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**Original Research**

# Swarm-Intelligent Multi-Hop Relay Selection for Throughput Maximization in Vehicular Ad Hoc Networks (VANETs)

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**Abstract**
Vehicular ad hoc networks are emerging as an essential communication substrate for cooperative driving, traffic safety, and infotainment services along road infrastructures. In these networks, moving vehicles form spontaneously connected topologies in which wireless links are short lived and subject to rapid fluctuations. Multi-hop relaying becomes necessary when direct connectivity to roadside infrastructure is intermittent, yet the dynamic nature of vehicular mobility makes relay selection and route construction challenging. Throughput maximization over such volatile paths requires relay decisions that balance link quality, contention, and path length while reacting to time-varying channel and topology conditions. Conventional deterministic optimization methods often rely on simplified assumptions that make them less adaptable to realistic vehicular environments. Swarm intelligence, which coordinates a large population of candidate solutions through low-complexity interactions, provides a flexible framework for exploring high-dimensional relay selection spaces under uncertainty. This work studies a swarm-intelligent multi-hop relay selection strategy for throughput maximization in vehicular ad hoc networks, formulating relay decision making as a constrained linear optimization problem embedded inside a population-based metaheuristic. The approach maps candidate relay sets to particles that traverse the solution space according to locally evaluated throughput and connectivity metrics. A linear capacity model and a compact representation of path feasibility guide the swarm search while remaining compatible with the stringent timing constraints of vehicular communications. The study examines how swarm parameters, mobility patterns, and channel models influence the achievable throughput and outlines several implementation considerations for deployment in realistic vehicular scenarios.

## 1. Introduction

Vehicular ad hoc networks rely on short range wireless communications between vehicles and roadside units to enable cooperative awareness and the dissemination of safety and non safety messages [1, 2]. The spatial distribution and mobility patterns of vehicles induce a time varying and often fragmented topology in which end to end connectivity cannot be assured by single hop links to infrastructure [3, 4, 1]. Multi hop communication, where packets are forwarded through intermediate vehicles, becomes a central mechanism for bridging coverage gaps and improving the effective communication range of roadside units [5]. However, the transient connectivity and heterogeneous speeds of vehicles make path construction and maintenance difficult, and naive forwarding choices may quickly degrade throughput because of rapidly degrading link qualities, hidden terminal effects, and queues building up at poorly chosen relays.

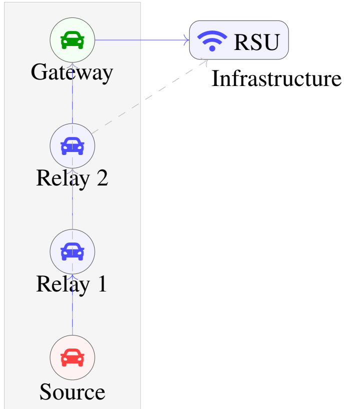


**Figure 1:** Highway VANET snapshot with swarm-selected multi-hop relay chain from a source vehicle to an RSU. Solid links represent the chosen high-throughput path, while dashed links show alternative candidate relays evaluated by the swarm.

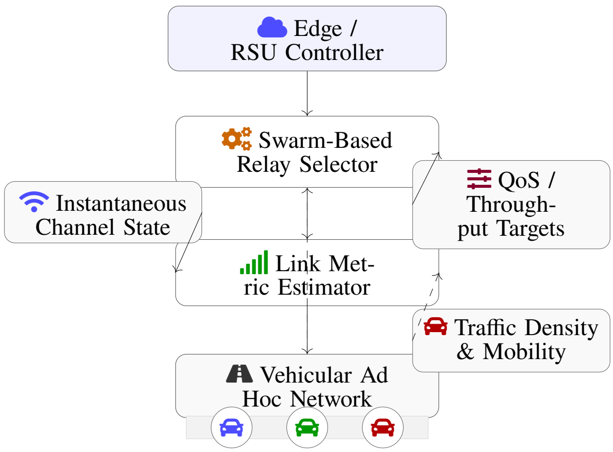


**Figure 2:** System architecture for swarm-intelligent multi-hop relay selection in a VANET. The edge controller coordinates a swarm-based relay selector driven by link metrics, channel state, traffic information, and QoS constraints, which in turn configures vehicular forwarding paths.

