quad (7)$$

313 where $Z = \frac{1}{2}(BU_{J,d}^i(t-1) + BU_{i,d}(t))$.

314 More details on the metrics definitions are discussed in [23].

315 In addition to the basic and composite metrics, CGrAnt uses two indica-
 316 tors: (1) **best_fwd_m**, which stores the current best forwarder for a specific
 317 message m and (2) **search_status**, which decides whether FAs must *explore*
 318 or *exploit* the network while seeking solutions for the DTN forwarding prob-
 319 lem.

320 3.2. Population Space

321 The population space is composed of FAs and BAs messages. The FAs
 322 look for sets of possible paths, i.e., one set P_m for each pair (s_m, d_m) . As-
 323 suming a total of M messages to be forwarded in the entire network, there
 324 will be several paths sets $\{P_1, \dots, P_m, \dots, P_M\}$ constructed simultaneously.
 325 Every paths set P_m represents a group of solutions generated whenever a
 326 message m originated in s_m must be sent to d_m . Each complete path p in P_m
 327 composed of a sequence of nodes is established when ant k reaches d_m and
 328 can be defined as:

$$p_{s_m, d_m}^k = \{s_m, \dots, n, \dots, d_m\}, k = 1, \dots, K_m.$$

329 For each node i with a message m , each time a better forwarder j for m
 330 appears, a new FA k is generated to begin its path construction, and a copy
 331 of m is sent to j . The partially constructed path from s_m to j remains the
 332 same. However, from j , the FA k is free to find d_m passing through different
 333 nodes n and can provide a different path into the population space. The
 334 K_m defines the number of FAs generated to find solutions for m . In general,
 335 $|P_m| \ll K_m$ because a subset of ants cannot find d_m . The parameter K_m
 336 is dynamically defined according to the belief space knowledge and message
 337 delivery success. Ant generation is thus auto-adaptive, as is the number of
 338 constructed paths, and both depend on the DTN dynamics.

339 3.3. Belief Space

340 In CGrAnt protocol, there is no element to centralize and share the gath-
 341 ered knowledge. The belief spaces are thus distributed over the network.
 342 Each belief space in a node encompasses three types of knowledge: Domain,
 343 History, and Situational, as detailed hereafter.

344 3.3.1. Domain Knowledge

345 introduced to support the analysis of local and specific DTN dynamics.
 346 Domain knowledge keeps CGrAnt updated on the relative local dynamics
 347 of each node i , which is evaluated in this paper based on the relationship
 348 between SD_i and SD_j^i . The knowledge is distributed among nodes, Dom_i ,
 349 for $i = 1, \dots, N$, where N is the number of nodes available in the network
 350 and Dom_i assists CGrAnt in characterizing i into three classes: a node with
 351 high, medium or low stagnation degree.

352 Based on this information and the specific heuristics of a DTN forwarding
 353 problem, the Domain knowledge can set the status of the path search (i.e.,
 354 exploration or exploitation). The *Acceptance* and *Update* functions of the
 355 Domain knowledge occur more frequently than its *Influence Function* because
 356 they are called during the node encounters. The *Influence Function* acts only
 357 during the message forwarding phase.

358 The *Acceptance Function* accepts information on the local dynamic of
 359 each neighboring node j , only if $SD_j \in (0, \infty)$. After accepting a new so-
 360 lution, the *Update Function* is called. It considers the event window $W(t)$

361 containing a list of local events of i , such as an encounter between i and a
 362 non-stationary node j .

363 The *Update Function* adds the pair $(SD_j(t), j)$ to the list and updates
 364 SD_j^i according to Eq. 5.

365 The *Influence Function* evaluates the stagnation degree of i with respect
 366 to its social network:

- 367 • *High stagnation degree*: A node i is characterized as a highly stagnated
 368 node when the following relations apply: $SD_i > SD_j^i + V_s$ and $SD_j^i \in$
 369 $(0, \infty)$. In this case, its improvement stagnation direction dr_i is set to
 370 $dr_i = +1$;
- 371 • *Low stagnation degree*: A node i has a low stagnation degree when the
 372 following relations apply: $SD_i < SD_j^i - V_i$ and $SD_j^i \in (0, \infty)$ hold. In
 373 this case, $dr_i = -1$;
- 374 • *Medium stagnation degree*: A node i is characterized as a medium stag-
 375 nation node when the previously described relations do not apply. In
 376 this case, $dr_i = 0$.

377 The V_i and V_s respectively define the decrement and increment in SD_j^i
 378 used to define the range of nodes with medium stagnation degree.

379 Based on dr_i , the *Influence Function* changes the value of the *search_status*
 380 indicator, which aids in defining whether an FA in node i must be sent to
 381 exploit or explore during the search for a solution of the DTN forwarding
 382 problem.

383 3.3.2. **History Knowledge**

384 introduced to adapt CGrAnt to changes in the network, thus increasing
 385 the ability to reflect the global network dynamics. This knowledge stores a
 386 history of important past events (in this case, the information that complete
 387 paths to d have been found). Due to the lack of a central component, the
 388 complete paths cannot be stored in the History knowledge. The betweenness
 389 utility metric (representing the partial information of a complete solution)
 390 is subsequently used and may subsequently influence the path search. The
 391 History Knowledge is distributed among the network, His_i , for $i = 1, \dots, N$.
 392 In each node i , this knowledge is divided in a total of D_i sub-knowledge:
 393 $His_i(t) = \{His_{i,1}(t), His_{i,2}(t), \dots, His_{i,D_i}(t)\}$, where $D_i \leq N$ represents
 394 the number of destination nodes for which node i originated or intermediated
 395 a path.

396 The *Acceptance and Update Functions* of the History knowledge are called
 397 in the backward phase, and its *Influence Function* acts in the message for-
 398 warding phase.

399 The *Acceptance Function* is called after node i receives a BA from a
 400 neighboring node (j or d), indicating that a complete path to d has just
 401 been found. The betweenness utility of i with respect to d ($BU_{i,d}$) is always
 402 accepted to update the belief space of i . The betweenness utility of the
 403 neighboring node j ($BU_{j,d}$) is also accepted to update the belief space of i
 404 if and only if the BA did not come from d . After the acceptance phase, the
 405 *Update Function* is called to calculate $BU_{J,d}^i$.

406 The $BU_{j,d}$ and $BU_{J,d}^i$ dynamics are considered by the *Influence Function*
 407 when evaluating the improvement directions of each neighboring node j as
 408 a candidate forwarder for message m to d : $dr_j = +1$, if $BU_{j,d} > BU_{J,d}^i$;
 409 $dr_j = -1$, if $BU_{j,d} < BU_{J,d}^i$; or $dr_j = 0$, if $BU_{j,d} = BU_{J,d}^i$. Based on these
 410 directions and the *search_status* indicator, the history knowledge influences
 411 the message forwarding by deciding whether an FA should be sent through
 412 a previously found path and thus exploit the path search.

413 3.3.3. *Situational Knowledge*

414 introduced in CGrAnt to provide a memory of the best solutions, and
 415 to influence the search process for a set of paths through these solutions.
 416 Its memory is partial instead of complete and is represented by the best
 417 forwarder of each message. The Situational Knowledge is distributed among
 418 the network nodes: Sit_i , for $i = 1, \dots, N$. In each node i , the Situational
 419 knowledge is divided in a total of M_i sub-knowledge:

$$420 \quad Sit_i(t) = \{Sit_{i,1}(t), \dots, Sit_{i,m}(t), \dots, Sit_{i,M_i}(t)\},$$

421 where M_i represents the number of data message m stored in node i 's buffer.

422 The *Acceptance, Update, and Influence* functions of the Situational knowl-
 423 edge are called during the message forwarding phase.

