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# Bio-inspired Probabilistic Opportunistic Routing for Vehicular Delay-Tolerant Networks Using A Hybrid Swarm Approach

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**Abstract**

Vehicular Delay Tolerant Network (VDTN) routing has been improved using probabilistic routing to improve the coverage of intermittent vehicular networks. VDTNs are characterized by large transmission ranges of vehicles, rapid vehicular speeds, and restricted mobility movements, particularly in urban areas. As a result, the probabilistic Sore-Carry-and-Forward (SCF) relay vehicle selection can be inaccurate when considering remote vehicles, leading to high overheads. To address this issue, a new bio-inspired VDTN routing protocol is proposed to better estimate the SCF capabilities of remote vehicles so that the duplicated generated bundles' copies are reduced without altering the bundles' delivery ratio and average delivery delay. This solution sequentially employs the Ant Colony Optimizer (ACO) and Glowworm Swarm Optimization (GSO) to adaptively control the replication of bundle copies at each bundle forwarding stage based on predefined probabilistic forwarding parameters. Simulation results from a sparse urban mobility scenario show reduced bundle replication rates compared to several probabilistic VDTN routing protocols.

## I. INTRODUCTION

Vehicular Delay Tolerant Networks (VDTNs) are a subcategory of Vehicular Ad-Hoc Networks (VANETs) specifically designed for sparse vehicular areas, where intermittent connectivity dominates communication time between vehicles. VDTN routing applies Delay-Tolerant Network (DTN) routing principles to sparse VANETs [1]. Opportunistic routing methods used between handheld devices in Mobile Ad-Hoc Networks (MANETs) [2] can be adapted to vehicles in VANET routing, considering factors such as a broader transmission range, faster speeds, and directed mobility. For DTNs, Store-Carry-Forward (SCF) serves as the default VDTN routing mechanism: SCF relies on predefined data replication parameters to determine the forwarding decision for buffered bundles. It is also linked to a custom buffer management policy that helps maintain an effective balance between buffer time and bundle replication speed, thereby improving the overall Qualit-of-service (QoS) performances [3].

Swarm-inspired VDTN routing optimization falls under the umbrella of bio-inspired VANET routing. Numerous swarm-based algorithms [4] have been efficiently used to solve various VANET routing problems [5]. VDTN routing faces a major challenge in tracking effective SCF vehicles while minimizing the number of bundle relays and reducing delivery delays. Consequently, various types of VDTN routing has been developed[6] [7] including probabilistic routing [8], which relies on stochastic bundles replication based on available vehicular routing information. Probabilistic VDTN routing helps predict future vehicle trajectories to efficiently distribute bundles to position as close as possible to their destinations which reduces the average bundle buffer time. However, it may suffer from a lack of accuracy due to factors such as radio obstacles, drastic change in destination speed, or movement changes, leading to uncontrolled overheads caused by excessive flooding in urban areas.

Another VDTN routing mode based on bio-inspired optimization has emerged recently, inspired by social-based grouping native to human behavior [9]. The intelligence of particles in nature has been utilized to mitigate the nodes' participation in data forwarding and to redirect bundles to their destinations more efficiently. Sparse density adds to the difficulty of anticipating better relay nodes to avoid long buffer time, particularly in VANETs characterized by high speeds and limited urban mobility patterns [10].

This paper discusses the challenge of leveraging the qualities of probabilistic VDTN routing within the context of swarm-based optimization to improve SCF vehicle selection and optimize flooding. The fitness of each vehicle for buffered bundle can be estimated base on predefined probabilistic routing parameters. To accomplish this, a new bio-inspired VDTN routing solution that combines two two metaheuristics, namely the Ant Colony Optimizer (ACO) [11] and Glowworm Swarm Optimization (GSO) [12] is proposed. The stochastic solution selection methods of ACO and GSO are integrated to anticipate a larger number of relay vehicles during early and advanced forwarding stages, respectively, which is expected to increase bundle delivery probability and reduce average delivery delays and flooding rates.

The remaining of this paper is organized as follows: Section 2 discusses the major probabilistic VDTN routing literature, including the bio-inspired VDTN routing. Section 3 provides a detailed explanation of the new bio-inspired routing solution, including the context of swarm-based optimization with its mathematical models and illustrations. Section 4 analyses and compares the simulation results of the realized work with few VDTN routing references. Section 5 concludes the manuscript and discusses future research directions related to this contribution.

## II. LITERATURE REVIEW

The probabilistic opportunistic routing has been widely developed in VANETs to address consistently-sparse networks. In this section, the notable probabilistic routing protocols are described as follows:

Adaptive ProPHET-based routing protocol (PRoPHET+) [13] is a modified version of the Probabilistic Historic of Encounters and Transitivity (ProPHET) [14] that introduces a predefined deliverability value (VD) to evaluate candidate nodes for next-SCF selection. The VD is calculated using four parameters that reflect the node's forwarding abilities, namely, the buffer parameter, power parameter, popularity parameter, and bandwidth parameter. These parameters represent the remaining buffer space, residual sending power, the ratio of performed data transmissions, and the ratio between sending and receiving bandwidth, respectively. Each parameter is weighted according to its impact on the VD.

Probabilistic Routing based on History of Messages (HOMME-ProPHET) [15] is a modified version of ProPHET that adjusts its default DP value for all known contacts by considering the history of previous hops traversed by the bundle. This adjustment helps predict better next-SCF nodes. The traversed hop count and the forwarding quality of passed nodes are added as prediction parameters to calculate the new DP of potential next-hop nodes. Thus, the routing decision links the quality of the passed path to the host vehicle and the forwarding abilities of the available direct contacts through deduced DP values.

Probabilistic Bundle Relaying Scheme (PBRS) [16] is a new DTN routing protocol that combines knowledge-based and prediction-based forwarding modes. For each buffered bundle in every host node, PBRS estimates the required time for the bundle's delivery to its destination for each candidate SCF node amongst the host's active contacts. To accomplish this task, a predefined release probability (Pr) value is calculated based on the node speed to estimate the probability of passing a bundle to the next-SCF node. This approach seeks to reduce the bundle's buffering time so that the final delivery delay is shortened.

Delivery Probability Routing (DPR) [17] is an improved Spray-and-Wait (SnW) [18] protocol that includes a delivery probability mechanism. Every DPR node exchanges its active contacts with encountered nodes using a probability vector (PV) which associates a delivery probability to each contact. Each node's PV is updated during both SnW phases. This mechanism defines a separate spray time for each node depending on the routing quality of SCF candidates, collected from the received PVs. Consequently, the Spray phase is shortened for each bundle relative to the number of remaining copies. The Wait phase starts at different times, allowing more replicated bundles to arrive sooner than the Wait phase. This approach significantly reduces average delivery delays.