Throughput maximization in vehicular ad hoc networks is influenced by a combination of physical, medium access, and network layer factors [6]. At the physical layer, fading, Doppler shifts, and shadowing caused by buildings or other vehicles introduce strong variations in signal to interference plus noise ratios, which in turn modulate the instantaneous link capacity. At the medium access layer, contention

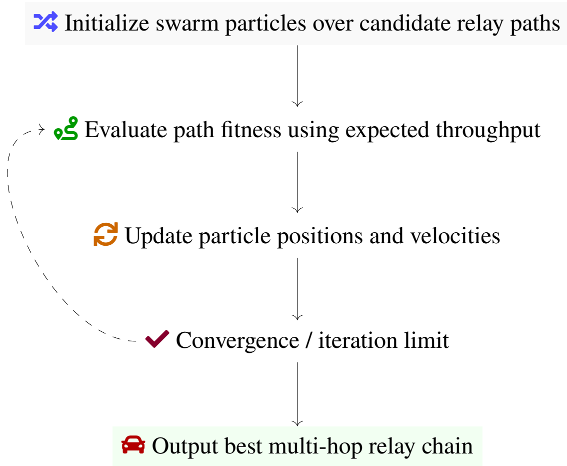


**Figure 3:** Algorithmic flow of the swarm-intelligent multi-hop relay selection procedure. Particles encode candidate relay chains, are evaluated via throughput-based fitness, and iteratively updated until convergence to a high-throughput path.

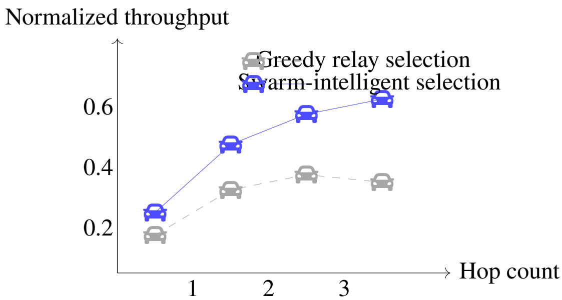


**Figure 5:** Conceptual throughput–hop-count tradeoff comparing greedy and swarm-intelligent relay selection. Swarm-based selection maintains higher normalized throughput as hop count grows by adaptively choosing robust multi-hop relay chains.

based mechanisms limit the number of packets that can be successfully delivered over a given time horizon, and coordination among forwarding vehicles becomes important to mitigate collisions and channel access delays. At the network layer, multi hop routing policies must account not only for path length but also for the stability and capacity of candidate relays [7]. These elements interact in ways that are difficult to capture by purely analytical routing metrics, so that heuristic or data driven strategies are often used to adapt to the environment.

Relay selection is a key component of multi hop communication in vehicular ad hoc networks [8]. The decision to choose a particular neighbor as next hop influences the probability of successful transmission, the expected queuing delay, and the robustness of the path to mobility induced breakages. Combining several such choices over a path from a source vehicle to a roadside unit or another vehicle defines the multi hop route and, indirectly, the throughput achievable under given traffic demands. The combinatorial nature of this selection is prominent in dense scenarios, where each vehicle may observe many neighbors with diverse movement and channel characteristics [9]. Exhaustive exploration of all possible relay combinations is computationally infeasible in realistic deployments, especially when the topology changes faster than an optimization solver could converge.

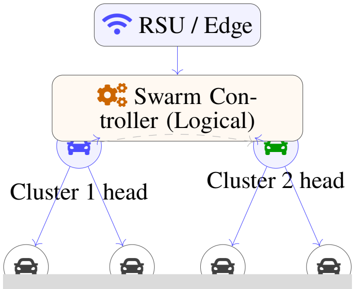


**Figure 6:** Cluster-based organization of VANET nodes where cluster-head vehicles act as primary relays. A swarm controller, logically co-located with the RSU, selects cluster heads and member links to form interference-aware multi-hop routes with high end-to-end throughput.

Swarm intelligence offers a means of exploring such combinatorial spaces through coordinated search processes inspired by the behavior of social organisms [10]. Algorithms such as particle swarm optimization and ant colony optimization maintain a population of candidate solutions that interact through simple update rules based on local evaluations of solution quality. Unlike approaches that rely solely on gradient information or deterministic branch and bound procedures, swarm based methods can accommodate non convex objective landscapes, discontinuous constraints, and noisy evaluations. For vehicular ad hoc networks, this ability to handle uncertainty and adapt online to new observations makes swarm intelligence attractive as a mechanism to drive relay selection toward high throughput configurations without requiring an exact global model [11].