424 The *Acceptance Function* operates with the understanding that if a new
 425 neighboring node j (partial solution) is found, it is accepted to update the
 426 belief space of i only if $U_{j,d} > U_{best_fwd_m,d}$, where $U_{best_fwd_m,d}$ is the current
 427 best forwarder utility for m stored in the sub-knowledge $Sit_{i,m}$. The accep-
 428 tance condition can be relaxed to accept nodes with the same utility of the
 429 best forwarder if the corresponding *search_status* exploration is true. Only
 430 one solution is accepted in each update. After accepting a new solution, the
 431 *Update and Influence* functions are called. The new solution thus replaces
 432 the previous solution ($best_fwd_m = j$), and the new solution quality ($U_{j,d}$)

433 updates $U_{best_fwd_m,d}$ (i.e., $U_{best_fwd_m,d} = U_{j,d}$). The *Influence* Function creates
 434 a new FA and forwards it along with m to the new solution j . The *Influence*
 435 function thus dictates the future of each path built for a pair $s_m - d_m$ and
 436 the number of generated ants.

437 In the following sections, we describe in more detail the two phases that
 438 dictate the main functioning of the GrAnt routing protocol: (1) **Message**
 439 **Forwarding** or **Path Search**, which is represented by FAs looking for a set
 440 of paths and the updating of selected knowledge and metrics. In this phase
 441 occurs the data message forwarding; and (2) **Backward**, which is represented
 442 by BAs updating the knowledge and metrics stored in the nodes.

443 3.4. Message Forwarding Phase

444 The message forwarding phase in CGrAnt is initialized on-demand when
 445 a message m stored in a node i must be delivered to d_m , as described by
 446 Algorithm 1. The FAs are subsequently created, encapsulated into m , and
 447 sent toward d_m via one or more neighboring nodes j .

448 During message forwarding, an FA at a node i decides whether to for-
 449 ward m to a new neighbor j according to the influence of the three types of
 450 knowledge stored in its belief space: Domain, History, and Situational.

451 Because node i is the first candidate solution for forwarding message m ,
 452 its identification and utility initialize the Situational knowledge (lines 9 and
 453 10). The decision on forwarding m to j may be to explore (i.e., it is not
 454 required that j has previously participated in a path to d_m) or exploit (i.e., j
 455 has previously participated in a path toward d_m). The decision is guided by
 456 the information on i in terms of $RD_{i,m}$ and SD_i stored in Dom_i . The status
 457 is initialized, enabling both exploitation and exploration of the path search
 458 space (lines 12 and 13). These conditions can change in two situations: (i)
 459 i is an intermediate node with a medium stagnation degree (in this case,
 460 the exploration stops (line 16)), or (ii) i is an intermediate node with a low
 461 stagnation degree (because i is a highly mobile node, it does not forward m ,
 462 thus, both exploration and exploitation are stopped (lines 19 and 20)).

463 Aside from Domain knowledge, the History and Situational knowledge
 464 also influence the CGrAnt message forwarding. The History knowledge in-
 465 fluences the forwarding (line 33) when the decision is to exploit the solutions
 466 already found: i forwards m to a solution j if node j 's betweenness util-
 467 ity ($BU_{j,d}$) is higher than the betweenness utility of node i 's social network
 468 ($BU_{J,d}^i$ stored in $His_{i,d}$, as observed in line 47). The Situational knowledge in-
 469 fluences CGrAnt (line 44) when the decision is to explore the network or when

470 better solutions appear. Node i only forwards m to a new solution j if one of
471 the following two conditions is satisfied: (i) The utility of j ($U_{j,d}$) is higher
472 than the utility of the best forwarder previously found for m ($U_{best_fwd_m,d}$,
473 which is stored in $Sit_{i,m}$, as observed in lines 53 and 54). This condition at-
474 tempts to locate a new best forwarder for m among the current neighboring
475 nodes of i ; (ii) At the beginning of the exploration (i.e., m was not forwarded
476 to any other node and $best_fwd_m = i$ and $U_{j,d} = U_{i,d}$, as in lines 26-27, 36-
477 38). The Situational and History knowledge are important contributions of
478 CGrAnt because they dynamically control the number of created ants and
479 the data message redundancy by setting each new best message forwarder
480 or forwarding m to already known good nodes, thus differing from the pure
481 ACO algorithms proposed for DTNs.

482 After analyzing the utility of every current neighbor j and inferring the
483 best choice, CGrAnt sends m to the designated forwarder (lines 33 and/or
484 44).

485 In addition to the data message forwarding, control messages are period-
486 ically and locally exchanged between i and its neighboring nodes j to update
487 Dom_i .

488 The search for new paths toward d_m continues until i performs one of
489 the following actions: (1) encounters d_m , (2) becomes aware of the successful
490 delivery of the corresponding data message to d_m , or (3) detects that the
491 Time to Live (TTL) field of the data message has expired.

492 Throughout its path search, an FA carries the following information: the
493 ID of s_m , the ID of d_m , the node IDs through which it passes (between s_m and
494 d_m), and the degree centrality of each visited node j (DC_j). The individual
495 qualities update the partial quality of the path under construction by the FA.
496 When an FA (along with m) reaches d_m , the final quality of the constructed
497 path ($Q_{p_{s_m,d_m}^k}$) is calculated as in Eq. 1. After calculating the quality of each
498 new and complete path p , a new control message, the BA, is created from
499 the information obtained by the FA, and the FA is deleted.

500 3.5. Backward Phase

501 During the backward phase, the BA returns to the node that originated
502 the message m through the reverse path selected by the FA. The concept
503 of using a reverse path in DTNs is motivated by wireless social networks in
504 which (i) individuals are often linked by a short chain of acquaintances, (ii)
505 certain encounters show repetitive behavior, and (iii) nodes have routines
506 that result in frequently visited locations and encounters.

507 In the reverse path, receiving a BA sent from node y to each neighboring
 508 node i produces three effects: (1) increasing the $BU_{i,d}$ value by one; (2)
 509 initializing or updating the $BU_{j,d}^i$ value according to Eq. 6 and 7, an effect
 510 that corresponds to the *Update Function* of the History Knowledge; and (3)
 511 updating the pheromone concentration toward d according to:

$$\tau_{(i,y),d}(t) = (1 - \rho) \times \tau_{(i,y),d}(t - 1) + Q_{p_{s_m}, d_m}^k(t), \quad (8)$$

512 where $\tau_{(i,y),d}(t - 1)$ is the pheromone on link (i, y) that was last updated
 513 at time $(t - 1)$. The evaporation process $(1 - \rho)$ is necessary for the ants "to
 514 forget" the previous pheromone values deposited on a link to a specific d .
 515 This evaporation reduces the influence of the path search history. When the
 516 pheromone is updated, all concentrations that belong to d are evaporated in
 517 i .

518 Even if the BA does not reach the node that originated the message
 519 (due to connection partitions), the message forwarding phase of the CGrAnt
 520 protocol is guided by a local path search provided by the heuristic function
 521 information. Differing from other protocols that use only global (pheromone
 522 concentration) or local (heuristic function) information, CGrAnt contains ad-
 523 ditional flexibility, because the decision is based on all available information
 524 (both ACO operators and knowledge stored in the CA belief space).

525 Additionally, the BA serves as an acknowledgment that m has achieved
 526 d_m , allowing the nodes that still maintain m to delete it and its associated
 527 variables. A node that encounters another node that has already received a
 528 BA for a given data message also deletes the corresponding message and its
 529 associated variables. When the source node receives it, the BA is deleted.
 530 Full paths are thus constructed for each destination using the information
 531 gathered by the ants during the path search phase.

532 4. Evaluation Methodology

533 This section describes the numerical analysis we conducted using the
 534 Opportunistic Network Environment (ONE) Simulator (Keränen et al., 2010)
 535 to investigate the benefits of the metrics and components incorporated into
 536 our proposal. Using ONE we can also assess both performance and accuracy
 537 of the CGrAnt protocol in simulation scenarios that consider two different
 538 movement models: Working Day (WD) (Ekman et al., 2008) and Points of
 539 Interest (PoI) (Keränen et al., 2010), both proposed by default in the ONE

540 simulator. The ONE default parameters were kept unchanged (whenever
541 possible) in order to confirm the results when compared with the others two
542 evaluated protocols (Epidemic and Prophet). Moreover, using the default
543 parameters, we intend to facilitate the dissemination of our proposal in the
544 simulation platform.