Epidemic-ProPHET [19] is a hybrid probabilistic DTN routing protocol that combines Epidemic Routing (ER) protocol [20] and ProPHET. This version uses ER during the early stages of the bundle's forwarding cycle enabling faster spreading of bundle copies across the nodes' neighborhoods. The forwarding policy during the advanced stages relies on ProPHET, which seeks a better-oriented replication of the spread bundle copies during the ER-based phase. The transition from ER-based to ProPHET-based forwarding is triggered when either a hop count threshold or a predefined number of forwarded bundles is surpassed.

ProPHET-based SnW routing protocol (ProPHET-SnW) [21] is a hybrid multi-copy DTN routing protocol deduced by applying the Delivery Predictability (DP) of ProPHET in SnW. ProPHET's DP is restricted to the spray phase, where only L bundle copies are distributed to neighboring nodes with a higher delivery probability. The Wait phase remains the same as defined in SnW. ProPHET-based SnW adds a buffer management control to solve the buffer overflow problem by checking the free buffer space of available candidate SCF nodes before storing new bundles according to their size.

A data dissemination mechanism based on evaluating behavior for VDTNs [22] defines a routing protocol that estimates traffic density for SCF node selection decisions. This mechanism also takes into account the behavior of vehicles under a predefined interaction score, calculated using four parameters; namely, node interaction freshness, node interaction dispersion, node interaction contribution, and node interaction participation. The first parameter reflects the vehicle's recent interaction activity, the second represents the communication time stability between pairs of vehicles. The third measures the participation degree of nodes in bundles forwarding, and the fourth parameter accounts for the communication frequency between vehicles pair.

The evolution of bio-inspired VDTN routing in probabilistic SCF forwarding has appeared in a few works, primarily focusing on DTNs. Some notable examples include:

AntProPHET by [23] is an ACO-inspired ProPHET-based routing protocol. To enhance the delivery probability and limit routing overheads, AntProPHET applies the process of food nest tracking from ant swarm behavior to select the next-SCF node. The predictability calculation for each next-hop candidate, as in PRoPHET, is updated using the ACO's pheromone decay formula. A probabilistic selection among the available candidate next-SCF nodes is performed, where the nodes generating lesser decay quantities, reflecting a higher pheromone quantity, having a higher selection rate.

Nature-inspired routing protocol for DTNs (BeeAntDTN) [24] is a bio-inspired probabilistic DTN routing protocol that uses the food foraging intelligence of insects modeled in ACO and Bee Colony Optimizer (BCO) [25]. Innitially, a BCO-based flooding mechanism is used to explore connectivity degree (CD) information for each node. Then, ACO tracks optimized forwarding routes. This requires forwarding delay between all recorded source-destination pairs, remainning energy of known nodes on receiving bundles, and the best CD-ranked nodes with each relay node. This information is used by the ACO to calculate a visibility value for candidate SCF nodes towards the bundle's destination to form a better-connected chain of relay SCF nodes.

Probabilistic Swarm-based VDTN routing [26] proposes a hybrid bio-inspired geographic protocol for next-SCF vehicle selection. Thus, two strategies are employed for regular and recovery routing, respectively: the first is a swarm-inspired probabilistic approach that combines the Firefly Algorithm (FA) [27] and GSO to track optimal SCF relay vehicles among available direct contacts. For each buffered bundle, every next-SCF candidate is evaluated based on its historic routing parameters, such as buffer capacity, node degree, average neighborhood lifetime, speed balance to its active contacts, and the number of former relayed bundles. If the first phase fails to find better SCF vehicles, geographic routing is performed based on bundles' restricted forwarding using the Minimum Estimated Time of Delivery (METD), as introduced in [28].

Recent probabilistic VDTN routing works, such as [29], use artificial intelligence to solve the trade-off between QoS metrics. DesCom [30] bases its SCF decision on time estimation, bundle TTL, and transmission rate. GR-PDR [31] solves the local maxima issue by using the delegation replication approach for both single and multiple copy forwarding, considering a buffer delivery priority. [32] proposes an improved VDTN routing based on K-means clustering.

## III. PROPOSED VDTN ROUTING SOLUTION

The concepts and optimization model of the new swarm-based VDTN routing protocol are detailed in this section:

### *A. Critics and assumptions*

The discussed literature exposes several challenges:

- The QoS performances of probabilistic DTN routing is subjected to deterioration in VDTNs, especially regarding delivery probability and flooding overflow. Bio-inspired optimization is expected to reduce the number of generated bundle copies.
- Hybridizing the probabilistic and bio-inspired forwarding to enhance the selection of the next-SCF vehicle has been introduced by [26]. However, the scope of the protocol is limited in terms of comparison protocols and simulation tests, and it lacks other essential modules such as buffer management, recovery forwarding, and flooding control.
- The discussed literature does not define a specific methodology to reduce network overheads. For instance, the swarm probabilistic protocol focuses on the optimal relay SCF vehicle selection by combining FA and GSO, while neglecting the reduction of the number of relayed bundle copies.
- Most literature lacks buffer management policy for routing priority and buffer space-saving. The first policy aims to alleviate congestion in vehicles, while the second is designed for vehicles whose energy is constrained by unexpected factors such as breakdowns and stop status.

The proposed contribution seeks to control routing overheads by adaptively avoiding the duplication of copies in networks at all forwarding stages of each bundle. To achieve this, a hybrid bio-inspired approach is suggested to manage the SCF vehicle selection process.

### *B. Swarm-inspired optimization from VANET to VDTN routing*

Bio-inspired optimization techniques have been introduced to various VANET routing problems [33]. Overall, these techniques have demonstrated promising performances in highly-dense networks, while the challenge lies in capitalizing on the stochastic swarm search abilities to perform equally well in sparse networks, where the end-to-end routing is not applicable. The unavailability of vehicles, particularly in urban VANET areas, complicates the ability of swarm-based search methods to apply the intelligent behaviors of particles in nature for extended periods, so as to progressively build an effective stochastic search to anticipate better SCF relay vehicles, similar to when the network is dense. To address this, we utilize specific historical SCF mobility information of vehicles to assist the SCF selection during all the bundle's routing stages toward its destinations.

The main challenge in VDTN routing is the control of SCF through the optimal bundle replication and next-SCF selection. This functionality is organized to limit flooding in the early forwarding stages and unicast SCF selection in the advanced forwarding stages.

The proposed swarm-based approach includes two metaheuristic techniques to guide the exploration and local search of SCF vehicle selection, respectively [34].

### *C. Next SCF vehicle selection approach*

The major function of VDTN forwarding, which controls the overall routing performances, invloves two back-to-back SCF selection phases executed within the framework of GSO and improved ACO, respectively:

- Exploration SCF phase (Global search): The stochastic qualities of ACO are used to apply restricted flooding of $L$ bundle copies following a probabilistic selection of $M$ vehicles among $N$ possible host's active contacts, with $M \leq N$. $M$ depends on the available $N$ contacts. The selected vehicles serve as the pheromone path nodes explorers, while the bundle act as ant agents that proceed to the local-search SCF selection phase.
- Exploitation SCF phase (Local search): Following the exploratory SCF selection, this phase employs GSO's probabilistic approach to select SCF relay nodes locally based on the ACO-explored vehicles in the direction of the bundle's destination. This phase is triggered after meeting a set of predefined conditions, which are described next in this section.