In the context of multi hop relay selection, swarm intelligence can be used to coordinate the search over possible relay sets and paths, while an underlying linear model quantifies the throughput associated with each candidate solution. The linear model serves as a concise abstraction of the interaction between link capacities, flow conservation constraints, and scheduling limitations [12]. Candidate relay selections generated by the swarm are mapped into binary decision vectors, which are then evaluated using the linear throughput model. This separation of concerns, with swarm dynamics operating in the combinatorial solution space and linear modeling acting as a fast evaluator, enables flexible adaptation to different propagation, traffic, and medium access assumptions by simply modifying the coefficients in the linear model [13].

This work considers a vehicular ad hoc network scenario in which vehicles move along road segments under general mobility patterns and may communicate with one or more roadside units. A control entity, which may be distributed or logically centralized, applies a swarm intelligent optimization method to select relay sets and construct multi hop paths for data flows that aim to maximize aggregate throughput under link capacity and connectivity constraints. The study develops a mathematical representation of the relay selection problem using linear constraints, describes the adaptation of swarm dynamics to the discrete space of feasible relay sets, and analyzes the resulting throughput behavior under various network conditions [14]. Attention is also given to computational complexity, the overhead incurred by disseminating swarm control information, and the sensitivity of performance to the choice of swarm parameters.

The remainder of the paper is organized into sections that progressively develop the system model, the swarm based algorithmic framework, theoretical properties of the formulation, and a performance evaluation based on simulation scenarios [15]. Throughout, the focus is placed on capturing the essential interactions between multi hop relaying, vehicular mobility, and swarm dynamics without assuming overly restrictive channel or traffic models. The presentation emphasizes the interpretation of the linear model coefficients and constraints in terms of physical and protocol level phenomena, thereby allowing potential adaptation to diverse vehicular communication standards and deployment environments.

## 2. System Model and Linear Problem Formulation

The vehicular ad hoc network is modeled as a time indexed sequence of directed graphs that represent the instantaneous communication topology among vehicles and roadside units [16]. At a given time index, the network can be described by a set of nodes and a set of directed links, where each node corresponds either to a vehicle or to a roadside unit. A directed link from node $i$ to node $j$ exists if the distance, relative orientation, and channel state between the two nodes permit communication with a minimum required signal to interference plus noise ratio [17]. The graph representation abstracts away low level waveform details while retaining the connectivity structure and link dependent characteristics required for throughput modeling.

To capture throughput, each directed link is associated with an achievable data rate, expressed as a capacity parameter that depends on the underlying modulation and coding scheme, channel state, and medium access configuration. For a fixed time horizon short enough that the topology can be treated quasi statically, these capacities are assumed constant and are collected into a vector whose components correspond to individual links [18]. Traffic demands are represented by source destination pairs, where each source may be a vehicle generating data intended for another vehicle or a roadside unit. For each demand, multi hop routes must be formed through sequences of directed links that connect the source to the destination while satisfying flow conservation and capacity constraints [19].

The relay selection and throughput maximization problem can be posed as a linear optimization model. Consider a vector of binary decision variables that indicate whether a given link is selected to carry traffic for a given flow in the considered time horizon. The aggregate throughput can then be expressed as a linear function of these variables, weighted by the respective link capacities [20]. Denote by $x$ the column vector of decision variables, and by $c$ the corresponding column vector of link capacities. The linear objective that measures total carried traffic can be written as [21]

$$\max_{x} \; c^{\top} x. \tag{2.1}$$

This objective captures the sum over all selected links weighted by their capacities, under the assumption that if a link is activated by the selection, its capacity can be fully utilized during the horizon.

To enforce flow conservation, a node edge incidence matrix is introduced to relate decision variables to net flow entering or leaving each node [22]. Let $A$ denote the matrix whose entries reflect whether a link enters or leaves a node, with positive entries for outgoing links and negative entries for incoming links. For a given demand, the net flow vector is defined such that it is positive at the source node, negative at the destination node, and zero at all relay nodes. The flow conservation constraints can be written in compact linear form as [23]

$$Ax = b, \tag{2.2}$$

where $b$ is the column vector encoding the required source and destination balances for each demand [24]. In this representation, multi hop routes emerge implicitly from the satisfaction of these equalities rather than being enumerated explicitly.

