Noname manuscript No.
(will be inserted by the editor)

A Novel Multi-Featured Metric for Adaptive Routing in Mobile Ad Hoc Networks

Songul HASDEMIR · Selim YILMAZ · Sevil SEN

Received: date / Accepted: date

Abstract The design of adaptive, scalable, and low cost routing protocols presents one of the most challenging research problems in mobile ad hoc networks (MANETs). Many routing protocols for MANETs have been proposed in the literature, which are based mainly on selecting the *shortest path* between communication endpoints. In this paper, a new evolution-based routing metric called EVO is proposed. This metric is generated automatically by means of genetic programming. In the evolution process of this metric, mobility- and traffic-related features are employed. In this study, the metric is applied to the Ad hoc On-Demand Distance Vector (AODV) protocol, one of the most popular on-demand routing algorithms for MANETs. The modified version of AODV, called EVO-AODV, ranks and selects routes according to the evolved multi-featured metric between communication endpoints. The performance of the proposed metric has been tested on networks with varying mobility and traffic patterns. The metric is also compared with AODV and two recently proposed routing metrics, the hop change metric (HOC) [63] and encounter-based routing metric (PER) [54]. The extensive simulation results demonstrate that the proposed approach improves the packet delivery ratio significantly and also decreases the packet drop rate, routing overhead, and end-to-end delay, especially on networks under medium traffic.

Keywords Mobile ad hoc networks (MANETs) · Reactive routing protocols · Routing metric · AODV · Evolutionary computation · Genetic programming · Adaptive routing

---

Songul HASDEMIR · Selim YILMAZ · Sevil SEN
WISE Lab., Department of Computer Engineering, Hacettepe University, Ankara, Turkey
Tel.: +90-312-780-7538
Songul HASDEMIR E-mail: songultozan@gmail.com
Selim YILMAZ E-mail: selimy@cs.hacettepe.edu.tr
Sevil SEN E-mail: ssen@cs.hacettepe.edu.tr

1 Introduction

Owing to their minimal dependence on a permanent infrastructure, mobile ad hoc networks (MANETs) can be used in a wide spectrum of applications from strategic and disaster recovery operations to virtual conferences. They combine wireless communication with a high degree of node mobility. In these dynamic networks, nodes that are within each other's transmission range, called neighbors, can communicate directly. Otherwise, they rely on intermediate nodes to relay messages. Routing protocols in such dynamic networks are employed to build and update multi-hop routes for packet delivery.

Message delivery in such dynamic, infrastructure-less networks is one of the most challenging research problems. In this context, the key is to find a route that minimizes energy consumption and time delay while maximizing delivery performance; this means that an appropriate routing algorithm is required. In general, routing protocols proposed for MANETs are divided into three main categories: *proactive*, *reactive*, and *hybrid*. In proactive routing protocols (*e.g.*, destination-sequenced distance vector (DSDV) [42] and optimized link state routing (OLSR) [27]), each node maintains routes to all other nodes in the network at all times. This results in a high overhead because of the large number of periodic control messages required to maintain an up-to-date routing table. However, in reactive algorithms (*e.g.*, ad hoc on-demand distance vector (AODV) [43] and dynamic source routing (DSR) [27]), the routing process is triggered by a source node when a route is needed, which can cause a delay before the packet transmission between endpoints start. In general, reactive algorithms are more scalable because of their ability to reduce the routing overhead [6]. Hybrid algorithms (*e.g.*, the zone routing protocol (ZRP) [21]), as the name suggests, combine the best of the proactive and reactive protocols.

In MANETs, there can be multiple routes between two endpoints. Most of the approaches proposed thus far have regarded the routing problem in MANETs as the shortest path problem and considered a single metric, mostly the hop count (HOP) [26], to represent the shortest path. However, HOP may not lead to the best path, as it is minimized regardless of the quality of radio links [38] and its performance is degraded sharply in very dynamic environments. In other words, the determination of a route based on such a single-featured metric does not take into account the mobility of the network and the traffic. Thus, every time a link breakage occurs, the route discovery mechanism is re-initiated, which results in additional overhead and a decrease in the throughput. Therefore, it is better to take mobility and traffic into consideration in such dynamic environments. In this research study, we investigate whether we could automatically find more stable and less busy routes, which may not be necessarily the shortest paths and improve the network performance in terms of packet delivery ratio (PDR), overhead (OVR) and end-to-end (E2E) delay.

In this study, an evolutionary computation-based technique has been employed because of its ability to discover the complex properties of MANETs [49]. A new routing metric, called the evolution-based routing (EVO) metric, is generated automatically and applied to AODV. The proposed method employs genetic programming (GP) to generate a routing metric automatically based on mobility- and traffic-related features. According to this metric, the method then ranks and selects routes between the communication endpoints.

The EVO metric is employed in networks with varying mobility and traffic patterns. The extensive simulation results demonstrate that EVO-AODV improves the network performance considerably as compared to the state-of-the-art protocols, including AODV [43] based on HOP, PER-AODV [54] based on the path encounter rate metric (PER), and LA-AODV [63] based on the hop change metric (HOC). However, clearly each metric has advantages and disadvantages. The proposed routing protocol based on the EVO-AODV metric produces much less routing control packets and end-to-end delay as compared to AODV, PER-AODV and LA-AODV metrics, regardless of the mobility level of the network. It should be noted that control packets are used for route discovery and maintenance mechanisms and cause undesirable delays in packet transmission. A non-parametric statistical test is also employed to investigate whether there exists any significant difference among the experimental results. The statistical results also corroborate that the EVO metric outperforms other metrics on such networks.