545 The WD movement model represents an activity-based environment that
546 simulates the daily lives (activities) of people who go to work in the morning,
547 spend the day working, may go to a public place for leisure activities with
548 friends at the end of day, and return to their houses at night. In WD, the
549 total area ($10,000 \times 8,000 m^2$) encompasses meeting points, buses, houses,
550 offices, and roads. The area is divided into four regions denoted by R_A to
551 R_D . Eight groups of nodes, denoted by A to H , are created to represent the
552 node movements into specific regions. Groups A to D simulate only intra-
553 region movements (e.g., group A simulates the node movements into region
554 R_A). Groups E , F , and G simulate node movements between R_A and other
555 regions, and H simulates movements among all regions. The assignment of
556 nodes per group is as follows: A has 258 nodes, B has 119, C has 154, D has
557 154, E has 102 (i.e., $E = A \cap B$), F has 122 (i.e., $F = A \cap C$), G has 122
558 (i.e., $G = A \cap D$), and H has 70 (i.e., $H = A \cap B \cap C \cap D$).

559 The WD movement model represents an activity-based environment that
560 simulates the daily lives (activities) of people who go to work in the morning,
561 spend the day working, may go to a public place for leisure activities with
562 friends at the end of day, and return to their houses at night. In WD, the
563 total area ($10,000 \times 8,000 m^2$) encompasses meeting points, buses, houses,
564 offices, and roads. The area is divided into four regions denoted by R_A to
565 R_D . Eight groups of nodes, denoted by A to H , are created to represent the
566 node movements into specific regions. Groups A to D simulate only intra-
567 region movements (e.g., group A simulates the node movements into region
568 R_A). Groups E , F , and G simulate node movements between R_A and other
569 regions, and H simulates movements among all regions. The assignment of
570 nodes per group is as follows: A has 258 nodes, B has 119, C has 154, D has
571 154, E has 102 (i.e., $E = A \cap B$), F has 122 (i.e., $F = A \cap C$), G has 122
572 (i.e., $G = A \cap D$), and H has 70 (i.e., $H = A \cap B \cap C \cap D$).

573 In the PoI movement model, the total area ($8,800 \times 7,800 m^2$) is divided
574 into five points of interest that simulate several communities of people who
575 eventually meet each other and exchange data. There are eight groups of
576 nodes (W1, X1, Y1, Z1, W2, X2, Y2, and Z2), each with different desti-
577 nation selection probabilities. The POIs movement model is similar to the

578 community model used by A. Lindgren et al.(Lindgren et al., 2003).

579 Groups W1, X1, Y1, and Z1 contain 30 nodes each. Groups W2, X2, Y2,
580 and Z2 have five nodes. Every node has one home PoI that is more likely
581 to be visited than the other PoIs; there is a high probability that nodes
582 meet each other within their same home community and a low probability
583 that they go to PoIs outside their home community. The nodes select a
584 destination, move in this direction (with $\overline{MS} \in [0.5, 1.5]$ m/s), wait during
585 a pause time (\overline{PT}) ranging from 100 to 200 seconds (for groups W1-Z1) or
586 4,000 to 5,000 seconds (for W2-Z2), and select the next destination, among
587 other actions. Table 2 shows the settings and communication parameters
588 applied in all experiments for the three protocols under comparison. Unless
589 otherwise described, the parameters used in both scenarios are emphasized
590 in Table 2.

591 In Section 5, we evaluate the CGrAnt performance with variations in
592 the setting parameters. We analyze the CGrAnt performance in the PoI
593 scenario in terms of the percentage of messages delivered to destinations.
594 The setting parameters emphasized represent those that provide the best
595 results for the CGrAnt protocol. Next, in Section 6, we investigate a subset
596 of the CGrAnt components by evaluating the protocol performance for both
597 scenarios (WD and PoI). Section 7 compares CGrAnt with the Epidemic
598 and PROPHET protocols in both scenarios and considers different aspects
599 of the communication network context. In all experiments, each message has
600 a size of 500 KB representing its payload and includes an FA with 8 bytes
601 representing its path quality. The BA size is 100 bytes on average (including
602 the header, path quality, and path hops).

603 The results discussed in Sections 5, 6 and 7 are presented in terms of mean
604 values and confidence intervals (at a 95% confidence level) for 30 runs in each
605 scenario. Due to the normality characteristics of the data under consider-
606 ation, we apply the ANOVA (ANalysis Of VAriance) parametric statistical
607 test together with its post hoc follow-up analysis over the independent groups
608 considered. The ANOVA statistical test returns a p-value > 0.05 indicating
609 (with 95% of confidence) that there are no statistical differences among the
610 groups and a p-value < 0.05 if there is at least one pair of groups with a
611 statistically significant difference. The intervals shown in the graphs for the
612 post hoc analysis are computed in such a way that (to a close approximation)
613 the two configurations compared are significantly different if their intervals
614 are disjoint and are not significantly different if their intervals overlap. In our
615 case, the delivery ratio interval associated with each group is represented by

616 a horizontal line (with a circle representing its mean value). For each graph,
617 we choose one group for emphasis (represented by a black horizontal line and
618 delimited by two vertical dashed lines).

619 5. Setting the Metrics of CGrAnt

620 This section investigates how selected metrics and ACO operators can
621 improve the communication among swarms in the population space and thus,
622 assist in obtaining better solutions. Sections 5.1 and 5.2 analyze the influence
623 of certain metrics associated with the ACO operators of CGrAnt. Section 5.3
624 analyzes the influence of selected metrics in characterizing the utility of each
625 node (solution) as a message forwarder.

626 5.1. Heuristic Function

627 We first analyze different sources of information in the ACO local operator
628 or Heuristic Function ($\eta_{n,d}(t)$). Recall that a node n is selected from a set
629 of candidates to forward a message m to its destination d . In this section,
630 the CGrAnt performance is evaluated by considering each of the following
631 metrics associated with $\eta_{n,d}(t)$: (1) $SP_{n,d}$, (2) DC_n , (3) $BU_{n,d}$, and (4) FB_n ,
632 which represents the free space available in the buffer of a node n .

633 The experimental results show that when CGrAnt uses the $SP_{n,d}$ metric,
634 it delivers more messages ($58.93 \pm 0.19\%$) than the DC_n ($47.21 \pm 0.17\%$), the
635 $BU_{n,d}$ ($53.92 \pm 0.17\%$), or the FB_n ($49.72 \pm 0.28\%$).

636 Figure 3 presents the *post hoc* analysis of ANOVA highlighting the $SP_{n,d}$
637 metric. The $SP_{n,d}$ metric guarantees the highest message delivery ratio.
638 This associated to the fact that there are no overlaps among the intervals
639 resulted from other metrics, lead us to conclude that $SP_{n,d}$ provides better
640 performance than the other metrics.

641 The main reasons for the better performance of the $SP_{n,d}$ metric are
642 listed as follows: (1) $SP_{n,d}$ indicates the proximity of n relative to d because
643 it provides an estimation of the probability of future encounters between n
644 and d . Moreover, $SP_{n,d}$ contains information available along all of the search
645 process. (2) DC_n indicates the popularity of n relative to all other nodes in
646 the network instead of specific information for the candidate forwarder and
647 d , as in $SP_{n,d}$. (3) $BU_{n,d}$ provides important information for the nodes that
648 successfully intermediated a communication to d ; however, it is only available
649 for n after a complete path has been found (which includes n), and n has
650 received the visit of a BA (as seen in Section 3.5). (4) In highly connected

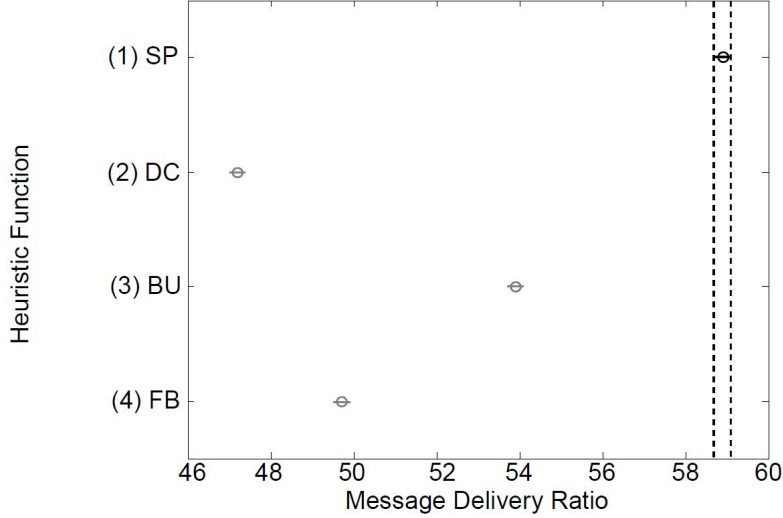


Figure 3: ANOVA results to Heuristic Function.