Capacity considerations impose upper bounds on the flow that can be carried by each link. If a normalized time horizon is assumed, in which a unit of decision variable corresponds to occupying the link for the entire horizon, the constraint that flow on a link cannot exceed its capacity translates simply into bounds on the decision variables [25]. In particular, for each link index, the corresponding decision variable is restricted to lie between zero and one. This yields the constraint set [26]

$$0 \le x \le \mathbf{1}, \tag{2.3}$$

where $\mathbf{1}$ denotes a column vector of ones of appropriate dimension. If the decision variables are further restricted to be binary, this corresponds to selecting a set of link activations that either fully exploit or do not use each link during the horizon. The binary nature of the variables models the fact that in highly dynamic vehicular environments, fine grained time sharing on time scales shorter than the swarm optimization period may not be practical.

The binary constraint can be stated formally as [27]

$$x_e \in \{0, 1\} \tag{2.4}$$

for each directed link index $e$. When this integrality condition is enforced, the model becomes a binary linear program, with a combinatorial feasible set defined by the intersection of the flow conservation equations and bound constraints [28]. The integrality captures the discrete nature of relay selection, while the linear objective and constraints preserve a structure amenable to efficient evaluation and approximate optimization within a swarm framework.

Additional linear constraints can encode implementation specific properties of the vehicular ad hoc network [29]. For instance, half duplex operation can be modeled by limiting the sum of decision variables corresponding to incoming and outgoing links of a node during the horizon. A simple representation is

$$Dx \leq \mathbf{1}, \tag{2.5}$$

where $D$ is a matrix that aggregates variables associated with the same node [30]. Each row of $D$ contains ones in columns corresponding to links incident to a particular node, and zeros elsewhere, thus enforcing that no node is scheduled on more than one link simultaneously in this abstraction. Likewise, constraints limiting the maximum path length or hop count for a flow can be expressed by summing appropriate decision variables and comparing the result to a fixed bound [31].

In this linear formulation, throughput maximization is constrained by flow balance, link capacity, and relay selection structure. The model does not assume a specific channel distribution or medium access mechanism beyond what is encoded in the link capacities and structural matrices. As a result, it can accommodate differing modulation, coding, and access schemes by adjusting the parameter vector $c$ and matrices $A$ and $D$ [32]. The main challenge lies not in evaluating a given selection, which reduces to computing the objective $c^\top x$ under constraints, but in navigating the binary feasible set induced by relay selection decisions. This challenge motivates the use of swarm intelligent search strategies that can exploit the linear structure of the model while exploring the combinatorial solution space.

## 3. Swarm Intelligent Relay Selection Algorithm

To couple the linear throughput model with an adaptive decision mechanism, a swarm intelligent algorithm is employed to search the discrete space of relay selections [33]. The algorithm maintains a population of agents, often referred to as particles, each representing a candidate vector of binary link activation decisions. The swarm evolves iteratively, guided by individual and collective experiences encoded through local objective evaluations. Over successive iterations, particles tend to move toward regions of the solution space that correspond to higher throughput as determined by the linear model, while maintaining diversity to avoid premature convergence [34].

A common choice for swarm based optimization is particle swarm optimization, originally formulated in continuous domains. Its basic mechanism can be adapted to the binary decision space arising from relay selection by defining appropriate representations and update rules [35]. Each particle is associated with a position vector that lies in a continuous relaxation of the binary cube, and a velocity vector that governs the change in that position between iterations. The position vector is subsequently mapped to a binary decision vector through a probabilistic or thresholding rule. The capacity to operate in a relaxed continuous space enables the use of well established particle swarm dynamics while ultimately producing discrete relay selections [36].

The canonical particle swarm update consists of combining an inertial component that preserves a portion of the previous velocity, a cognitive component that encourages movement toward the best position found so far by the particle itself, and a social component that biases motion toward the best position found by the entire swarm. Let $x_n^t$ denote the position vector of particle $n$ at iteration $t$, and let $v_n^t$ denote its velocity vector. The cognitive best position of the particle is denoted by $p_n^t$, and the global best position of the swarm is $g^t$. The velocity update can be expressed as [37]

$$v_n^{t+1} = \omega v_n^t + \phi_1 r_1 \left(p_n^t - x_n^t\right) \tag{3.1}$$
$$+ \phi_2 r_2 \left(g^t - x_n^t\right), \tag{3.2}$$

where $\omega$ is the inertia coefficient, $\phi_1$ and $\phi_2$ are acceleration coefficients weighting the cognitive and social components, and $r_1$ and $r_2$ are vectors of independent uniform random variables sampled in each iteration and dimension. The position update then becomes [38]

$$x_n^{t+1} = x_n^t + v_n^{t+1}, \tag{3.3}$$

with optional clamping to keep positions within a bounded interval.