The rest of the paper is organized as follows. Section 2 introduces AODV and summarizes the improvements of AODV in the literature. Our contributions are also presented in this section. Section 3 discusses the issues in MANETs' routing and presents the idea behind our approach. Section 4 introduces the simulation environment. In subsection 4.2.1, PER-AODV using the PER metric [54] and LA-AODV using the HOC metric [63] are also described in detail. Section 5 provides the experimental results for EVO-AODV and its performance comparison with AODV, PER-AODV, and LA-AODV. In Section 6, the advantages and disadvantages of each metric are discussed. Section 7 concludes this paper.

2 Related Work

2.1 Ad hoc On-Demand Distance Vector Routing (AODV)

AODV is one of the most popular routing protocols for MANETs. It is designed for networks consisting of tens to thousands of mobile nodes [41]. It has also been claimed that it can handle low to moderate mobility, as well as a variety of data traffic levels [41]. AODV is based on two main mechanisms: *route discovery* and *route maintenance.*

2.1.1 Route Discovery Mechanism

Route discovery is initiated when a source node wants to communicate with another node but has no fresh information about this destination node in its routing table. The source node S starts the route discovery mechanism by broadcasting route request (RREQ) packets to its neighbors. An RREQ packet contains the following information: *source address*, *source sequence number*, *broadcast id*, *destination address*, *destination sequence number*, and *hop count* [43]. Since the routes frequently change in MANETs, the source sequence number is used to ensure the freshness of the reverse route to the source. The destination sequence number also indicates the freshness of a route to the destination. The broadcast id is created uniquely and incremented when a source node publishes an RREQ packet. The hop count, which is called the HOC metric in this paper, shows the number of hops between two communication endpoints.

The nodes that receive this route request either send a route reply (RREP) packet to the source node or forward the RREQ packet to other nodes. If an intermediate node has a fresh valid entry about the destination in its routing table, it sends a unicast reply to the source node; otherwise, it increases the hop count and rebroadcasts the RREQ packet. The fresh entry means that its sequence number is equal to or greater than that contained in the RREQ message. If the sequence numbers are the same, the shorter route (having a fewer number of hops) is selected. A node may receive multiple RREQs from different neighbors. However, it processes only the first RREQ packet and drops the others. A node records the address of the neighbor from which it receives the first copy of the RREQ packet and establishes the route reverse path.

2.1.2 Route Maintenance Mechanism

When a broken link is detected in the network, nodes use route error (RERR) packets to warn other nodes to change the hop metric value to the unreachable symbol in their routing tables. The RERR message is frequently broadcast to the whole network. The nodes that receive an RERR message start the route discovery process if they want to pursue communication with the unreachable destination nodes through other paths.

The local connectivity is maintained by using one or more of the available link or network layer mechanisms in AODV [41], such as link layer notification or passive acknowledgement, or by using periodic *hello* messages at the routing layer.

2.2 Improvements on AODV

Many studies have been conducted on developing suitable routing metrics for MANETs. In this section, we focus mainly on outlining studies in which a metric other than HOP was employed to increase the performance of MANETs. The reader may refer to [5][58] for a detailed review of routing protocols in MANETs.

A metric based on the per-hop round-trip time (RTT) [2] was proposed in 2004. The RTT metric is calculated by sending a probe packet from a node to its one-hop neighbors. The sender then renews the average RTT values that are registered in its routing table. The aim of this particular routing approach is to determine a path having the minimum-valued RTT. However, the evaluation of the RTT value using periodic propagation of probe packets may cause overhead in the network, and therefore, this metric is not very efficient for resource-constrained MANETs.

Metrics based on the expected transmission count (ETX) also exist in the literature. The ETX presents the throughput of transmission links. Two factors are used to determine the value of ETX: *the forward delivery ratio* (d_f) and *the reverse delivery ratio* (d_r). The former indicates the possibility of data successfully reaching the receiver, whereas the latter indicates the possibility of data being successfully received. The protocol selects the link having the minimum ETX value for forwarding data packets [11]. This metric finds routes with a higher throughput; however it does not take mobility into account. In 2012, the expected cooperative transmission count (ECTX) [48], a modified version of the ETX, was proposed. Simulation results showed that the throughput of ECTX is 30% higher than that of the original ETX.

Another metric, called mobility factor (MF) [34, 59], is used by some routing schemes for relatively dynamic scenarios, whereby the link stability is considered before the packet is forwarded. The symmetric difference of the neighbors of a node between two consecutive hello messages is taken as the basis in the calculation of this factor. While transmitting data packets, the MF metric helps a routing protocol select the best fixed path for transmitting data packets, which results in showing a better performance than the original AODV protocol [34, 59]. However, each node needs to maintain a table in order to record the current neighbor list, together with the historical neighbor list for calculating the MF value, which may cause scalability issues.

Yang and Wang provided design guidelines for the selection of the appropriate combination of routing protocol and routing metric [61]. Karzakis *et al.* [29] also supported the notion that the routing metric to be used depends on the application, and proposed composite metrics. In addition to single or composite metrics [29, 53], approaches that use more than one metric exist, which adaptively select different metrics for static networks and mobile networks [51, 52].