651 scenarios where the set of global solutions is always available and the same
 652 solution can be frequently selected, the percentage of available resources (e.g.,
 653 the buffer) may be an important metric to consider; nevertheless, in an en-
 654 vironment where the contacts are sparse (as in the DTNs), information on
 655 the social proximity between two nodes seems more important.

656 5.2. Pheromone Concentration

657 In this work, the pheromone concentration in the ACO global operator
 658 is associated with the quality of a complete path constructed by an ant k
 659 between the s_m and d_m nodes (i.e., $\tau_{(i,y),d}^k(t) = Q_{p_{s_m,d_m}^k}(t)$). Next, after
 660 defining the Heuristic function, we evaluate which type of information have
 661 more influence on $Q_{p_{s_m,d_m}^k}(t)$. The CGrAnt performance is evaluated using
 662 different metrics to predict the path quality: (1) the average Degree Central-
 663 ity (DC) of nodes n belonging to the path along with the reciprocal of the
 664 existing number of hops ($|p|$) in the constructed path, i.e., as in Eq. 1; (2) only
 665 the second term of Eq. 1; (3) only the first term of Eq. 1; and (4) the average
 666 *Betweenness Utility* of node n relative to d (i.e., $Q_{p_{s_m,d_m}^k}(t) = \frac{\sum_n BU_{n,d}}{|p|}$).

667 The simulation results show that when using a composite metric encom-
 668 passing DC and $|p|$, CGrAnt delivers more messages ($58.93 \pm 0.19\%$) than
 669 when it uses only the basic metrics $|p|$ ($51.11 \pm 0.22\%$), DC ($51.10 \pm 0.21\%$),
 670 and BU ($49.89 \pm 0.22\%$).

671 Figure 4 presents the *post hoc* analysis of ANOVA highlighting the com-
672 posite metric (DC and $|p|$). As shown, the composite metric provides the
673 best message delivery ratio. In addition, because there are no overlaps among
674 the intervals of other metrics, we conclude that the composite metric pro-
675 vides better performance than the basic metrics. This result indicates that
676 the node popularity is a good indicator of the node’s ability to forward mes-
677 sages. This is particularly true in scenarios with intermittent connections, as
678 in DTNs. Moreover, the importance of $|p|$ is due to the fact that the smaller
679 is the path, the fewer are the network resources consumed and the less is the
680 communication interference that occurs.

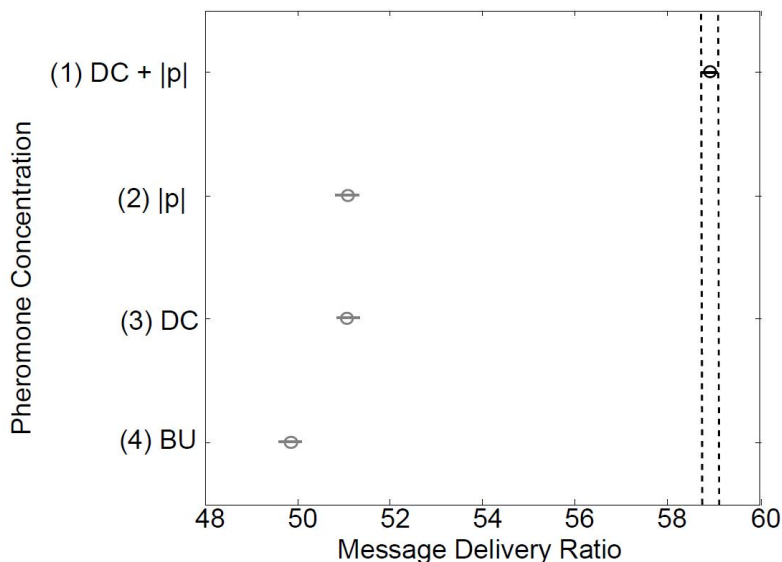


Figure 4: ANOVA results to Pheromone Concentration.

681 5.3. Node Utility

682 Finally, we analyze the utility ($U_{n,d}$) of each node n as a forwarder of a
683 message m to d . The CGrAnt performance is evaluated using four different
684 metrics to describe the utility of n related to a reference node i , which con-
685 tains a message m to be delivered to d . The investigated metrics are the
686 following: (1) only local information represented by the *Heuristic Function*
687 ($U_{n,d} = \eta_{n,d}(t)$); (2) only global information represented by the *Pheromone*
688 *Concentration* ($U_{n,d} = \tau_{(i,y),d}(t)$); (3) the *Heuristic Function* and *Pheromone*
689 *Concentration* ($U_{n,d} = \eta_{n,d}(t) + \tau_{(i,y),d}(t)$); and (4) the *Heuristic Function*,

690 *Pheromone Concentration*, and the *Relationship Degree* ($RD_{i,m}$) metric (ac-
 691 cording to Eq. 2).

692 The results show that when both ACO operators (heuristic function and
 693 pheromone concentration) and the $RD_{i,m}$ metric are considered (composition
 694 4), the CGrAnt protocol delivers more messages ($58.93 \pm 0.19\%$) compared
 695 with composition (1) in which it uses only the heuristic function ($55.95 \pm$
 696 0.23%), composition (2) in which it uses only the pheromone concentration
 697 ($49.29 \pm 0.18\%$), and composition (3) in which it uses the heuristic function
 698 and the pheromone concentration without the $RD_{i,m}$ metric ($58.02 \pm 0.20\%$).

699 Figure 5 presents the *post hoc* analysis of ANOVA highlighting the best
 700 composition (4). As depicted, there is no overlap among the intervals. This
 701 behavior verifies that the use of both local and global information (heuristic
 702 function and pheromone concentration) along with the $RD_{i,m}$ metric achieves
 703 higher performance.

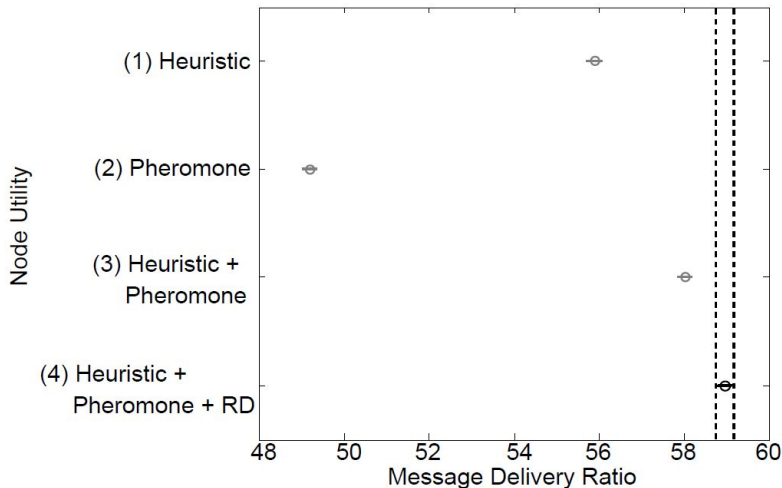


Figure 5: ANOVA results to Node's Utility Analysis.

704 6. CGrAnt Component Analysis

705 The influence of the CGrAnt's components on the message delivery ratio
 706 and message redundancy ratio are evaluated for the PoI and WD scenarios.
 707 The message redundancy ratio is expressed as $Redundancy = (B_{transm} -$
 708 $B_{delivery})/B_{delivery}$, in which B_{transm} represents the number of bytes trans-

709 mitted to nodes, and $B_{delivery}$, which is the number of bytes delivered to
710 their destination.