To obtain a binary relay selection vector from the continuous position representation, a mapping function is applied component wise. A simple approach uses a sigmoid function as an activation probability, where each component of the position vector is transformed according to [39]

$$s\left(x_{n,e}^t\right) = \frac{1}{1 + \exp(-x_{n,e}^t)}, \tag{3.4}$$

and the corresponding binary decision is set to one with probability equal to this value and zero otherwise. Alternatively, a deterministic thresholding rule can be used, where components exceeding a fixed threshold are mapped to one and others to zero [40]. The choice between probabilistic and deterministic mapping influences the exploration behavior and the degree of variability observed in the swarm across iterations.

Once a binary decision vector is obtained for a particle, it is evaluated by the linear throughput model. Specifically, the vector is checked for feasibility with respect to the flow conservation and capacity constraints [41]. If the candidate violates some constraints, correction strategies can be employed, such as projecting the vector onto the closest feasible set under a simple norm or applying repair heuristics that adjust individual decisions to restore feasibility. After obtaining a feasible vector, the throughput is computed using the objective $c^\top x$, providing a scalar fitness value for the particle. This value is then used to update the cognitive best position of the particle and, if appropriate, the global best position of the swarm [42].

In the vehicular ad hoc network context, the swarm can be operated periodically, with each optimization window corresponding to a time interval over which the topology and channel conditions are considered approximately constant. At the beginning of each window, the link capacity vector and structural matrices are updated based on current measurements or predictions of channel quality and node positions. The swarm then performs a fixed number of iterations to refine relay selections before the resulting decisions are applied to actual packet forwarding [43]. This periodic reoptimization allows the swarm to adapt to changing conditions, while the linear evaluation model provides a computationally efficient way to guide particle updates.

The distribution of the swarm computation itself can be realized in several ways [44]. In a centralized configuration, a roadside unit may collect topology and channel information from vehicles, execute the particle swarm algorithm, and disseminate selected relay configurations back to the vehicles. In a distributed configuration, each vehicle may maintain a local subset of particles and exchange partial state information with neighbors, approximating global best positions through consensus or gossip mechanisms [45]. The choice depends on the underlying infrastructure support and the acceptable level of control overhead. Regardless of the specific realization, the separation between linear evaluation and swarm dynamics is preserved.

Parameter selection for the swarm influences both convergence speed and the quality of the relay selections [46]. The inertia coefficient and acceleration coefficients affect how aggressively particles exploit known good solutions versus exploring new regions of the decision space. Values that emphasize inertia may slow adaptation to rapid topology changes, while values that emphasize acceleration may lead to oscillatory behavior and instability in relay decisions [47]. Bounding the velocity components and limiting the range of position vectors can help maintain controlled exploration. Additionally, the number of particles and iterations per optimization window determine the computational burden and the degree of refinement achievable before decisions are applied to the network.

The integration of swarm intelligent relay selection with practical vehicular communication protocols requires careful coordination with medium access and routing mechanisms [48]. Selected relay sets must be translated into forwarding tables or schedules that can be implemented in the underlying protocol stack. This may involve mapping link activation decisions to priority weights in neighbor selection algorithms or to time slot reservations in time division multiple access schemes [49]. The linear model can be extended to incorporate such protocol specific details by adding appropriate constraints and adjusting the interpretation of decision variables, while the swarm based search continues to operate on the resulting structured decision space.

## 4. Theoretical Properties and Linear Analysis

The combination of a linear throughput model with swarm intelligent optimization raises several theoretical questions regarding feasibility, convergence behavior, and performance bounds. While the swarm algorithm is inherently heuristic and does not guarantee global optimality in finite time, the linear structure of the evaluation model permits certain analytical observations about the nature of the solution space and the potential improvement over baseline relay selection strategies [50]. These observations revolve around the geometry of the feasible set defined by the linear constraints and the way swarm dynamics interact with this geometry.

The feasible set of the linear model, when integrality constraints are relaxed, forms a polytope in the space of decision variables [51]. This polytope is defined by the intersection of hyperplanes representing flow conservation and half spaces representing capacity and structural constraints. The vertices of this polytope correspond to extreme points, many of which are associated with particular multi hop routing configurations. When binary constraints are reintroduced, feasible relay selections correspond to a subset of these vertices and possibly additional integral points inside the polytope [52]. The linear objective function defines a family of parallel hyperplanes whose intersection with the feasible region determines the optimal solution. In the absence of integrality, linear programming theory ensures that an optimum exists at a vertex of the polytope under mild conditions [53].