Many researchers have recently addressed the MANETs' routing problem by adopting Artificial Intelligence (AI). There is a paucity of studies in the literature that consider various quality of service (QoS) parameters for route selection using AI-based approaches. Ant colony optimization (ACO), inspired by the ability of ants to find the shortest path between their nest and a food source, is frequently applied for solving optimal route selection problems for both wired and wireless networks. Most ACO-based routing approaches slightly differ in the evaluation criteria that they consider. In 2005, a hybrid ACO-based multipath routing algorithm (AntHocNet) [13] that considers only E2E delay and hop count for the evaluation of different routes was proposed. AntHocNet initiates a path setup with forward ants that are generated and broadcast by the source node s. At each node, a forward ant is either unicast or broadcast depending on the routing information of the node to destination node *d*. Upon visiting node *d*, a forward ant becomes a backward ant and then travels back to the source node by retracing the intermediate nodes. AntHocNet considers the link failures by using the path repair ants, which follow one of the other paths to the destination. Ant colony-based energy-aware routing algorithms [25, 36] optimize the number of hops, as well as the remaining battery energy for each node. Their path construction phase is similar to that presented in AntHocNet [13]. Since energy is one of the main constraints in ad hoc networks, there are many other optimization algorithm proposals that take into account both length and energy consumption of routes [65][56]. Recently, another bio-inspired routing algorithm based on cuckoo search, AODVCS [31], is proposed and shown to be better than AntHocNet [13], even when the number of nodes in the network increases. A detailed comparative analysis on ACO-based routing protocols [64] showed that this approach is suitable for dynamic problems such as routing in MANETs. The recent ACO-based routing approaches mainly target to develop energy-aware, location-aware or secure-aware solutions besides to find the optimal routes in MANETs [64].

The ACO-based approaches mentioned above consider mainly one or two metrics and do not correlate the multiple route selection parameters. To achieve this, a fuzzy ant colony-based algorithm (FACO) [19] was proposed in 2009. Here, a fuzzy inference system (FIS) determines the interplays of different QoS parameters (buffer occupancy, remaining battery power, and signal stability) through its membership function and fuzzy rules. In FACO, every node in the participating route calculates its fuzzy cost, which is the weighted sum of three different QoS parameters. Forward and backward ants perform the route discovery phase, as described in AntHocNet [13]. Another dynamic fuzzy-based energy-aware routing protocol [9] was proposed in 2016. This approach determines a path depending on the “willingness” of each participatory node. Here, the willingness is calculated using the node’s residual energy and energy drain rate, which are also inputs to the fuzzy system. The only difference from the aforementioned fuzzy-based protocol is that, rather than a static, it uses a dynamic membership function, claiming that the willingness of a node changes over time as nodes’ energy is not static.

A similar, but evolutionary-based fuzzy route selection process [35] was proposed in 2004. When selecting a route, different objectives are considered: E2E delay, PDR, and the lifetime of batteries. To meet these objectives and to produce the single fuzzy cost of a route, several metrics (remaining battery capacity, buffer length, link stability, and the number of intermediate nodes in the route) are employed. These metrics are the inputs of the fuzzy controller, and the evolutionary approach is used to tune the fuzzy rule tables. The best route is selected among the possible routes based on the fuzzy cost of each route.

In 2003, a genetic algorithm (GA) based routing method for MANETs (GAMAN) [4] was proposed. The network is expressed by a tree network and the genes are expressed by tree junctions. Thereby, a chromosome represents a route. Every gene in a chromosome has two states: active and inactive. A gene is called active if the junction is in the route to the destination; otherwise, its state is inactive. Genetic operations are applied only on active genes. GAMAN uses two QoS metrics (time delay and transmission success) to evaluate the routes. GA-based multicast routing algorithms for MANETs [62, 40], were proposed to find a route based on the sum of each link cost considering bandwidth and end-to-end delay constraints. In 2008, a hybrid approach (HPSO) [8] based on particle swarm optimization (PSO) and GA was proposed to improve the E2E delay. However, HPSO supports only paths with a maximum of 10 nodes. The particles in HPSO denote different routes and the movement of a particle is determined through the genetic operations of GA instead of the arithmetic operations of PSO. Besides the route shortness, tranmission delay is also taken into account in a recent study based on reinforcement learning [18]. In 2010, the multi-objective evolutionary algorithm (MOEAQ) was proposed for solving multicast routing problem in MANETs [24]. It employs four QoS parameters (*bandwidth*, *delay*, *packet loss*, and *jitter*) to construct the multi-objective function. Each chromosome represents a route as in GAMAN [4]. The algorithm produces a Pareto optimal set of non-dominated solutions, which represents different trade-offs among the four objectives. A recent survey underlines that many applications of evolutionary algorithms for MANETs use a multi-objective fitness function [46]. Recently, a lightweight genetic algorithm is proposed in order to predict mobility which could improve the MANET routing protocols [55].

Because of issues such as mobility and energy conservation, the changes in network topology over time make the routing problem in MANETs a dynamic optimization problem. Therefore, few dynamic evolutionary methods are proposed in the literature. In 2010, an improved GA with immigrant and memory schemes was developed to enhance the search capability in the dynamic environment of MANETs [60]. As in MOEAQ [24], every chromosome represents a route and the genes represent the nodes in visiting order. In GA with an immigrant scheme, a portion of the current individuals is replaced with randomly generated individuals at every generation in order to maintain a diverse population as possible, which ensures that GA is adaptive to the changing topology. GA with a memory scheme, however, stores good individuals (usually the best) from the current generation and reuses them later when a topological change is detected. Every stored individual is re-evaluated at every generation in order to detect any environmental change that occurs. The inclusion of the memory scheme enables the GA to adapt to a new environment more directly than when an immigrant scheme is used. However, the re-evaluation of the fitness of the individuals at every generation leads to an additional computational load. In 2016, a very similar approach [28] was proposed to target Dynamic Load-Balanced Clustering Problem (DLBCP) in MANETs. Recently, another hybrid Multi-population Memetic Algorithm (MMA) [57] was proposed for the optimization of dynamic shortest path routing (DSPR) problem in MANETs. The idea behind MMA is that the population is divided into the sub-populations so that each searches different area of the dynamic space. All best solutions found at every iteration from sub-populations are stored then released back to be merged with population to effectively deal with the dynamic optimization problem.