711 Initially, an additive methodology is adopted in which components are
712 added one by one to the previous protocol configuration until its final ver-
713 sion (configuration 6) is reached (see Table 3). The first two configurations
714 represent the CGrAnt protocol that considers only the ACO metaheuristic.
715 The pheromone concentration slightly increases the delivery ratio and
716 reduces the number of replicated messages. The influence of the new com-
717 ponents incorporated into CGrAnt (i.e., CA’s belief space) is analyzed for
718 configurations 3 to 6.

719 When comparing the results obtained from the pure ACO metaheuristic
720 (configuration 2) with the final performance of CGrAnt (configuration 6),
721 the following gains are achieved:

- 722 • in the POI scenario, the configuration 2 obtains 48.61% against 58.93%
723 of message delivery in the configuration 6. This represents a percentage
724 increase of message delivery in 21.23%;
- 725 • in the WD scenario, the configuration 2 obtains 54.97% against 63.19%
726 of message delivery in the configuration 6. This represents a percentage
727 increase of message delivery in 14.95%;
- 728 • in the POI scenario, the configuration 2 obtains 15.97% against 10.37%
729 of message redundancy in the configuration 6. This represents a per-
730 centage decrease of message redundancy in 35.07%;
- 731 • in the WD scenario, the configuration 2 obtains 68.62% against 12.43%
732 of message delivery in the configuration 6. This represents a percentage
733 decrease of message redundancy in 81.86%.

734 The Situational knowledge (configuration 4) aims to dynamically restrict
735 the number of FAs (and, consequently, the number of messages replicated) to
736 only the most promising forwarders. The History knowledge (configuration 5)
737 provides the exploitation of already known good solutions and consequently
738 increases the message delivery ratio. The Domain knowledge 1 (configuration
739 3) privileges the exploration of the search space and the Domain knowledge
740 2 (configuration 6) favors the exploitation. According to the analysis of
741 configurations 3 and 6, the Domain knowledge aims to increase the message
742 delivery and reduce the redundancy ratio.

743 GrAnt, our previous ACO-based protocol presented in (Vendramin et al.,
744 2012b), performs better than CGrAnt in PoI (i.e., GrAnt provides $62.10 \pm$
745 0.2% of message delivery and 7.05 ± 0.1 of message redundancy). However, for
746 the WD scenario, CGrAnt outperforms GrAnt (the latter achieved $60.25 \pm$
747 0.75% for delivery and 13.65 ± 0.14 for redundancy). CGrAnt presents better
748 performance in WD rather than in POI scenario because of the Domain
749 Knowledge. The Domain Knowledge considers the node mobility in order
750 to determinate if a node is a good message forwarder and, consequently,
751 if that node must exploit or explore the search space. In WD there are
752 several mobility patterns, i.e., buses and vagabonds nodes with high mobility.
753 Otherwise, in POI, the mobility of nodes is very similar and the information
754 of the Domain knowledge is less relevant.

755 Additionally, CGrAnt has the advantage of modeling at a higher abstrac-
756 tion level that enables the elimination of any knowledge of the CA belief
757 space in a simple way (e.g., the history knowledge can be eliminated when
758 the environment is more connected and fewer messages need to be forwarded).

759 Table 4 represents the eliminatory analysis of the CA’s belief space pro-
760 posed by CGrAnt. The first configuration in Table 4 represents the CGrAnt
761 protocol including all components. In analyzing this table we conclude the
762 following:

- 763 • **Domain Knowledge** aims to increase the message delivery ratio and
764 reduces the message replication. This is particularly true in the WD
765 scenario in which the nodes generally have a stagnation degree (SD_n)
766 lower than the average stagnation of its social network (SD_J), and
767 consequently, the Domain knowledge has greater influence. Without
768 this knowledge, the message delivery ratio is reduced by 1.77% (PoI)
769 and 1.40% (WD) and the message redundancy ratio increased by 0.77%
770 (PoI) and 92.27% (WD);
- 771 • **Situational Knowledge** aims to dynamically restrict the FAs to only
772 good forwarders, and its influence on the message redundancy ratio
773 is therefore greater. Without this knowledge influence, we observe an
774 increase of 51.78% (PoI) and 248.51% (WD) in the message redundancy
775 ratio and a reduction in the message delivery ratio of 9.15% (PoI). In
776 the WD scenario we have an increase of message delivery ratio of 1.65%;
- 777 • **History Knowledge** aims to enhance already known good solutions
778 and thus increases the message delivery ratio. Without the influence of

779 this knowledge, there is a reduction of 3.78% (PoI) and 3.4% (WD) in
780 the message delivery ratio with a lowest cost incurred in the replication
781 of messages -33.85% (PoI) and -12.55% (WD).

782 It may be noted that the use of the multiple knowledge incorporated in
783 CGrAnt improves its final performance. As the use of multiple techniques in
784 ensemble systems, the combination of a set of techniques on an suitable con-
785 sensus function provides better performance than each individual technique.

786 7. The CGrAnt Overall Performance

787 This section investigates how CGrAnt performs as a forwarding protocol
788 when compared with the Epidemic and PROPHET protocols under varying
789 networking parameters. We performed 30 runs, and the reported results rep-
790 resent the mean and confidence intervals (at a 95% confidence level) values.
791 To evaluate the reliability and the cost of the three protocols, we consid-
792 ered the following three performance metrics: (1) message delivery ratio, (2)
793 message redundancy ratio, and (3) average message delivery delay.

794 7.1. Analysis of Different Buffer Sizes

795 Figure 6 depicts the performance of the three protocols with variation of
796 the buffer sizes (from 4 MB to 16 MB) for the PoI scenario. The dashed
797 curves with empty points denotes the results for nodes that operate at a
798 communication range of 10 m and a transmission rate of 2 Mbps (repre-
799 senting bluetooth devices). The solid curves with black points show the
800 results for nodes that operate at a 100 m range and a transmission rate of
801 10 Mbps (representing WiFi devices). Figures 6(a) and 6(b) show that with
802 the use of CGrAnt, more messages are delivered and less buffer space is de-
803 voted to message replications. For instance, for a buffer size of 8MB and a
804 communication range of 100 m, CGrAnt delivers $93.27 \pm 0.10\%$ of messages
805 (versus $66.52 \pm 0.16\%$ for Epidemic and $46.84 \pm 0.15\%$ for PROPHET) with
806 a message replication of only $15.23 \pm 0.06\%$ ($38.90 \pm 0.13\%$ for Epidemic and
807 $41.85 \pm 0.19\%$ for PROPHET). Figure 6(c) shows that CGrAnt provides the
808 lowest delivery delay when using a higher buffer size (i.e., 10 MB to 16 MB).

809 Note that for buffer sizes lower than 8MB, PROPHET presents better
810 results in terms of delivery delay. This is due to its lowest Message Delivery
811 ratio, almost -50% than CGrAnt, only short route with short delivery delay
812 is used.

813 7.2. Analysis of Different Message TTLs

814 Figure 7 shows the performance of the CGrAnt, Epidemic, and PROPHEt
815 protocols with variation of the message TTL (Time-To-Live, i.e., how long
816 the message lives in the network in minutes) for the PoI scenario. Figures 7(a)
817 and 7(b) show that CGrAnt provides the best results in terms of message
818 delivery and redundancy ratios for all message TTLs and both communica-
819 tion ranges. For instance, with a 10 m range and a TTL of 2,100 minutes,
820 CGrAnt delivers $61.09 \pm 0.23\%$ of messages (versus $35.39 \pm 0.17\%$ for Epi-
821 demic, $30.50 \pm 0.14\%$ for PROPHEt), with a message redundancy of only
822 $10.21 \pm 0.05\%$ ($30.47 \pm 0.18\%$ for Epidemic, $32.82 \pm 0.17\%$ for PROPHEt).
823 These results show that a node with an efficient routing protocol such as
824 CGrAnt, with guidance from the CA knowledge and the ACO operators is
825 able to efficiently manage message forwarding and dynamically limit message
826 redundancy. Figure 7(c) shows that PROPHEt provided the best results in
827 terms of delivery delay; this is the only metric for which CGrAnt cannot pro-
828 vide the best results, a lack that is justified by its lowest Message Delivery
829 ratio, almost -40% than CGrAnt, only short route with short delivery delay
830 is used.