Figure 1 illustrates an example of the performed SCF selection strategy between the source and destination vehicles:

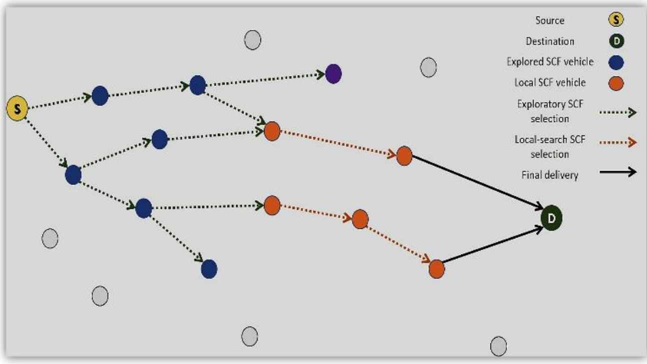


Figure 1. Proposed hybrid ACO-GSO SCF bundle flooding

The transition time from exploration to local search for each bundle can differ from one copy to another, influenced by the SCF quality of the exploration process.

*1) Exploration-based SCF selection using the Ant Colony Optimizer (ACO)*

The early stages of bundle forwarding involve limited selective flooding of bundle copies towards relay vehicles. The replication of bundles is determined based on the fulfillment of predefined routing parameters set, described next in this section.

*a) Ant Colony Optimizer (ACO)*

ACO was introduced by [33] to model the intelligence of ant swarm to track food sources via the most frequented discovered paths. Ants use pheromone substances to notify antecedent ants about the shortest paths to food sources. ACO models this behavior in an optimization approach that reflects the ability of ant swarms to adaptively update the optimum path to food sources regarding natural conditions like route obstacles. ACO has proven its ability to accelerate convergence towards global-best solutions in classic VANET routing.

According to the calculated pheromone concentration for path edge (i,j) as in Eq.2, the selection probability of an edge by an ant is extracted in Eq.3:

$$\tau(t+1) = (1-\rho).\tau(t) + \Delta\tau \tag{2}$$

$$p_{ij} = \frac{\tau_{ij}.\eta_{ij}}{\sum_{l \in Neighbors(i)} \tau_{il}.\eta_{il}} \tag{3}$$

Considering:

- $\tau(t)$: pheromone concentration at given time $t$.
- $\rho$: pheromone decay factor regarding $0 \leq \rho \leq 1$.
- $\Delta\tau$: deposited pheromone quantity during the interval $[t, t+1]$.

Eq.4 details the formula that updates the pheromone concentration between food nest pair nodes (i,j):

$$\tau(t+1) = (1-\rho).\tau(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{4}$$

Where:

- $i$,$j$: is a pair of nodes $i$ and $j$ of the food nest path.
- $\tau_{ij}$: pheromone concentration between $i$ and $j$.
- $\Delta\tau_{ij}$: deposited pheromone quantity between $i$ and $j$.

Considering $j \neq l$ and $\eta$ is a heuristic value adjusted according to the problem at hand. From Eq.2 we deduce:

$$\Delta\tau = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$$

*b) Application of ACO-based SCF selection*

The proposed implementation of ACO in VDTN routing is used to explore better SCF node alternatives through the detection of relay vehicles that possess more pheromone attractiveness towards all stored bundles' destinations. It is considered that vehicles that are more frequented by bundles towards different destinations will have higher pheromone concentrations.

Table 1 summarizes the mapping of modeled components of the ACO algorithm to VDTN routing characteristics. The quality of an SCF vehicle as a relay node for a bundle's destination is evaluated by the pheromone concentration between the connection linking the bundle's host vehicle and this node. In this solution, it is considered that vehicles more frequented by incoming bundle copies for different destinations are more likely to be selected as relay vehicles. Thus, vehicles handling more ant bundles generally indicate more reliable nodes that shorten distances to a maximum number of food nests (bundle destinations). The exploration of VDTN relay vehicles seeks to detect simultaneously optimized directions to multiple destinations for buffered bundles. This approach is expected to reduce flooding and maintain optimized delivery delays.

Table 1
ACO-VDTN mapping

| ACO elements | VDTN routing |
|---|---|
| Pheromone | SCF quality |
| *Ant* | Bundle copy |
| *Food path node* | SCF relay vehicle |
| *Evaporation* | Forwarding quality update |
| *Ants' nest* | Source vehicle |
| *Food source* | Destination vehicle |

For each stored bundle's destination, every node takes on the role of a landmark towards the food source (destination). As illustrated in the example in Figure 2, a pheromone table is set up in all vehicles to store a pheromone value (*PH)* for every buffered destination for all active connections linkingthe host vehicle to its direct contacts. This *PH* value is refreshed after the passage of a bundle to that destination, while the destination entries are continually updated based on the neighboring connectivity and buffer status changes.

The illustrated example in Figure 2 shows the pheromone fitness evaluation of two contacts *A* and *B* of host vehicle *S* for stored bundles. For instance, it is observed that vehicle *B* is buffering two bundles for the destination *V6*, while vehicle *A* is buffering one bundle (*B5)* to *V6*. Thus, when host S handles a new bundle with *V6* as its destination, it is more likely to select *B* as the next SCF vehicle for the new bundle than *A* the since the connection [*S*-*B*] has a higher pheromone concentration than the connection [*S*-*A*].

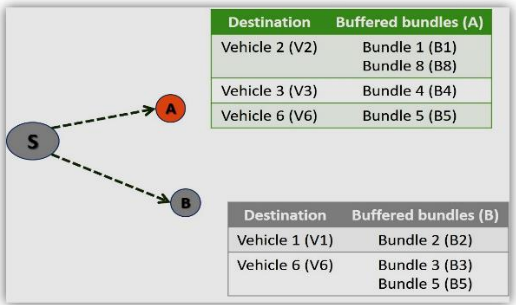


Figure 2. Illustration of pheromone update on VDTN relay vehicles

A predefined set of parameters is considered to explore better trajectories towards the destination through relay vehicles. Thus, both the forwarding history and buffer status of vehicles are taken into account to estimate the probabilistic selection as the next-SCF hop. The discussed fitness parameters for SCF selection are detailed below:

- Historic forwarding parameter (HP): considers the ratio of utilization of the host as a relay node. HP is the ratio of the number of relayed bundles to the total number of received bundles, as calculated in Eq.5:

$$HP_j = \frac{Nb_{Relays(j)}}{Nb_{Relays(j)} + Nb_{Targets(j)}} \tag{5}$$

Considering:

- $Nb_{Relays(j)}$: the number of received bundles by candidate SCF node $j$ as a relay vehicle
- $Nb_{Targets(j)}$: the number of received bundles by candidate $j$ as a destination vehicle.

It is worth noting that $0 \leq HP_j \leq 1$.