2.3 Our Contributions

Many studies on improving routing protocols for MANETs have been published in the literature, as summarized above. However, we present a number of highlights that differentiate EVO-AODV from other studies in the literature. Our contributions can be summarized as follows:

- In this study, we explore the use of GP for generating a routing metric automatically and introduce a new metric (EVO), which characterizes changes in the network. To the best of our knowledge, this is the first use of the GP approach for generating a routing metric automatically. Other evolutionary computation- or AI-based approaches exist; however, they either in general apply online learning to find optimal paths dynamically, which is not suitable for such resource-constrained networks, or they do not take route stability into account. Furthermore, by generating routing metric automatically, the proposed approach differs from other routing protocols based on link stability [37]. While a chromosome represents a route in other evolutionary computation-based approaches, in our approach it represents a routing metric instead. Our approach is different in that it generates a routing metric offline and makes only small modifications to the routing protocol.
- The improved version of AODV, called EVO-AODV, is introduced and, simulated on networks with varying mobility and traffic patterns. While mobility-aware approaches presented in the literature are based on static scenarios [54] or the environments that fit particular scenarios, we here present an extensive analysis of each routing metric on 900 networks (50 networks for each mobility and traffic pattern). Six different mobility levels and three different traffic levels are considered in the evaluation.
- The proposed approach is compared with other metrics presented in the literature. In addition to the well-known HOP metric, the evolved metric is in particular compared with the PER metric, which outperforms many metrics proposed in the literature (HOP, ETX [11], MF [59,34]), and the HOC metric, which is the most recently proposed metric to the best of our knowledge. The comprehensive comparison shows that the EVO metric represents the network characteristics considerably better than other metrics, HOP [43], PER [54], and HOC [63], and builds more stable routes on networks having medium traffic. To the best of our knowledge, ours is the most comprehensive and up-to-date comparison of routing metrics, since the study that the following routing metrics were compared: *hop count*, *expected transmission count*, *round trip time*, and *packet pair delay* [14].

3 EVO-AODV: AODV using Evolution-based Routing Metric

In this study, our objective is to improve AODV by selecting more stable and less busy routes in the route discovery mechanism. In standard AODV [43], the path along which an RREP packet first arrives at the source node is selected as the shortest path. In general, this path has fewer hops than other candidate paths. From this viewpoint, it can be deduced that AODV minimizes only one parameter, i.e., the *hop count*. Because AODV does not consider the mobility of a path, this method may not always be effective, in particular on highly mobile networks. The route with the minimum number of hops can be very mobile, and hence, a new route must be discovered because of link breakages on this route. However, a route discovery process consumes network resources and delays the arrival time of data packets. Therefore, features representing the mobility can help improve the routing protocol's performance, as in this study. While some of these mobility-related features, such as changes in the number of neighbors, give information about mobility directly, others, such as changes in the routing table, represent mobility indirectly [50]. In this study, we employ both mobility-related features.

The load on nodes can also affect the performance of the routing protocol. The density of traffic is also not taken into consideration in the original AODV. If a route with a high load is selected, the data packets can be dropped because of overload and then they need to be resent. This situation also negatively affects the throughput and increases overhead and delay. In order to represent data traffic in the network, data packet-related features, such as forwarded/received packets per unit time, are also included in this study.

The main hypothesis in this study is that no one particular feature of MANETs (such as hop count) is a sufficiently good measure of a path's quality in such dynamic networks. Furthermore, it is not easy to manually determine a metric that represents the complex properties of MANETs and the performance of such a metric cannot be good. It is believed that GP is a good candidate means of automatically finding a metric representing the network characteristics [49], and we employed it in this study.

3.1 Evolution-based Routing Metric (EVO)

3.1.1 Genetic Programming (GP)

GP, inspired by natural evolution, is one of the most widely employed evolutionary computation techniques. GP was first proposed by Cramer [10] and, later further developed by Koza [32].

The general steps of generational GP algorithm are given in Algorithm 1. First, a population of individuals, which are candidate solutions for the target problem, is initialized. Each solution in GP is represented as a tree. The leaf nodes of a GP tree are called terminals and the intermediate nodes and root are called non-terminals or functions. The first population is in general randomly initialized. The individuals can be computer programs, formulas, or the representative solutions of the problem. Each individual is evaluated by a fitness function, which shows the extent to which the individual solves or comes close to solving the problem.

Two main generic operators are applied to nodes: *crossover* and *mutation*. One or two individuals, depending on the type of operator, are selected as the parent [44]. The better the fitness value of an individual, the more likely it is to be selected as a parent. After two parents have been selected, subtrees are determined by selecting a crossover point, which is a node. Finally, two offspring are created by replacing the subtrees of the parents. In the mutation operator, a mutation point in a parent tree is randomly selected and the subtree already rooted there is substituted by a new, randomly generated subtree. The fitness of the newly generated individual is then evaluated. Generation-by-generation, the population is transformed into a new, hopefully better, population of individuals by using genetic operators. New populations are generated iteratively until the termination condition is satisfied. The termination condition can be based on the criterion that the algorithm has run for the maximum number of generations or it can also be based on the attainment of a solution of sufficient quality.

```
Initialize population;
repeat
    Evaluate the fitness of each individual;
    Rank the population according to fitness values;
    Apply generic operators (crossover, mutation etc.) and reproduce new
      population;
until termination criterion is satisfied;
return best-of-run individual
```

Algorithm 1: General steps of generational genetic programming

3.1.2 Evolution of Routing Metric

In this study, we aim to evolve a routing metric through GP, as shown in Fig. 3. Therefore, each individual provides a mathematical expression that represents a routing metric. An individual is represented by a tree in GP. Hence, the routing metric is an expression that is extracted from a GP tree by in-order tree traversal. The grammar definition of the GP trees is given in Fig. 1. According to this grammar, a GP tree is built of functions and features. The basic mathematical functions are used as non-terminals, as shown in Table 1. The terminals are features giving information about nodes and the network.