831 The performance of the three DTN protocols with variations in the buffer
832 sizes and message TTLs in the WD scenario is presented in (Vendramin et al.,
833 2012a). The results in (Vendramin et al., 2012a) show that CGrAnt achieves
834 a higher message delivery ratio and a lower redundancy ratio than those of
835 Epidemic and PROPHEt.

836 7.3. Analysis of Different Simulation Times

837 We also perform an experiment to evaluate the number of messages de-
838 livered by the three protocols along the simulation time in the PoI (4MB of
839 buffer size and message TTL of 600) and the WD scenarios (10MB of buffer
840 size and message TTL of 1,800), both with a communication range of 10m.
841 The aim in this section is to demonstrate that a better delivery ratio can be
842 achieved as the time increases.

843 Figure 8 shows the message delivery ratio obtained by the three protocols
844 over time in the PoI and WD scenarios with a 10 m range. In CGrAnt, the
845 performance gain is greater mainly in the WD scenario. When the simulation
846 time is increased from 400,000 to 2,800,000 seconds, CGrAnt delivers slightly
847 better performance via an increase of 7.37% (PoI) and 17.45% (WD) in the
848 message delivery ratio. This gain is justified by the fact that the more is the
849 gathered information by CGrAnt over time, the better are the choices it can

850 make concerning message forwarding candidates. In contrast, PROPHET
851 and Epidemic did not exhibit any significant variation of performance when
852 the simulation time was increased.

853 7.4. Analysis of Operation Costs

854 Another important consideration in protocol performance is the cost of
855 initializing/updating and storing the state of the network and nodes. This
856 cost covers the amount of the following types of information: (1) locally
857 exchanged between every two nodes i and j during any contact opportunity,
858 and (2) locally stored in each node i of the network. For this analysis, we
859 considered the PoI scenario with the emphasized parameters presented in
860 Table 2.

861 For the storage cost in terms of the total number of bytes exchanged be-
862 tween nodes i and j during every contact opportunity, PROPHET displays a
863 higher cost due to the exchange of its delivery predictability list. Due to the
864 transitive property of PROPHET, the number of records in the predictabil-
865 ity list of a node rapidly reaches the total number of network nodes (139,
866 excluding itself). Thus, the number of bytes exchanged in both directions
867 of the contact is 2,224 bytes (139×16 bytes), as it is shown in Table 5.
868 For the CGrAnt protocol, during the message forwarding phase, 16 bytes
869 are sent by i to its neighboring node j , identifying a data message m to be
870 sent and the stagnation degree of i . At the same time, 29 bytes are sent
871 by j to i representing node j on how well it can perform as a forwarder for
872 m : including its stagnation degree, its degree centrality, its social proximity
873 with the destination d of the message m stored in node i , its betweenness
874 utility relative to d , and an indication (true or false) that it knows that m
875 was already received by d .

876 For the cost in terms of the total number of bytes stored in each node i ,
877 because Epidemic relies on the message replications to eventually deliver its
878 messages, its storage cost is null (i.e., it is a stateless protocol). Although
879 CGrAnt generates a higher storage cost compared with PROPHET and Epi-
880 demic, in the worst case, that cost (11.28 KB) represents only 0.28% of the
881 total capacity of a node buffer, if considering a limiting buffer size of 4 MB
882 per node.

883 Finally, we investigate the operational cost provided by CGrAnt when
884 considering only its control messages related to the ACO ants (FAs and
885 BAs) in both PoI (*buffer* of 4 MB and message TTL of 600 minutes) and WD
886 (*buffer* of 10 MB and message TTL of 1,800 minutes) scenarios. In the PoI

887 scenario, the control bytes corresponding to the FAs and BAs represent only
888 $0.0131 \pm 0,0009\%$ (communication range of 10 m) and $0.0186 \pm 0,0002\%$ (100
889 m range) of the total bytes generated by CGrAnt (counting the bytes related
890 to data messages, FAs, and BAs). In the WD scenario, the FAs and BAs
891 bytes represent, respectively, $0.0194 \pm 0,0003\%$ (10 m) and $0.079 \pm 0,0022\%$
892 (100 m) of the total bytes generated. Nevertheless, even if accounting for the
893 extra cost of these control bytes (for the FAs and BAs) in the total amount (in
894 bytes) of replicated messages in the network, CGrAnt propagates fewer bytes
895 in the network compared with Epidemic and PROPHET due to the high
896 number of data messages replicated by the latter protocols. When compared
897 with Epidemic, CGrAnt provides a reduction of $39.99 \pm 0,16\%$ (in PoI with
898 a 10 m range), $59.60 \pm 0,11\%$ (PoI with a 100 m range), $83.60 \pm 0,19\%$
899 (WD with a 10 m range), and $89.49 \pm 0,26\%$ (WD with a 100 m range)
900 in the total number of bytes generated in the network. Similarly, when
901 compared with PROPHET, these reductions are $34.86 \pm 0,18\%$ (PoI with 10
902 m), $43.37 \pm 0,15\%$ (PoI with 100 m), $74.59 \pm 0,34\%$ (WD with 10 m), and
903 $78.57 \pm 0,56\%$ (WD with 100 m) in total bytes generated in the network.
904 Therefore, we conclude that with the smallest generated overhead, CGrAnt
905 is able to choose the best message forwarders and reduce the total number
906 of data bytes replicated in the network.

907 It is important to highlight that the algorithmic complexity for the CGrAnt
908 protocol is linear $[O(n)]$ in the number of network nodes, as shown in Algo-
909 rithm 1.

910 8. Conclusions

911 The importance of inferring the social behavior of nodes to efficiently
912 deliver data in mobile and intermittently connected networks has motivated
913 the development of the hybrid swarm intelligence-based CGrAnt protocol.
914 Using a greedy version of ACO and CA, CGrAnt characterizes the utility of
915 each node as a message forwarder by considering a set of social-aware met-
916 rics. We performed a set of experiments to analyze the influence of selected
917 metrics associated with the ACO operators and the use of different metrics to
918 characterize the utility of each node as a message forwarder. Once the group
919 of metrics was set, we analyzed the influence of the ACO operators and CA
920 knowledge on the CGrAnt performance. Finally, we compared the perfor-
921 mance of CGrAnt with the Epidemic and PROPHET protocols under varying
922 networking parameters. The simulation results showed that CGrAnt outper-

923 formed PROPHET and Epidemic forwarding protocols in terms of message
924 delivery (gains of 99.12% compared with PROPHET and 40.21% compared
925 with Epidemic) and message replication (63.60% lower than PROPHET and
926 60.84% lower than Epidemic). In addition, despite a higher storage cost com-
927 pared to PROPHET and Epidemic (11.28 KB in the worst case), CGrAnt
928 propagates fewer bytes in the network due to the high number of data mes-
929 sages replicated by the latter protocols (a reduction of 43.37% when compared
930 to PROPHET and 59.60% when compared to Epidemic). In future work, we
931 intend to study in more details the adaptive capabilities of CGrAnt, when
932 operating in a scenario with varying mobility conditions, i.e., from an almost
933 static to a completely mobile and disconnected networking environment. For
934 this work, we will investigate the self-adaptation of social-aware metrics,
935 which can be combined with and applied to each CGrAnt component. Fi-
936 nally, the comparison of CGrAnt performance with other related social-based
937 forwarding protocols as well as the use of real data sets is such analysis will
938 be also let for future works.

939 9. Curriculum Vitae

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964 performance.