- Forwarding parameter (FP): this factor evaluates the forwarding quality of candidate vehicles by considering the ratio of relayed bundles within a predefined threshold period, calculated using Eq.6. A higher FP value indicates a faster forwarding dynamic.

$$FP_j = \frac{Nb_{Replica(j)}}{Nb_{Forwards(j)}} \quad (6)$$

Considering:

- $Nb_{Replica(j)}$: the accumulated number of replicated bundles by candidate vehicle $j$ within a threshold time $Th$.
- $Nb_{Forwards(j)}$: the accumulated number of forwarded bundles by candidate $j$.

It is worth noting that $0 \leq FP \leq 1$.

- SCF parameter (SP): complements the FP by focusing on the average store time of bundles in the buffer cache. The SP is extracted from a predefined store time ratio value which equals the percentage of average buffer time from the average travel time of stored bundles, calculated using Eq.7. A higher SP value indicates better SCF quality.

$$SP_j = 1 - \frac{\sum_{m=1}^{Nb_{Bundles}} Buffer_j^m}{\sum_{m=1}^{Nb_{Bundles}} Travel_{Src,j}^m} \quad (7)$$

Considering:

- $m$: the stored bundle copy by the candidate vehicle $j$.
- $Nb_{Bundles}$: the number of forwarded bundles.
- $Buffer_j^m$: the store time of $m$ in $j$.
- $Travel_{Src,j}^m$: the travel time of $m$ in $j$.

It is worth noting also that $0 \leq SP \leq 1$.

The forwarding quality of a candidate vehicle $j$ from every host $i$ for a given bundle (ant) is calculated using Eq.8:

$$Fitness_{ij} = (\alpha_1 \times HP_j) + (\alpha_2 \times FP_j^{Th}) + (\alpha_3 \times SP_j) \quad (8)$$

Where: $\alpha_1$, $\alpha_2$, $\alpha_3$: the affected weights to the fitness parameters regarding $\alpha_1 + \alpha_2 + \alpha_3 = 1$.

Since all above-described fitness parameters vary between 0 and 1, we can notice that $0 \leq Fitness_{ij} \leq 1$.

The accumulated pheromone quantity from every host $i$ to the candidate $j$ is equivalent to Eq.9:

$$\sum_{k=1}^{M} \Delta\tau_{ij}^k = \sum_{ant=1}^{Nb_{Bundles}} Fitness_{ij}^{ant} \quad (9)$$

Considering:

- $M$: the number of ants traversing the food path's node $i$.
- $Nb_{Bundles}$: the number of bundles relayed by the host vehicle $i$ to candidate vehicle $j$.
- $Fitness_{ij}$: the accumulated pheromone quality of the reception of new ant bundle from host $i$ to candidate $j$.

The pheromone update is performed using Eq.10:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \sum_{ant=1}^{Nb_{Bundles}} Fitness_{ij}^{ant} \quad (10)$$

Considering:

- $Nb_{Bundles}$: the number of relayed ant bundles from $i$ to $j$.
- $Fitness_{ij}$: the fitness of a relayed ant bundle within the delivery time from $i$ to $j$.

Considering $\eta = 1$ in Eq.3, the selection probability of the next food nest node is performed using Eq.11:

$$p_{ij} = \frac{\tau_{ij}}{\sum_{l \in Neighbors(i)} \tau_{il}} \quad (11)$$

The flowchart synchronizing the steps of ACO-based SCF node selection is illustrated in Figure 3.

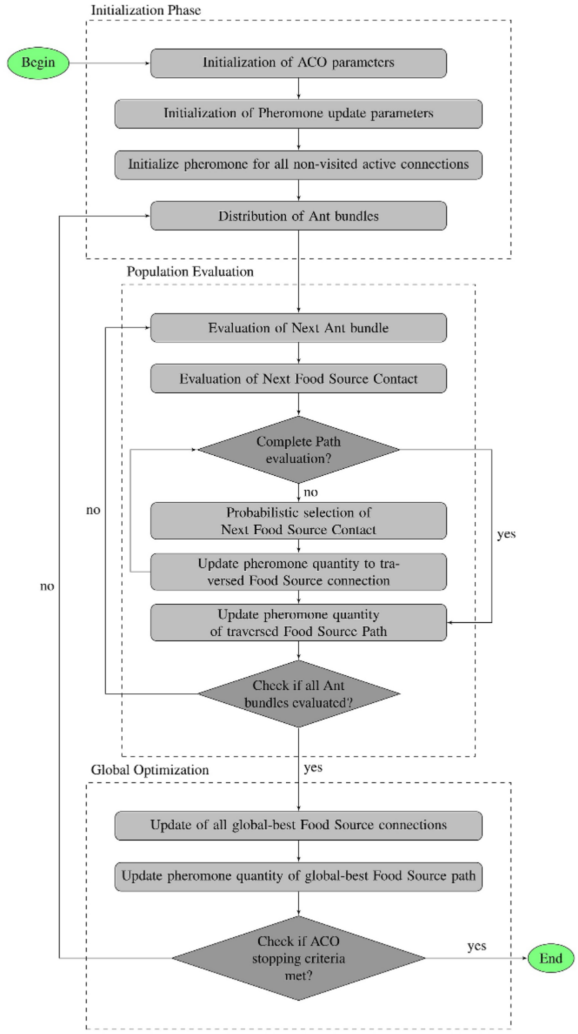


Figure 3. ACO-based exploratory SCF selection flowchart

### 2) *Local search SCF selection using Glowworm Swarm Optimization (GSO)*

The passage from the exploratory SCF selection to the local-search SCF phase using GSO is conditioned by the advancement of every bundle copy towards its destination. One of the predefined following transition parameters must be met to trigger the GSO-based SCF selection:

#### a) *Glowworm Swarm Optimization (GSO)*

GSO is a swarm-inspired metaheuristic suggested by [32] to model the collective movement of lightning flies called glowworms. This movement is controlled by the changing quantity of a luminescent substance called luciferin. The interactive behavior between glowworms in food search and swarm organization depends mainly on the luciferin intensity. GSO serializes the glowworm swarm activity in four steps:

- Initialization phase: regroups a set of candidate glowworm agents that forms the initial population.
- Neighbors tracking: represents the interactive movement between adjacent glowworms to displace towards better positions.
- Luciferin update: refreshes new positions of glowworms and deduces the partial-best positions.
- Location update: extracts the global-best position according to the discovered local-best positions.