A simple individual (GP tree) is given in Fig. 2. The routing metric corresponding to this tree is given in Eq. 1. While `dropped_data`, `neighbors` and `repaired_routes` are some features collected by nodes in the network, the mathematical functions `+`, `-`, `sin`, `cos`, and `sqrt` at the intermediate nodes

```
(1)              <expr>::= (<expr><op><expr>)
                         | <pre-op>(<expr>)
                         | <var>
(2)                <op>::= + | - | * | /
(3)            <pre-op>::= sqrt | abs | ceil
                         | floor | exp | ln
                         | log | cos | sin
(4)               <var>::= Features in Appx. A
```

Fig. 1: The grammar definition of the GP trees

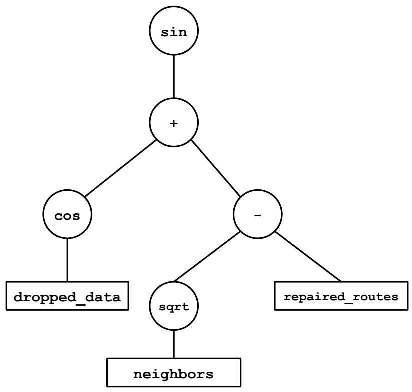


Fig. 2: An example GP tree representing a routing metric candidate

represent the functions considered for route evaluation. As explained previously, both traffic- and mobility-related features are taken into consideration for route evaluation. The full list of features is given in Table 9 in Appendix A. The feature selection is an important part of any machine learning system. Here, we try to extract all related features that could give information about the quality of a route in terms of mobility and traffic, and allow GP to select the most representative ones. The features are collected periodically by each node throughout the simulation. While some of the features such as features related to data packets are obtained by parsing the output log of the simulator, some functions have been added to the ns-2 simulator to collect other features such as features about neighborhood, features obtained from the routing tables of nodes.

$$metric = \sin(\cos(dropped\_data) + (\sqrt{(neighbors)} - repaired\_routes)) \quad (1)$$

During the application of GP, the routing metric of each and every candidate individual is distributed to each and every node of the network to evaluate paths according to EVO-AODV, which is introduced in the subsequent section. The success of GP strongly depends on the selection of the fitness function that is used to determine how well an individual represents a solution for the problem of interest. In this study, PDR is used for the fitness evaluation of individuals. In a network, the routes are built according to the candidate metric (a GP individual), then data packets are sent through these routes, and finally the PDR value is computed. Instead of on a single network, each GP tree is evaluated on 10 simulated networks, so that the EVO metric performs a robust selection. The positive effect of simulating 10 networks instead of one for evaluating the fitness function was also observed empirically. The number of networks simulated could be increased in the experiments; however, there is a trade-off between the performance of the evolved metric and the running time of the GP. Hence, the fitness value is calculated as the average PDR value of 10 networks.

Network topologies, traffic and mobility patterns of these 10 networks are created randomly at the beginning of the training. In each GP run, the same networks are used for evaluating the evolved metrics. However, these networks need to be re-run for each individual, since the evolved metrics could change the routes that the routing algorithm selects. The same situation occurs for the networks used in the testing, hence static datasets are not used neither in training nor in testing.

In the experiments, the elite part of individuals are preserved. The GP algorithm is run 10 times and the best individual among these runs is selected as the routing metric. The GP parameters are listed in Table 1. The parameters not listed here are the default parameters of Java-based evolutionary computation toolkit, called ECJ [15]. The parameters of the simulated networks are given in Table 2, which will be explained shortly.

Table 1: Genetic programming parameters

Parameters	Value
Functions	+, -, *, /, sqrt, abs, ceil, floor exp, ln, log, cos, sin
Terminals	features in the Appendix A
Population Size	40
Generations	50
Crossover Probability	0.9
Mutation Probability	0.1
Selection Strategy	Tournament selection (Tournament size: 7)
Number of Elite Individuals	3

3.2 EVO-AODV

3.2.1 Route Discovery Mechanism

In order to evaluate each individual, instead of AODV, the EVO-AODV routing protocol is employed on the simulated networks in the training. As a result of running the GP algorithm 10 times, the metric given in Eq. 2 is obtained. Hence, EVO-AODV employs the evolved metric in order to select a more

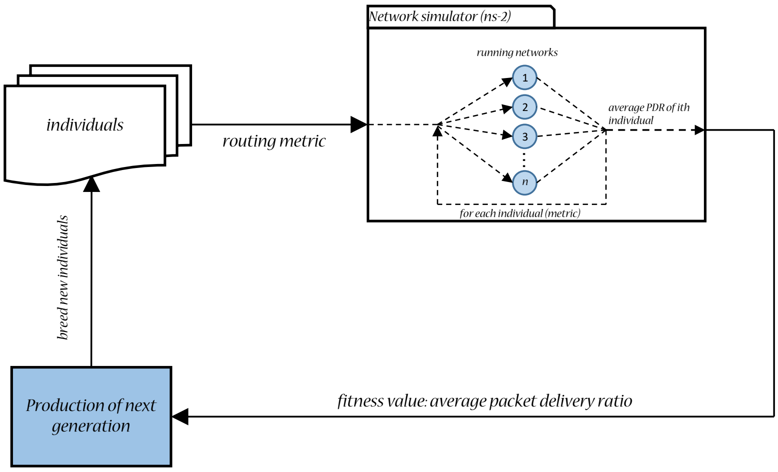
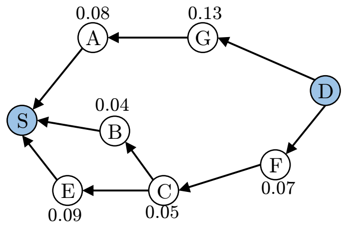