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Table 1: Summary of the metrics and variables used to describe the network and CGrAnt

Network Variables	
m	A specific data message
s	A general source node (s_m : refers to the source of m)
d	A general destination node (d_m : the destination node of m)
i	Node with a data message to be forwarded
j	Neighboring node of i
n	A generic node, i or j
y	A generic node, j or d in a link toward d
N	The total number of nodes available in the network
M	The total number of data messages to be forwarded
J	Set of nodes j encountered by the node i (social network of i)
D_i	The total number of destination nodes for which i originated or intermediated a path
CGrAnt Variables	
FA/BA	A general Forward/Backward Ant
k	A specific FA/BA
K_m	The total number of FAs generated for a message m
p	A complete path with a total of $ p $ hops
P_m	Group of paths p constructed by ants for a message m
W	Event window
dr_n	Improvement direction of a node n
V_i/V_s	Inferior/Superior limits which define the range of medium stagnation degree
CGrAnt Local Metrics	
$FE_{n,d}$	Frequency of Encounters between n and d
$DE_{n,d}$	Duration of an Encounter between n and d
PT_n	Average Pause Time in the places visited by a node n
MS_n	Average Movement Speed of a node n
DC_n	Degree Centrality of a node n
$RD_{i,m}$	Relationship Degree of a node i with respect to a specific buffered data message m
CGrAnt Global Metrics	
$ p $	Number of hops in a complete path p
$BU_{n,d}$	Betweenness Utility of a node n in relation to d
CGrAnt Composite Metrics	
$BU_{J,d}^i$	Betweenness Utility of the social network of i in relation to a destination d
$SP_{n,d}$	Social Proximity between nodes n and d
$U_{n,d}$	Utility of a node n as a message forwarder to d
$\eta_{n,d}$	Heuristic Function measured by $SP_{n,d}$
$\tau_{(i,y),d}$	Pheromone concentration on each link (i,y) belonging to a path to node d
SD_n	Stagnation Degree of a node n
SD_J^i	Stagnation Degree of the social network of node i
$Q_{p_{s_m,d_m}}^k$	Quality of a path p (from s_m to d_m) constructed by FA k
CGrAnt Knowledge	
Dom_i	Domain Knowledge of node i
$His_{i,d}$	History Knowledge of i with respect to d
$Sit_{i,m}$	Situational Knowledge of i with respect to m

Algorithm 1 Pseudo-code of the CGrAnt Message Forwarding.

```
1: Algorithm Initialization
2: for each message  $m$  in the buffer of node  $i$  do
3:    $best\_fwd_m \leftarrow \emptyset$ ; {No forwarder is assigned to  $m$ }
4: end for
5: { $BU$ , Pheromone concentration, and History knowledge are updated during the backward phase}
6: for each message  $m$  in the buffer of node  $i$  do
7:    $U_{i,d} \leftarrow U_{n,d}$ ; {Updating node  $i$  utility, as in Eq. 2}
8:   if ( $best\_fwd_m = \emptyset$ ) then
9:      $best\_fwd_{m,d} \leftarrow i$  {Initializing the Situational Knowledge};
10:     $U_{best\_fwd_{m,d}} \leftarrow U_{i,d}$ ; {Utility of the best forwarder for  $m$ }
11:   end if
12:    $search\_status\_exploration \leftarrow true$ ;
13:    $search\_status\_exploitation \leftarrow true$ ;
14:   {Domain Knowledge Influence}
15:   if ( $(RD_{i,m} \neq s_m)$  AND  $(dr_i = 0)$ ) { $Dom_i = medium SD_i$ } then
16:      $search\_status\_exploration \leftarrow false$ ;
17:   end if
18:   if ( $(RD_{i,m} \neq s_m)$  AND  $(dr_i = -1)$ ) { $Dom_i = low SD_i$ } then
19:      $search\_status\_exploration \leftarrow false$ ;
20:      $search\_status\_exploitation \leftarrow false$ ;
21:   end if
22:   

---


23:   Message Forwarding
24:   for all connections  $j$  do
25:      $U_{j,d} \leftarrow U_{n,d}$  {Updating node  $j$  utility, as in Eq. 2}
26:     if ( $(search\_status\_exploration)$  AND  $(best\_fwd_m = i)$  AND  $(U_{i,d} = U_{j,d})$ ) then
27:        $initial\_exploration \leftarrow true$ ;
28:     else
29:        $initial\_exploration \leftarrow false$ ;
30:     end if
31:     {Influence of History and Situational Knowledge}
32:     if ( $(search\_status\_exploitation)$  AND  $(History\_Influence\_Function())$ ) then
33:       Forward  $m$  to  $j$  {History Knowledge Influence}
34:     else
35:       if ( $(initial\_exploration)$  OR  $(Situational\_Acceptance\_Function())$ ) then
36:         {Situational Knowledge Update}
37:          $best\_fwd_m \leftarrow j$ ;
38:          $U_{best\_fwd_{m,d}} \leftarrow U_{j,d}$ ;
39:       end if
40:     end if
41:   end for
42: end for
43: if ( $best\_fwd_m \neq i$ ) then
44:   Forward  $m$  to  $j$  {Situational Knowledge Influence}
45: end if
46:  $History\_Influence\_Function()$ 
47: if ( $BU_{j,d} > His_{i,d}$ ) then
48:   Return TRUE { $dr_j = +1$ }
49: else
50:   Return FALSE { $dr_j = -1$  or  $dr_j = 0$ }
51: end if
52:  $Situational\_Acceptance\_Function()$ 
53: if ( $U_{j,d} > Sit_{i,m}$ ) then
54:   Return TRUE{Accept the solution  $j$ }
55: else
56:   Return FALSE
57: end if
```

Table 2: Simulation parameters.

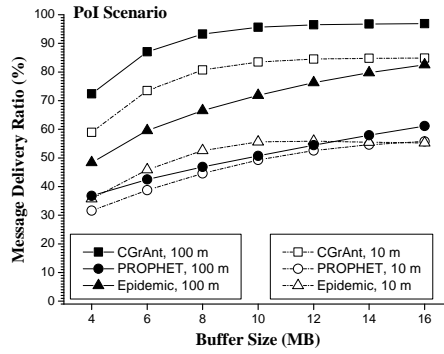
Protocol	Setting Parameters	Both scenarios	
CGrAnt	Pheromone evaporation rate	0.1	
	Heuristic function	$\{\mathbf{SP}_{n,d}, DC_n, BU_{n,d}, FB_n\}$	
	Pheromone concentration	$\{p, DC_n, BU_n, \mathbf{DC}_n + p \}$	
	Utility of a node	$\{\text{Heuristic}, \text{Pheromone}, \text{Heuristic}+\text{Pheromone}, \mathbf{Heuristic} + \text{Pheromone} + \mathbf{RD}_{i,m}\}$	
PROPHET	Hop-count field (hops)	11	
	P_{mic}	0.75	
	γ	0.98	
	One time unit $Unit$ (s)	30	
Epidemic	φ	0.25	
	Hop-count field (hops)	11	
Protocol	Communication Parameters	PoI	WD
All	Number of nodes (N)	140	339
	Area (m^2)	8,800 x 7,800	10,000 x 8,000
	Nodes speed (m/s)	[0.5,1.5]	[0.8,1.4] (pedestrian), [7.0,10.0] (car and bus)
	Waiting time (s)	100-200 (W1-Z1), 4000-5000 (W2-Z2)	300-500 (H), 10-30 (bus)
	Traffic generation rate (s)	50-90	100-150
	Message TTL (min)	{300, 600, 900, 1200, 1500, 1800, 2100}	{300, 600, 900, 1200, 1500, 1800, 2100}
	Nodes buffer (MB)	{4, 6, 8, 10, 12, 14, 16}	{4, 6, 8, 10, 12, 14, 16}
	Simulation time (s)	800,000	
	Warm up period (s)	5,000	
	Communication range (m)	10 (Bluetooth Devices), 100 (WiFi Devices)	
Transmission rate (Mbps)	2 (Bluetooth Devices), 10 (WiFi Devices)		
Number of simulations	30		