Table 2
GSO peudo-algorithm

```
GSO ()
{
1.  Initialize dimension size of glowworm population GSO Population.
2.  Initialize luciferin update factor λ and luciferin enhancement
    constant γ.
3.  Initialize GSO maximum iteration number Max_Iter.
4.  Define Pos(i): position of glowworm i at instant t.
5.  Define N(i): neighbors of i.
6.  Define Cand_List: candidate solutions list of i.
7.  Set initial Luciferin L_0 intensity for all glowworms.
8.  Set random initial position for all glowworms
9.  While Max_Iter not reached {
10. For each glowworm(i) in GSO Population  {
11. For each glowworm(j) in GSO Population {
12. Lj (t + 1) = (1 − λ) × Lj (t) + γ.f (Pos_j (t)); /* luciferin update of
    glowworm i towards candidate j */
    }
13. For each glowworm(i) in GSO Population {
14. For each glowworm(j) in N(i) {
15. if Lj (t) > Li(t) {
16. Prob_ij = (L_j(t) − L_i(t)) / (Σ_{k=1}^{N_j} L_k(t) − L_i(t))  /* calculate the selection probability */
17. Record (j, Prob_ij , Cand_List);
    }
    }
18. n = GSO_Selection(Cand_List) /* probabilistic selection of next
    glowworm n */
19. Pos_i(t + 1) = Pos_i(t) + S ( (Pos_n(t) − Pos_i(t)) / |Pos_n(t) − Pos_i(t)| )
20. |Pos_n(t)−Pos_i(t)| ) /* position update according to step size 'S' */
    }
    }
    }
}
```

GSO is an extracted variant of the ACO metaheuristic that is conceived to solve combinatorial continuous problems [34]. Compared to ACO, GSO offers a faster local-search convergence and can detect multiple local-optimum solutions in the multimodal functions.

GSO updates the luciferin intensity $L_{ij}$ of glowworm agent $i$ after moving towards glowworm $j$ within time interval from instant $t$ to $t+1$ following Eq.12:

$$L_j(t+1) = (1-\lambda)L_j(t) + \gamma.f(Pos_i(t)) \tag{12}$$

Considering:

- $L_j(t)$ and $L_j(t+1)$: the luciferin value gathered from glowworm $i$ after displacing towards glowworm $j$ within the time interval $[t, t+1]$.
- $\lambda$: the luciferin update factor considering $0 \leq \lambda \leq 1$.
- $Pos_j(t)$: position of glowworm $j$ at time $t$.
- $f_j(t)$: the objective function of position of $j$ at $t$.
- $\gamma$: the luciferin enhancement constant.

Eq.13 approximates the probability of selection ($Pb_{ij}$) of an attractive glowworm $j$ for each candidate glowworm $i$ amongst available candidates according to its luciferin intensity:

$$Pb_{ij} = \frac{L_j - L_i}{\sum_{l=1}^{Nb_{Cand}} L_l - L_i} \tag{13}$$

Considering:

- $Nb_{Cand}$: the number of glowworm candidates likely to move towards attractive glowworm $j$.
- $L_j$ - $L_i$: the difference between luciferin intensity of glowworms $i$ and $j$.

The pseudo-code of GSO procedure is given in Table 2.

*b) Application of GSO-based SCF selection*

The concepts of GSO are applied to VDTN routing through the next-SCF vehicle selection process. The candidate SCF vehicles discovered through ACO-based exploration serve as the initial population of candidate solutions by GSO, which then conducts a local search for each population entity separately. GSO is expected to overcome the limitations of ACO in the exploitation search of local optima in this context. Table 3 summarizes the mapping of GSO algorithm to VDTN routing:

Table 3
GSO-VDTN mapping

| GSO elements | VDTN routing |
|---|---|
| Luciferin intensity | SCF quality |
| *Attracted glowworm* | Bundle copy |
| *Attractive glowworm* | SCF relay vehicle |
| *Interactive movement* | Bundle forwarding |
| *Prey/food source* | Destination vehicle |

The initial luciferin value ($Luciferin_{INIT}$) of each bundle takes the value of the pheromone concentration at the host vehicle ($Pheromone_{FINAL}$), as shown in Eq.14:

$$Luciferin_{INIT}(i) = \tau_{bundle}(host) \tag{14}$$

Where: $i$ = *host*.

Bundles starting with a higher $Luciferin_{INIT}$ indicate a better forwarding towards their destinations. Thus, such bundles are more likely to be delivered with shortened delays.

GSO is applied for local search on the basis of ACO-explored relay vehicles. Thus, a predefined set of fitness parameters, with values ranging between 0 and 1 is set to prioritize candidate relay nodes' position rather than the quality of their historical SCF forwarding. The parameters considered by GSO for SCF selection are:

- Historic factor (HF):Contrarily to the calculated HP parameter defined in ACO-based fitness evaluation, HF evaluates the historical participation of the host vehicle as a destination node. HF considers the ratio of utilization of the host vehicle as a destination to the total number of handled bundles, calculated using Eq.15:

$$HF_j^m = \frac{Nb_{Targets(j)}}{Nb_{Relays(j)} + Nb_{Targets(j)}} \tag{15}$$

- Mobility factor (MF): This parameter evaluates the mobility characteristics of candidate SCF vehicles. MF considers the ratio of the candidate vehicle's relative speed towards the bundle's destination to its absolute speed, as calculated using Eq.16:

$$MF_j = \frac{Rel_{j,dest}}{Sp_j} \tag{16}$$

Considering:

- $Rel_{j,dest}$: relative speed of candidate vehicle $j$ towards the destination of bundle $m$.

- $Sp_j$: absolute speed of candidate *j*.

It is worth noting that $0 \le HF \le 1$ and $0 \le MF \le 1$.

The above-cited GSO's SFC parameters mentioned above are used to calculate the GSO fitness formula of all candidate SCF contacts of the host vehicle using Eq.17:

$$GSO_{Fitness(j)} = (\omega_1 \times HF_j) + (\omega_2 \times MF_j) \qquad (17)$$

Considering $\omega_1$ and $\omega_2$ are the affected fitness weights for HF and MF parameters, respectively, regarding $\omega_1 + \omega_2 = 1$.

The GSO-based SCF selection probability formula is deduced in Eq.18:

$$Pb_{ij} = \frac{L_j - L_i}{\sum_{l=1}^{Nb_{Cand}} L_l - L_i} \qquad (18)$$

It is worth noting that the node's selection probability increases with its GSO fitness.

Any contact with a negative GSO fitness balance compared to the host's fitness is eliminated from the selection since it indicates that the host is a better relay vehicle for the bundle than the candidate contact (Eq.19).

$$GSO_{Contact_L} \le GSO_{Host} \qquad (19)$$

Contrarily to the ACO-based SCF approach, only one contact is selected probabilistically according to Eq.18 to forward the bundle. This operation is repeated until finding the contact that is linked directly to the bundle's destination.

*3) Synthesis*

The predefined SCF historic factors used for calculating the predefined SCF selection parameters in both ACO-based and GSO-based processes are reset to zero after each static cyclic loop time, fixed at 3600 seconds. As a result, the impact of historic forwarding is kept close to the ongoing forwarding ability of vehicles. Specifically, the $Nb_{Relays(j)}$, $Nb_{Destinations(j)}$, $Nb_{Replica(j)}$, and $Nb_{Forwards(j)}$ are reset.

The bundle reception procedure is illustrated in the flowchart in Figure 4.