Fig. 3: Evolution of a routing metric

stable/less active route between two communication endpoints. It is a replacement for the HOP metric. After the metric is determined by GP, the nodes periodically re-evaluate the value of the predetermined function. Each node re-evaluates EVO value every 15 s, which is determined experimentally.

EVO-AODV follows the same route discovery steps as the original AODV; however, the route selection mechanism is modified in terms of establishing a route among received route reply packets. In the original AODV, the source node builds the route immediately after receiving an RREP packet, which indicates the shortest path to the destination. In EVO-AODV, the source node waits for other RREP packets to arrive in order to make a decision on the route to the destination. The decision is made based on the aggregated EVO value to the destination. Therefore, a new field is added to RREP packets called *aggregated EVO*, which represents the EVO value of the route. This field demonstrates the stability/traffic density of the intermediate nodes between the source and the destination. This value is increased at each intermediate node between the source and destination nodes by the node summing its own *EVO* value (the output of Eq. 2). Each node calculates its own value every 15 s. The source node in the EVO-AODV receives all the RREP packets containing the *aggregated EVO* value for a certain amount of time (say t) and then selects a route with the smallest value. We found t=2 s empirically (see Sect. 4.2.2).

To elaborate further, the proposed route discovery mechanism is illustrated in Fig. 4. The source node S receives three RREP packets from the destination node D. The first route is S-A-G-D, the second route is S-B-C-F-D, and the final route is S-E-C-F-D. Each node on these routes has its own periodically updated output of the *EVO metric*. *Aggregated EVO* is obtained at the source nodes by cumulatively adding each node's EVO value on the route. In this scenario, the source node selects a route, the *aggregated EVO* value of which is the minimum, which is *Route 2*. Finally, the source node selects the more stable route (S-B-C-F-D) and starts sending its data packets to node D using this route. Please note that it is not the shortest path between the source and the destination. If the metrics are equal, the shortest path is chosen. As in the original AODV protocol, the intermediate nodes can also send route reply packets in EVO-AODV.



Aggregated EVO_1 = 0.13+0.08 = 0.21

Aggregated EVO_2 = 0.07+0.05+0.04=0.19

Aggregated EVO_3 = 0.07+0.05+0.09=0.21

Fig. 4: Route selection in EVO-AODV

3.2.2 Route Maintenance Mechanism

EVO-AODV does not modify the route maintenance mechanism. The local connectivity can be provided at the link layer or at the network layer. When a link breakage is detected by the mechanism of choice, RERR packets are sent as in the original AODV.

4 Experimental Settings

4.1 Network Simulation

The performance of the proposed EVO-AODV depends on the generated EVO metric. The evolution process of the EVO metric, which is the training phase of the study, is explained in Sect. 3.1.2. This process begins with a set of randomly generated individuals. The routing metric of each and every candidate individual is distributed to each and every node of the network to evaluate the paths. Then, the fitness of each individual, each candidate routing metric, is evaluated on simulated networks. New individuals are generated by applying genetic operators to individuals selected by using tournament selection. In this selection strategy, a few individuals (=7) are selected at random from the population and then that with the best fitness value is selected for applying genetic operators. This completes one generation of training, which continues for 50 generations before the program terminates.

$$
\begin{gathered}
EVO\ metric = \left\lfloor \left| \frac{\log(\lfloor|\sin(frw\_rrep)|\rfloor)}{(\alpha \times \beta)} \right| \right\rfloor \\
\alpha = \left| \left(\left\lfloor \cos\left(recvb\_rerr - \left(\left| \sqrt{\sin(frw\_rrep)} \right| \right) \right) \right\rfloor \right) \times invroutes\_timeout \right| \\
\beta = \left(\left\lceil \sin\left(\frac{invalidates\_routes}{invroutes\_timeout} \right) \right\rceil \times invalidates\_routes \right)
\end{gathered}
\tag{2}
$$

GP is implemented in ECJ [15]. As mentioned previously, the training is executed by simulating a number of networks rather than a single network. The experimental results show that training a metric on a single network cannot be sufficient to produce satisfactory results on the test networks. Therefore, 10 networks are randomly generated to train the metric. In this study, the networks are simulated by using the network simulator ns-2 [39]. The simulation parameters of ns-2 and their values are provided in Table 2. BonnMotion [3], a tool that creates mobility scenarios, is used for creating the movements of nodes within the network simulation by using the *random waypoint mobility model*. This model is one of the most frequently employed mobility models in the literature. In the *random waypoint mobility* model, a node randomly selects a destination node in its area and moves with constant speed toward that node. After waiting for a specified pause time, it then selects a new destination node and a new speed, and moves with that constant speed to the new destination [7].