From the perspective of swarm dynamics, each particle explores the continuous relaxation of this polytope and is periodically mapped to a discrete point in or near the set of feasible relay selections. The velocity updates can be interpreted as stochastic approximations of gradient like movements toward regions where the objective hyperplanes intersect the feasible polytope at higher values [54]. Although the swarm does not compute exact gradients, the correlation between position updates and observed fitness improvements induces a directional bias. Over time, the distribution of particles tends to concentrate near favorable regions of the polytope, and the global best position tracks a sequence of candidate solutions with non decreasing objective values.

To gain insight into the potential throughput improvement achievable by the swarm based approach, consider a baseline relay selection strategy that selects neighboring relays according to a localized metric such as received signal strength or instantaneous link capacity without considering multi hop interactions or global flow conservation [55]. Such local strategies effectively operate on a reduced feasible set that enforces constraints only in the immediate neighborhood of each node. By contrast, the linear model enforces global consistency through the incidence matrix relationships [56]. The feasible throughput under local strategies can be viewed as the value of the objective function over a restricted subset of the polytope, while the swarm based approach explores a larger portion of the feasible region. Under mild assumptions that the restricted subset does not contain all optimal extreme points, there exist configurations where the swarm can reach relay selections yielding strictly higher throughput than purely local methods.

Complexity considerations arise from the dimensionality of the decision space and the cost of evaluating feasibility and objective values [57]. Let the number of directed links be denoted by $E$. The dimension of the decision vector is then $E$, and the evaluation of the linear objective requires a scalar product of length $E$, which has complexity proportional to $E$ [58]. The evaluation of the flow conservation constraints involves multiplying the incidence matrix $A$ by the decision vector $x$, which, for sparse vehicular topologies, also has complexity proportional to $E$. Thus, the cost per particle and per iteration scales linearly with the number of links, making it feasible to apply the swarm based method in network instances where $E$ is moderate. The aggregate cost is proportional to the product of the number of particles, the number of iterations per optimization window, and the number of links [59].

Another aspect of interest is the effect of integrality on the solution quality. If the binary constraints are relaxed to continuous bounds, the resulting linear program can be solved optimally using standard techniques, and its solution provides an upper bound on the throughput achievable by any integral selection [60]. In practice, solving a full linear program may be computationally demanding in large and rapidly changing networks, motivating the use of swarm based approximations. Nevertheless, the optimal value of the relaxed program offers a benchmark [61]. Let $x^\star$ denote an optimal solution to the relaxed program with objective value $c^\top x^\star$, and let $\hat{x}$ denote a solution obtained by the swarm algorithm with objective value $c^\top \hat{x}$. The difference

$$\Delta = c^\top x^\star - c^\top \hat{x} \tag{4.1}$$

represents the integrality and heuristic gap [62]. While exact evaluation of this gap requires solving the relaxed program, analytical estimates may be derived for specific network structures, such as line or grid topologies, where incidence matrices exhibit regular patterns.

Stability of swarm dynamics in the context of time varying vehicular topologies is also relevant [63]. The parameter region in which particle positions remain bounded and do not diverge has been studied for classical particle swarm optimization in static objective functions. These analyses typically relate the inertia and acceleration coefficients through inequalities that ensure convergence of velocities and positions. In the vehicular setting, the objective function changes over time as capacities and topologies evolve, introducing an additional perturbation [64]. A simplified linear analysis treats the dynamic objective as a sequence of static functions and examines whether the swarm tracks the moving optimum with bounded deviation. Under moderate rates of change, choices of parameters that guarantee convergence in static cases often yield tracking behavior in dynamic settings, although precise bounds on tracking error are more intricate to derive [65].

Furthermore, the discrete mapping from continuous positions to binary selections introduces randomness that affects convergence. When probabilistic mapping is used, the resulting swarm process can be modeled as a Markov chain in the space of binary decision vectors, with transition probabilities depending on current positions, velocities, and random variables $r_1$ and $r_2$. Exact characterization of this chain is generally infeasible due to the high dimensionality, but qualitative properties can be inferred. For example, unless velocities are driven to zero and positions become frozen, the chain remains ergodic over a subset of feasible selections, permitting ongoing exploration [66]. However, concentrating particles near certain regions of the polytope reduces effective exploration and can slow adaptation when conditions change.