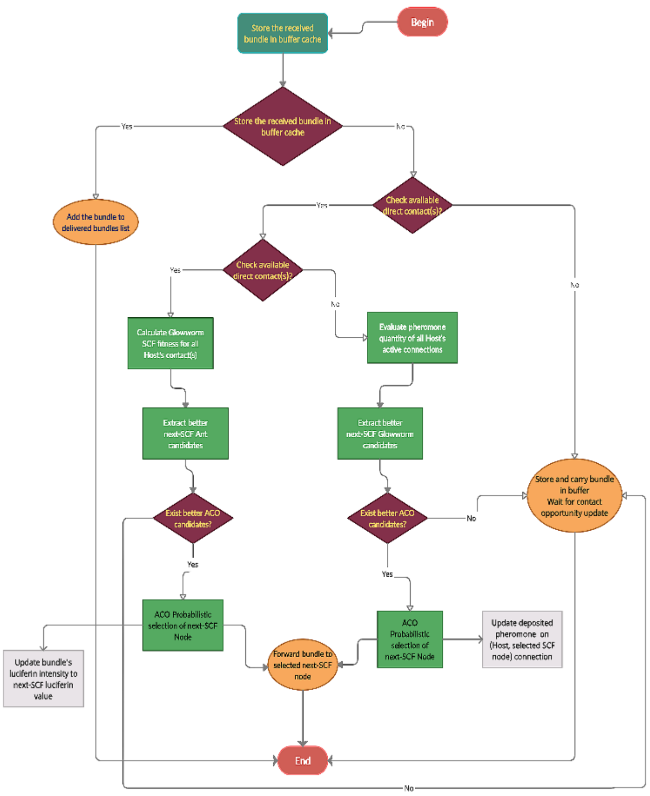


Figure 4. Bundle handling process flowchart

*4) Bundle's forwarding priority in Buffer*

Although vehicles are not constrained by buffer capacity limitations, it is still preferable to consider critical use cases that can compromise unlimited bundle storage time such as old cars, stopping vehicles like taxis and buses, breaking down vehicles, or those with aging batteries. Therefore, a bundle replication priority mechanism is neededfor buffer caches to reduce the number of lost copies and speed up bundles forwarding. Additionally, considering the large number of bundle copies that can be stored simultaneously in the buffer cache, vehicles may not be able to transmit a high number of bundles concurrently due to the bandwidth limitations and the short contact opportunity times in some cases. Furthermore, it is advisable to consider different types of vehicles in terms of buffer size differences, so a priority order considering available buffer space is used to better manage storage utilization of smaller buffers.

An adaptive approach that considers transmission and deletion priority is suggested for the proposed solution to reduce the average buffer time. As the storage limits of vehicles are a minority concern, the proposed buffer ranking mainly depends on the swarming phase and fitness since they are the most significant indicators of the routing quality. The remaining parameters are set by order as tiebreakers in cases where two bundles are being forwarded within the same swarm phase or they share tied-swarm fitness. Thus, the bundle's host SCF vehicle is evaluated through a set of predefined transmission priority parameters, as illustrated in Figure 5, to order bundles from the least to the most forwarding necessity. The described ranking parameters below follow a descendent tie-breaking priority:

- Swarm-based SCF phase (SP): The priority of buffer storage is given to bundles within the ACO-based exploration SCF phase, while GSO-based bundles are the first to be transmitted. This order seeks to optimize delivery delay.
- Bundle's swarm fitness (SF): A pair of bundles sharing the same swarm phase are ranked according to their swarm fitness; the bundle with lower ACO fitness for exploring vehicles (or GSO fitness for local-search vehicles) is prioritized to remain in the buffer cache. This is because bundles with better fitness values need to be delivered or forwarded
- Bundle's hop count (HC): Bundles traversing a higher number of hops are considered increasingly aged in the buffer cache. Thus, bundles with higher hop counts are prioritized for buffering since they risk a decreasing delivery expectancy, while the newer bundles are transmitted first.
- Bundle's size: Bundles with larger sizes are less privileged to stay for extended periods in the buffer cache; thus, they are transmitted first. The smaller the average bundle's size, the greater the number of bundles saved.
- Longevity of bundle in host buffer (HB): Bundles residing longer in the buffer increasingly lose their buffer priority and are transmitted first. Buffer space is prioritized for newly created bundles.
- Ratio of bundle size occupation in buffer (BSO): Bundles occupying larger buffer space lose their buffer priority increasingly; hence, they are transmitted first.

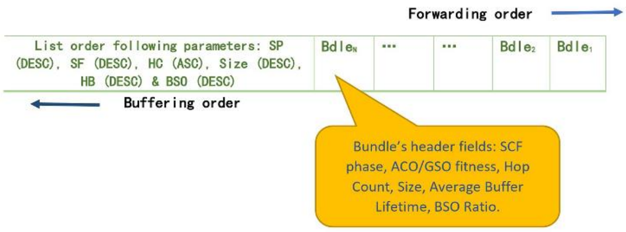


Figure 5. Buffer forwarding priority policy

## IV. EXPERIMENTS AND RESULTS ANALYSIS

The Opportunistic Network Environment (ONE) simulator [35] is used to implement and simulate the proposed VDTN solution, while Open Jump [36] is used to generate the urban mobility model as illustrated in Figure 6. This figure represents the map of the constructed urban city scenario in which all roads are bidirections.

The proposed swarm-based VDTN routing protocol (Hybrid-Swarm) is compared to a few probabilistic VDTN routing references, namely:

- ProPHET: a standard probabilistic DTN routing reference.
- Historic-ProPHET: an enhanced ProPHET version for VDTNs as discussed in the literature.
- SnW-ProPHET routing protocols,: another enhanced ProPHET version for VDTNs as discussed in the literature.
- Hybrid FA-GSO VDTN routing (Swarm-Proba): a bio-inspired probabilistic VDTN routing solution.

The performance evaluation considers four QoS metrics; namely, the average delivery delay, the bundles' delivery probability, overheads, and the bundles' replication cost. The formulas of these indicators are calculated in Eq.20, Eq.21, Eq.22, and Eq.23, respectively.

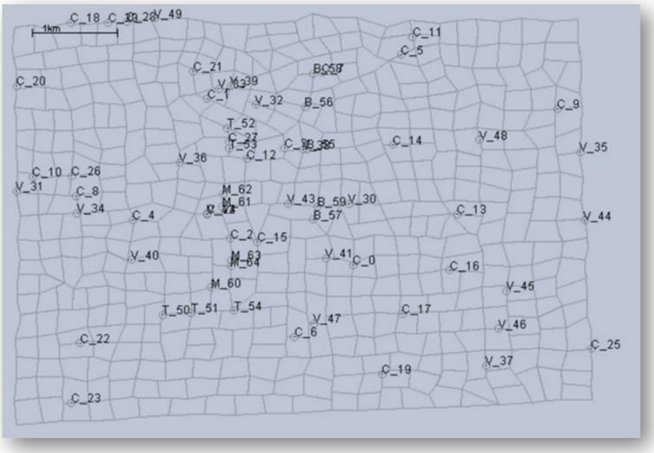

Figure 6. Simulation of proposed urban scenario

$$Average\ Delivery\ Delay = \frac{1}{Number\ of\ delivered\ bundles} \times \sum_{i=1}^{Number\ of\ delivered\ bundles} Delivery\ Delay\ (B_i) \quad (20)$$

Considering $B_i$ the i[th] stored bundle in the buffer cache.

$$Delivery\ Probability = \frac{Number\ of\ delivered\ bundles}{Number\ of\ generated\ bundles} \quad (21)$$

$$Overhead = \frac{Number\ of\ \ transferred\ bundles}{Number\ of\ delivered\ bundles} \quad (22)$$

$$Relay\ cost = \frac{Number\ of\ replicated\ bundles}{Number\ of\ generated\ bundles} \quad (23)$$

The network and mobility configurations of the tested simulations are detailed respectively in Table 4 and Table 5, respectively.