Table 3: Additive Analysis of the CGrAnt's Components

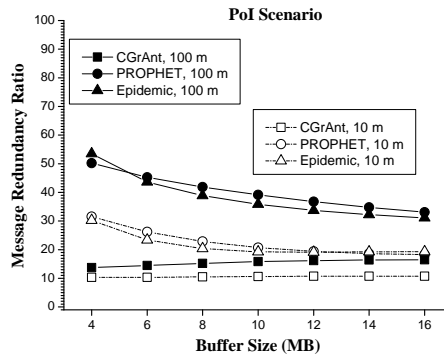
Configuration	(PoI WD) Message Delivery %	(PoI WD) Message Redundancy
1. Heuristic Function	46.26 \pm 0.18 53.38 \pm 0.60	18.36 \pm 0.08 85.87 \pm 0.94
2. Pheromone Concentration + RD	48.61 \pm 0.20 54.97 \pm 0.61	15.97 \pm 0.08 68.62 \pm 0.96
3. Domain Knowledge 1	49.40 \pm 0.21 64.26 \pm 0.63	15.11 \pm 0.09 43.18 \pm 0.41
4. Situational Knowledge	56.70 \pm 0.27 61.04 \pm 0.68	6.86 \pm 0.04 10.87 \pm 0.11
5. History Knowledge	58.93 \pm 0.19 63.70 \pm 0.69	10.37 \pm 0.05 19.04 \pm 0.16
6. Domain Knowledge 2	58.93 \pm 0.19 63.19 \pm 0.72	10.37 \pm 0.05 12.43 \pm 0.12

Table 4: Eliminatory Analysis of the CGrAnt's Components

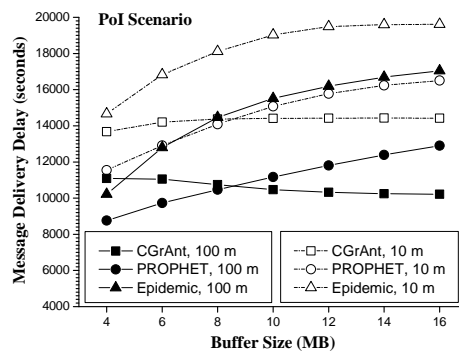
CGrAnt	(PoI WD) Message Delivery %	(PoI WD) Message Redundancy
All components	58.93 \pm 0.19 63.19 \pm 0.72	10.37 \pm 0.05 12.43 \pm 0.12
Without Domain Knowledge	57.90 \pm 0.22 62.30 \pm 0.67	10.45 \pm 0.04 23.90 \pm 0.28
Without Situational Knowledge	53.54 \pm 0.22 64.23 \pm 0.64	15.74 \pm 0.07 43.32 \pm 0.43
Without History Knowledge	56.70 \pm 0.27 61.04 \pm 0.68	6.86 \pm 0.04 10.87 \pm 0.11



(a) Delivery Ratio

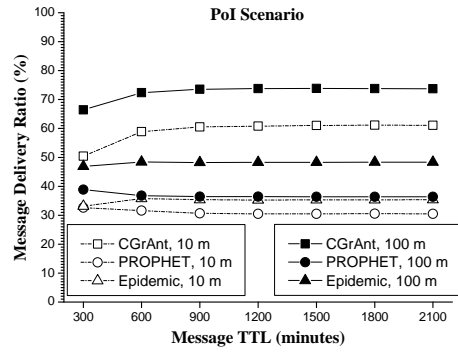


(b) Redundancy Ratio

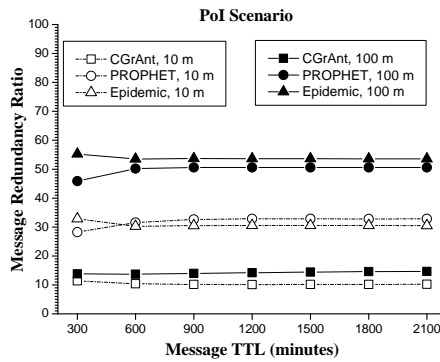


(c) Delivery Delay

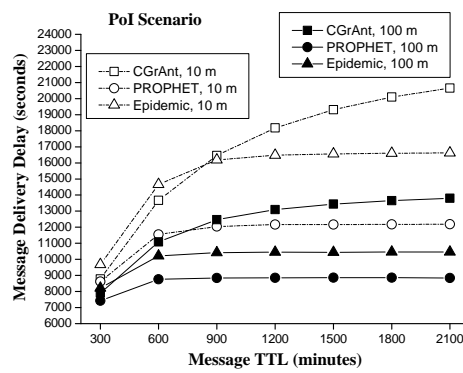
Figure 6: Protocols' performance over different buffer sizes - PoI scenario.



(a) Delivery Ratio

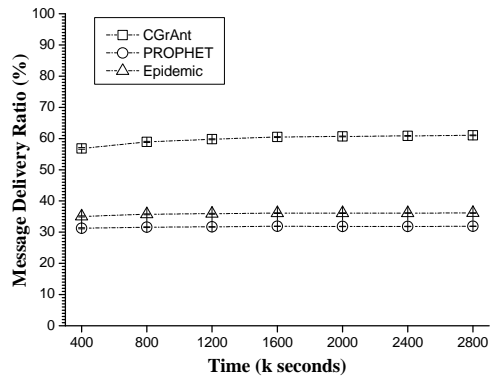


(b) Redundancy Ratio

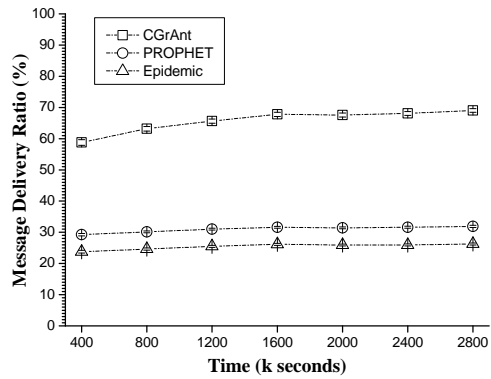


(c) Delivery Delay

Figure 7: Protocols' performance over different message TTLs - PoI scenario.



(a) Delivery Ratio - PoI scenario



(b) Delivery Ratio - WD scenario

Figure 8: Message Delivery Ratio over Different Simulation Time.

Table 5: Storage cost over different simulation time

Protocols/ Simulation Time	Registers/Bytes (100k sec.)	Registers/Bytes (200k sec.)	Registers/Bytes (300k sec.)	Registers/Bytes (400k sec.)	Registers/Bytes (500k sec.)	Registers/Bytes (600k sec.)	Registers/Bytes (700k sec.)
CGrAnt							
$FE_{i,d}$	93.97/1,127.65	116.01/1,392.17	126.73/1,520.74	131.67/1,580.06	134.79/1,617.43	136.51/1,638.17	137.54/1,650.51
$DE_{i,d}$	93.97/2,255.31	116.01/2,784	126.73/3,041.49	131.67/3,160.11	134.79/3,234.86	136.51/3,276.34	137.54/3,301.03
DC_i	2/16	2/16	2/16	2/16	2/16	2/16	2/16
PT_i and MS_i	2/16	2/16	2/16	2/16	2/16	2/16	2/16
SD_j	90.82/1,453.14	116.01/1,856.23	126.73/2,027.66	131.67/2,106.74	134.79/2,156.57	136.51/2,184.23	137.54/2,200.69
$U_{best_fwd_m}$	22.55/360.8	43.64/698.29	62.99/1,007.89	81.72/1,307.54	98.99/1,583.77	115.63/1,850.06	131.94/2,111.09
Pheromone Table	9.56/229.54	17.76/426.34	23.94/574.63	28.76/690.17	32.56/781.54	35.96/862.97	38.74/929.66
$BU_{i,d}$	8.58/102.94	16.1/193.2	22.04/264.43	26.76/321.09	30.54/366.51	33.88/406.54	36.74/440.91
$BU_{j,d}$	9.56/153.03	17.76/284.23	23.94/383.09	28.76/460.11	32.56/521.03	35.96/575.31	38.74/619.77
PROPHET							
Delivery Predictability List	139/2,224	139/2,224	139/2,224	139/2,224	139/2,224	139/2,224	139/2,224