The linear model also allows derivation of simple upper and lower bounds on achievable throughput based on network parameters [67]. A trivial upper bound is obtained by assuming that all links can be activated without interference or scheduling constraints, leading to a bound equal to the sum of capacities along idealized disjoint routes. A more refined bound considers cut constraints, where the total throughput of flows crossing a cut in the graph cannot exceed the sum of capacities of links in the cut. Given a partition of nodes into two sets, the cut capacity is expressed as [68]

$$C_{\text{cut}} = \sum_{e \in \delta(S)} c_e, \tag{4.2}$$

where $\delta(S)$ denotes the set of links with one endpoint in set $S$ and the other in its complement. For any set of flows that must traverse this cut, the aggregate throughput is bounded above by $C_{\text{cut}}$. In vehicular ad hoc networks, cuts corresponding to bottleneck road segments or intersections can significantly constrain throughput, and relay selection strategies can be interpreted as attempting to route flows to avoid or mitigate such bottlenecks within the mobility constraints [69].

Lower bounds on throughput can be established by constructing explicit relay selection policies with guaranteed performance under specific conditions. For instance, a simple policy that always selects the relay with maximum instantaneous capacity within a restricted neighborhood yields a certain minimum throughput as long as there exists at least one path connecting sources and destinations with nonzero capacities [70]. While such bounds are generally conservative and depend on simplifying assumptions, they offer insight into worst case performance and provide a reference against which the swarm based approach can be compared.

## 5. Performance Evaluation and Discussion

The performance of the swarm intelligent multi hop relay selection strategy can be investigated through simulation studies that model vehicular mobility, wireless channels, and communication protocols at appropriate levels of detail. A typical scenario involves vehicles moving along single or multi lane roads with varying speeds, accelerations, and lane changes governed by a microscopic mobility model [71]. Roadside units are placed at fixed positions along the road, providing infrastructure connectivity when vehicles are within communication range. The wireless channel incorporates large scale path loss, log normal shadowing, and small scale fading, with parameters chosen to represent urban, suburban, or highway environments [72]. Medium access is modeled as a contention based mechanism with collision and backoff behavior, and traffic sources generate data flows with specified rates and destinations.

In this setting, the swarm based relay selection is integrated as a decision layer that periodically computes multi hop routes for active flows. At the beginning of each decision period, the topology and channel state are sampled or estimated, and link capacities are determined based on instantaneous or averaged signal to interference plus noise ratios and medium access conditions [73]. The linear throughput model is instantiated with these capacities and structural matrices, and the swarm performs a predetermined number of iterations to refine candidate relay selections. The resulting decisions are then applied to route packets during the subsequent period [74]. Throughput is measured as the amount of data successfully delivered to intended destinations over time, normalized by the decision period and, optionally, by the number of flows.

Different simulation configurations can be used to explore the sensitivity of performance to environmental and algorithmic parameters. Vehicle density affects the number of available relay candidates and the connectivity of the network [75]. At low densities, multi hop paths may be sparse or nonexistent, and throughput gains from relay optimization may be limited by connectivity rather than selection quality. As density increases, more relay options become available, but contention and interference also grow, making careful selection more beneficial [76]. Speed distributions influence how quickly link conditions change, potentially shortening the duration over which a relay selection remains effective. Swarm parameters, including population size, inertia, and acceleration coefficients, shape the balance between exploration and exploitation in the relay selection process [77].

Comparisons with baseline schemes help contextualize the performance of the swarm based method. Simple baselines might include shortest path routing based on hop count, where vehicles always forward to the neighbor closest to the destination, and greedy schemes that select next hops with maximum instantaneous received signal strength or link capacity without accounting for end to end effects. Another baseline may be a static routing configuration determined at initialization and not updated in response to mobility [78]. In evaluations, metrics of interest include aggregate throughput, per flow throughput, end to end delay, packet delivery ratio, and fairness among flows. The swarm based approach is expected to adapt relay selections to prevailing conditions, potentially improving throughput and balancing load across multiple candidate paths, while baselines may suffer from congestion and unbalanced utilization of links [79].

An important aspect of the evaluation is the computational and signaling overhead associated with the swarm operation. Computationally, the cost scales with the number of particles and iterations used in each decision period. The choice of these values must reconcile the desire for thorough exploration with limitations of processing power available in roadside units or vehicles [80]. Simulations can measure the time required to execute the swarm optimization for different swarm sizes and dimensions, providing guidelines for feasible parameter settings. Signaling overhead arises when topology and channel state information must be disseminated to the entity executing the swarm and when relay decisions must be communicated back to vehicles [81]. Evaluations can quantify the additional bandwidth consumed by control messages and assess the impact on data throughput.