Table 4
Network settings of simulation tests

| Parameter | Value |
|---|---|
| Network simulator | ONE 1.5.1 RC1 |
| *Monility generator* | Open Jump |
| *Mobility support* | WKT file |
| *Mobility map dimensions* | 6.9 × 5.1 km |
| *Simulation time* | 24000 Seconds |
| *Scenario warm-up* | 400 Seconds |
| *Number of random simulations* | 7 |
| *Density* | [35;50;65;80;95;110] vehicles |
| *Transmission range* | 40 meters |
| *Bundle's Time-To-Live (TTL)* | {30; 60} Minutes |
| *Bundle size* | [500kB, 1MB] |
| *Bundle creation interval* | [15, 30] Seconds |
| *Buffer size* | [10, 20] MB |
| *Node's wait time* | [0, 120] Seconds |

Table 5
Mobility settings of simulation tests

| Vehicle type | Mobility model | Speed interval | Density ratio (%) | Number of trams |
|---|---|---|---|---|
| Car | Shortest Path Map-based Movement | [12.6, 68.4] km/h | 72.63% | full map |
| *Bus* | Bus Movement | [12.6, 68.4] km/h | 8.73% | 1 |
| *Tram* | Map Route Movement | [12.6, 68.4] km/h | 18.62% | 2 |

The simulation has been varied based on the network density level and different bundle TTL limits. The density factor seeks to evaluate the impact of connectivity degree between vehicles on the overall QoS performance of the proposed protocol. The bundle TTL factor evaluates the effectiveness of the solution relative to comparison protocols.

The analysis of simulation results is detailed on the basis of the graphs presented in the figures below:

Figures 7 and 8 show the delivery delay performances when TTL = 30 minutes and 60 minutes, respectively The hybrid-swarm protocol achieves optimal returns regardless of the bundle's TTL, while the proposed swarm probabilistic protocol outperforms the conventional protocols. The hybrid FA-GSO proves more effective than the ACO-GSO approach in reducing the average delivery delay, demonstrating the superiority of the FA-GSO selection over the ACO-based exploration and the GSO-based local search in identifying better local-SCF vehicles towards bundle destinations. On the other hand, the bundle's TTL does not affect the tendency of results in all simulated protocols, while extending TTL significantly reduces the average delay as it allows more time for bundles to reach their targets.

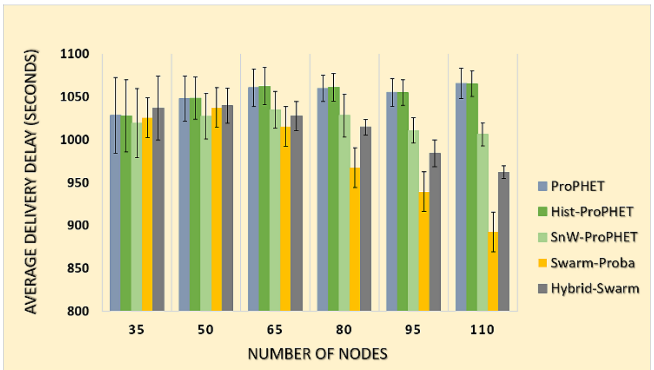


Figure 7. Average Delivery Delay vs Bundle TTL = 30 mn

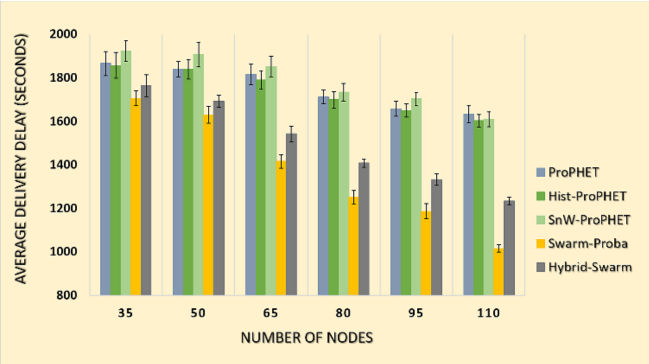


Figure 8. Average Delivery Delay vs Bundle TTL = 60 mn

Figures 9 and 10 show the overhead performance when TTL = 30 minutes and 60 minutes, respectively. SnW-ProPHET achieves the best returns in this metric compared to all other protocols. The application of SnW phases on ProPHET drastically reduces the number of flooded copies compared to the other routing models. ACO-GSO protocol achieves optimized overhead compared to the rest of the protocols, notably relative to the FA-GSO model. The ACO-based exploration is more effective than the FA-GSO SCF selection in reducing the number of replicated copies and delivering a high number of bundles. The collected overhead results are proportional to the bundle's TTL for ProPHET and Hist-ProPHET, while they remain stable for SnW-ProPHET, FA-GSO, and ACO-GSO protocols. This difference shows the consistency of the bio-inspired protocols in terms of bundle replication rate due to the high delivery probability.