In testing, each routing protocol is evaluated on 50 networks for each mobility and traffic pattern. The maximum number of connections is set to 30, 60, and 90 to represent low, medium, and high traffic loads, respectively. Each connection indicates that there exists network data traffic between two endpoints. Please note that the traffic load parameter is more realistic than the parameters used in many simulations in the literature [9][29][51–54], since it covers many network scenarios. As shown in the results, the traffic load is one of the important factors that negatively affect the performance of a network. The maximum speed of nodes is set at 20 m/sec, and the pause time between movements ranges from 0 s to 25 s to simulate different mobility levels. Six different mobility levels and three different traffic levels are used. In summary, 900 networks (=50×6×3) are employed for evaluating each routing metric. Since four routing metrics (EVO, HOP, PER, and HOC) are compared in the results, in total, 3600 (900×4) networks are run in the simulations. Please note that the 10 networks used in the training are simulated under medium mobility and medium traffic.

In the experiments, the performance of each metric is evaluated using three criteria: PDR, E2E, and OVR. PDR is the ratio of packets successfully received to the total sent, E2E is the average time taken for packets to be transmitted across the network from source nodes to destination nodes, and OVR is the ratio of the number of data packets to the number of routing control packets (RREQ, RREP, and RERR) received.

Table 2: Parameters of simulated networks

Parameter	Explanation	Value
Network dimensions	size of the network	1000 m * 1000 m
Number of Nodes	total number of nodes	100
Network Traffic	traffic type & number of connections	CBR, 30/60/90 conn.
Nodes' Speed	min and max speed of nodes	0-20 m/s
Nodes' Pause time (in training)	waiting times of nodes between movements	10 ms
Nodes' Pause time (in testing)	waiting times of nodes between movements	0, 5, 10, 15, 20, 25 ms
Transmission Range	maximum distance a node can send its data to	250 m
Simulation Time	total time of the simulation	500 s
Mobility Model	model defining the movements of nodes	Random waypoint
Radio Propagation Model	characterization of radio wave propagation	Two-ray ground model
Local Link Connectivity	method detecting link breakages	AODV, hello messages

4.2 Comparison

4.2.1 Routing Protocols

The AODV, LA-AODV and PER-AODV routing protocols are employed here as protocols with which to compare our approach. We especially compare our approach with LA-AODV [63], because it chooses more stable routes than AODV, and with PER-AODV [54] because of its superior performance to other metrics (HOP, ETX [11], and MF [59,34]) in MANETs [54]. Therefore, to provide a better understanding we explain PER-AODV and LA-AODV in this section.

PER-AODV: Recently, the PER metric was introduced to improve AODV [54]. This metric has been proven to represent the mobility and/or density of the networks better, and hence helps select routes having a longer duration. In this approach, each node has an *average encounter rate* (AER) value, which is calculated as

$$AER_A = \frac{|E_A|}{T} \tag{3}$$

where E_A is the set of new encounters experienced by the node A per time unit T. AER is shown to increase linearly with node density [30]. An encounter is counted only once in its life time, which is set to 15 s in the simulations. The PER is defined for a route or a path in the form of a sum of the square root of the AER values of all nodes along that route. PER is calculated as

$$PER = \sum\nolimits_{i=1}^{m} AER_i^2 \tag{4}$$

where m indicates the number of nodes along the path, including the source and destination nodes. Among the available paths to the destination, the path with the lowest PER value is selected by the routing protocol. The simulation shows a better routing performance under the PER metric than under the the traditional HOP metric in various mobility and density scenarios [54]. The improvement provided by PER is considerably greater on networks under high mobility and high density because of the decrement of AODV's performance in such scenarios. Moreover, the advantages from the viewpoint of resource usage and computational complexity over well-known metrics such as HOP [43], MF [59,34], and ETX [11] are emphasized. The authors improved their approach by adaptively selecting the ETX metric for static networks or the PER metric for mobile networks [51].

LA-AODV (lightweight adaptive AODV) : LA-AODV utilizes a new metric called the hop change metric (HOC), which represents the changes in the number of hops in the routing table. The calculation of the HOC metric is given in Eq. 5. The equation represents the average changes in the hop count of the routing entries in a routing table. Each node calculates the metric independently of other nodes. Here, $Hop\ Count^i_{New}$ represents the number of hops between the current node and node i at the most recent update. $Hop\ Count^i_{Previous}$ shows the number of hops between the current node and node i obtained at the previous update. $t_{NewUpdate}$ and $t_{PreviousUpdate}$ are the last and the previous update period times, respectively. *Number of nodes* represents the number of nodes in the routing table of the node calculating the *hop change metric*. Each node on reactive routing protocols can obtain different hop change values, because they have different routing tables constructed based on their traffic patterns. It is claimed to be a simple and low cost approach in terms of computation and communication [63].

$$hop\ change\ metric = \frac{\sum_{i=0}^{i=Number\ of\ nodes} \frac{|Hop\ Count^i_{new} - Hop\ Count^i_{previous}|}{t_{New\ Update} - t_{Previous\ Update}}}{Number\ of\ Nodes} \tag{5}$$

In AODV, the route reply message that arrives first at the source node indicates the shortest path to the destination. In LA-AODV, the source node waits for additional route reply packets to arrive in order to make a decision on the route to the destination. The decision is based on the total hop change value of the route to the destination; the route with the smallest HOC value is selected. LA-AODV waits for only the two route reply packets that arrived first from the destination because of the empirical results, and selects the most stable one according to the metric. The simulation results show that LA-AODV increases the throughput with less OVR and E2E delay than AODV.