Robustness of the swarm based relay selection to inaccuracies in topology and channel state information is another factor of interest. In practice, position and channel estimates may be delayed or noisy, leading to mismatches between the model parameters used in optimization and the actual network state when relay decisions are applied [82]. Simulations can introduce controlled levels of estimation error and delay to study their effect on throughput and the stability of relay configurations. The linear model can accommodate such uncertainties by incorporating conservative capacity estimates or by considering average or worst case values over time windows, but this may introduce trade offs between robustness and efficiency [83].

The evaluation also examines how the swarm adapts to sudden changes in network conditions, such as the appearance of congestion hotspots, link blockages due to obstacles, or sudden increases in traffic load. For example, an incident causing vehicles to slow down or stop in a particular segment may change link characteristics and introduce potential bottlenecks. The swarm based method, by continuously updating relay selections, may redirect flows through alternative paths when available, whereas static or purely local strategies may take longer to react [84]. Metrics such as time to recovery of throughput after a perturbation and variability in per flow throughput over time provide insight into the dynamic responsiveness of the approach.

Although simulation based evaluation provides a flexible platform for experimentation, it remains an abstraction of real world vehicular environments [85]. Nevertheless, careful parameterization and scenario design can approximate key phenomena affecting multi hop relay performance. By systematically varying parameters such as vehicle density, speed distributions, channel conditions, traffic patterns, and swarm configuration, a range of behaviors can be observed and analyzed [86]. These observations can inform the selection of swarm parameters for deployment and highlight regimes where the swarm based approach is more or less advantageous compared to simpler methods.

## 6. Conclusion

Multi hop relay selection for throughput maximization in vehicular ad hoc networks presents a complex optimization problem with a combinatorial feasible set and time varying constraints driven by mobility and wireless channel dynamics. By formulating the problem using linear objective functions and constraints that capture flow conservation, capacity limitations, and structural properties of the network, it becomes possible to evaluate candidate relay selections efficiently and to analyze the geometric structure of the feasible region [87]. At the same time, the combinatorial nature of binary relay decisions and the dynamic environment limit the practicality of conventional exact optimization techniques in real time vehicular applications.

Swarm intelligent methods, particularly those derived from particle swarm optimization, offer a means of exploring the discrete relay selection space by coordinating a population of candidate solutions through simple update rules [88]. Adapting these methods to binary decision variables through continuous relaxations and mapping functions allows them to operate in harmony with the linear throughput model. The resulting framework separates evaluation and search, using the linear model as a fast evaluator while swarm dynamics guide exploration toward relay configurations that yield higher throughput under the prevailing network conditions.

Analytical considerations based on the linear model provide insight into the structure of the solution space, potential performance bounds, and complexity scaling [89]. The feasible set formed by linear constraints can be interpreted as a polytope whose vertices and extreme points correspond to multi hop routing patterns. The swarm explores this polytope stochastically, and while it does not guarantee global optimality, it can access regions of the feasible space that are beyond the reach of simple local heuristics [90]. The linear nature of the evaluation ensures that the computational cost per particle remains moderate even as the network grows, provided that the topology remains sparse.

Simulation based evaluations, although abstracting from full real world complexity, suggest that swarm based relay selection can adapt to variations in vehicle density, speed, and channel conditions, and can respond to changes in traffic demand and network disruptions. The periodic optimization window structure allows the method to track the dynamic network state, while the adjustable parameters of the swarm provide a means of tuning the balance between exploration and exploitation according to application requirements and processing capabilities [91]. Overhead considerations, both computational and signaling related, remain important factors in determining practical deployment strategies, and the linear model facilitates estimation and control of these costs. The integration of swarm intelligent optimization with linear throughput modeling yields a flexible framework for multi hop relay selection in vehicular ad hoc networks [92]. The approach aligns with the constraints and variability of vehicular environments by avoiding overly rigid assumptions and by providing mechanisms to adapt to observed conditions. Further work may examine variations of swarm dynamics, alternative mapping functions between continuous and discrete spaces, and extended linear models that incorporate additional protocol layers and performance metrics. Such extensions can refine the applicability of the framework across diverse vehicular communication scenarios while maintaining the underlying balance between modeling tractability and adaptive decision making [93].

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