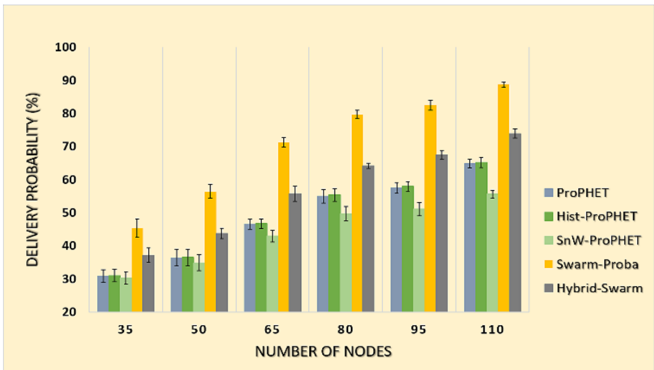


Figure 9. Delivery probability vs Bundle TTL = 30 mn

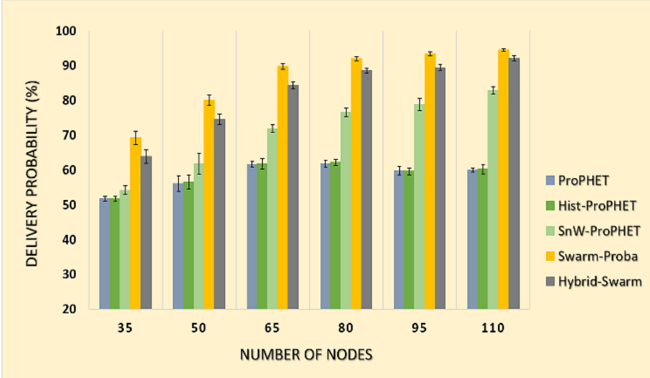


Figure 10. Delivery probability vs Bundle TTL = 60 mn

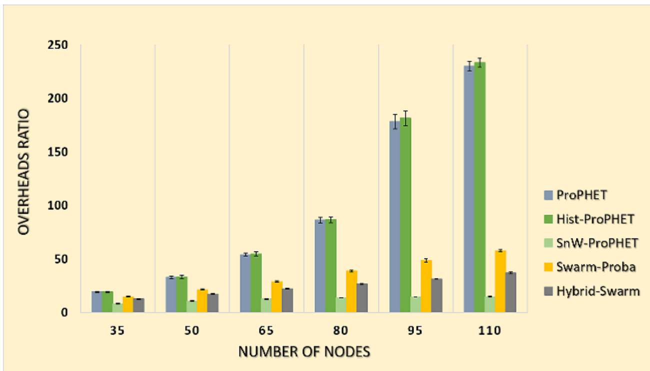


Figure 11. Overheads vs Bundle TTL = 30 mn

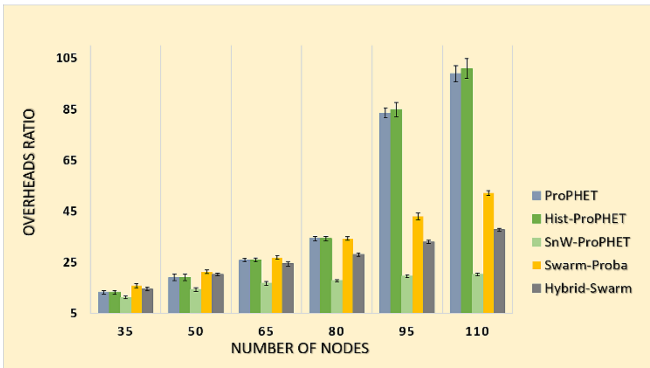


Figure 12. Overheads vs Bundle TTL = 60 mn

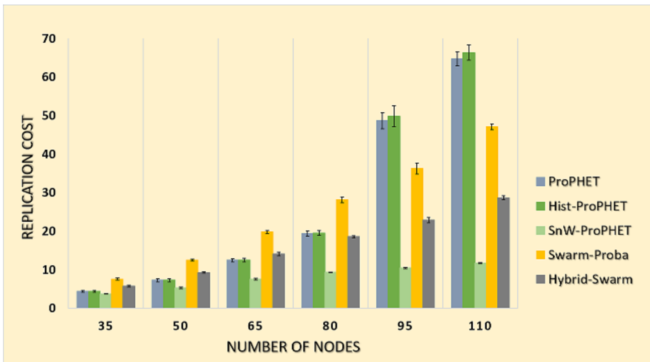


Figure 13. Bundles relay cost vs Bundle TTL = 30 mn

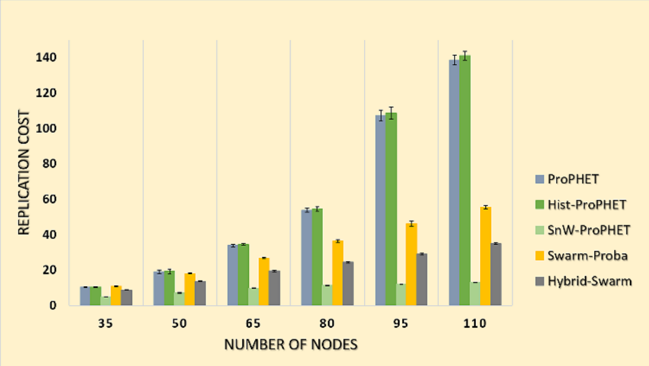


Figure 14. Bundles relay cost vs Bundle TTL = 60 mn

Figures 11 and 12 show the replication cost when TTL = 30 minutes and 60 minutes, respectively. The performances of this metric are very similar to that of overheads, with the SnW-ProPHET leading the evaluated protocols in all density levels. The proposed protocol surpasses the swarm probabilistic protocol in this indicator, similar to the case of overheads. This difference is attributed to the minimization of duplicated bundle copies during both the ACO-based exploration and the GSO-based local-search phases. Contrarily to the ProPHET and the Hist-ProPHET, the SnW-ProPHET and the bio-inspired VDTN models demonstrate great abilities to slow down overheads' progress in high-density levels while maintaining stable overheads for long bundle TTLs.

Figures 13 and 14 showcase the replication cost when TTL = 30 minutes and 60 minutes, respectively. The collected results closely resemble those of overheads, with the SnW-ProPHET leading the evaluated protocols across all density levels. The proposed protocol outperforms the swarm probabilistic protocol in this metric, as the case of the overheads. This difference is justified by the minimization of duplicated bundle copies during both the ACO-based exploration and the GSO-based local-search phases. Contrary to the ProPHET and the Hist-ProPHET, the SnW-ProPHET and the bio-inspired VDTN models show strong capabilities to reduce overheads in high-dense areas while keeping overheads stable for long bundle TTLs.

In summary, the proposed solution effectively reduces the bundle flooding rates, as evidenced by the collected routing overheads and replication cost statistics, while maintaining satisfactory levels of delivery delay and delivery ratio across all densities. However, the performance in delivery delay and probability shows some limitations compared to the swarm probabilistic protocol. This study encourages further investigation of more effective mechanisms to optimize returns for all QoS metrics.

## V. CONCLUSION AND PERSPECTIVES

In this paper, a hybrid swarm-inspired routing approach for VDTNs is proposed. The conceived routing protocol leverages the global and local optimization qualities of ACO and GSO metaheuristics, respectively, to optimize the SCF vehicle selection. The ACO-based SCF seeks to explore better relay vehicles, which are then handled by the GSO-based SCF to identify superior local data forwarders. For this purpose, the ACO's exploration fitness evaluation takes into consideration the forwarding history of vehicles and ongoing SCF quality, while the GSO's local search fitness considers the forwarding history related to the bundle's destination and real-time node mobility information. Simulation tests of the bio-inspired solution indicated optimum flooding rates compared to the other VDTN protocols, while maintaining satisfactory delivery delay and probability performance. However, there remains room for improvement in these latter metrics, as the combined ACO-GSO approach is found to be somewhat limited compared to FA-GSO in finding the shortest and most reliable trajectories to the bundles' destinations. Swarm computation can be extended to different types of sparse vehicular routing in urban areas with sparse connectivity, involving Road Side Units (RSUs) and Unmanned Aerial Vehicles (UAVs) [37]. The incorporation of evolutionary computation [38] is also recommended to further expand VDTN routing modes, such as knowledge-based routing.

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