4.2.2 Parameter Settings

We conducted a number of pre-experiments in an attempt to obtain the optimal values of some parameters of EVO-AODV and the competitor protocols. As mentioned previously, EVO-AODV differs from AODV in the route selection phase and waits for a period of time for other RREP packets to arrive. Here, the optimal waiting period of time for RREP packets was investigated empirically and 10 different networks under medium mobility and medium traffic were simulated. The average PDR, E2E, and OVR values of these networks were evaluated. Based on these results, the waiting time for RREP packets was set to 2 s. In the original LA-AODV protocol [63], the source node waits for only two RREP packets to arrive. The same setting is employed in the simulations of the current study.

All the nodes in EVO-AODV and LA-AODV update their routing tables by calculating their own outputs of metrics (EVO and HOC, respectively) periodically. For LA-AODV, a period of 10 s was empirically found to yield the best performance [63]. Therefore, each node updated its HOC value every 10 s also in this study. As for EVO-AODV, we explored the metric update period by simulating EVO-AODV on 10 randomly generated networks under medium mobility and medium traffic. Based on this simulation, the update period of EVO value was set to 15 s. Contrary to other protocols, PER-AODV possesses a distinctive parameter called *encounter's lifetime*. Within this lifetime, an encounter is counted only once, even if it leaves and returns to one hop neighborhood more than once. To ensure fairness, this parameter was set to 15 s, as in the original study [54].

5 Experimental Results

Our main hypothesis is that GP allows a routing metric to be created that discovers the complex properties of MANETs. Since the EVO metric does not cover only one parameter (*e.g.*, shortest path or maximum flow [20]), but instead takes several parameters into consideration when constructing a route, such as stability and density, the extent to which the selected routes are close to the optimal routes cannot be measured as in [20]. Therefore, we employ an experimental comparison to evaluate the performance of the EVO metric, as was usually done for other metrics in the literature.

In order to verify the effectiveness of our contribution, we compared the proposed EVO-AODV protocol with recently proposed and well-known routing protocols, which are outlined in Table 3. In the experiments, EVO-AODV, as well as its competitors, are simulated using different mobility (which corresponds to *pause time*) and traffic levels. The effectiveness of the generated metric for each mobility and traffic level is measured over 50 networks, each of which has different topologies. The comparative results, which are the averages taken from 50 different network runs, are illustrated in both Figures 5 and 6 and Tables 4, 5, and 6. These results show that the traffic level is the main factor that affects the results. Although they perform relatively better as the nodes in the network become more stable, the change in the mobility level does not affect the performances of the protocols as acutely as the change in the data traffic level. For this reason, we show the comparative results and interpret them under three different traffic levels: *low*, *medium*, and *high*.

5.1 Low Traffic

Figure 5 shows the performance of the protocols under low traffic (which corresponds to 30 connections) in boxplots. For such a traffic pattern, the average

Table 3: Outline of the routing metrics

Metric	Equation	Represent	Routing Protocol
HOP	number of traversed nodes	length of a route	AODV
PER	Eq. 3, 4	stability/density of a route	PER-AODV
HOC	Eq. 5	stability of a route	LA-AODV
EVO	Eq. 2 (automatically generated)	stability/density of a route	EVO-AODV

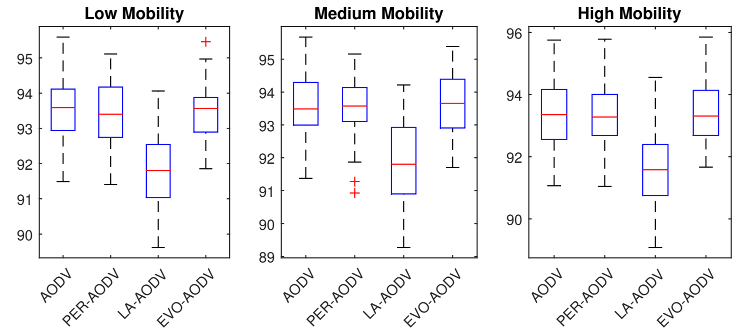
performance of each routing protocols on networks under different mobility patterns is presented in Table 4. It is clearly seen that the proposed metrics do not improve the performance of AODV on networks having low traffic density; they can even perform more poorly in terms of some performance metrics. For instance, EVO-AODV requires considerably more time for transmitting a data packet under a low traffic level because it waits for additional RREP packets to arrive at the source node. Likewise, an excessive delay is observed in LA-AODV, which also waits for one additional RREP packet to arrive before sending data packets. Not surprisingly, AODV and PER-AODV transmit data packets with minimum latency and no significant difference is observed. In terms of PDR and OVR; AODV, PER-AODV, and EVO-AODV show very similar performances. However, LA-AODV performs very poorly in this setting.

Table 4: Average performance of routing protocols on networks with varying mobility levels under low traffic

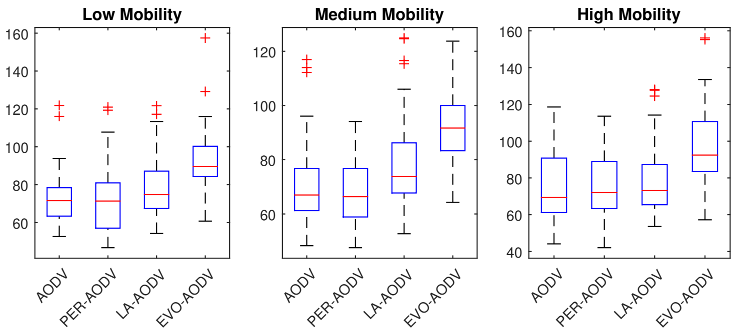
	Pause Time	AODV	PER-AODV	LA-AODV	EVO-AODV
PDR	0	93.40	93.35	91.67	**93.42**
	5	93.59	93.58	91.86	**93.66**
	10	**93.62**	93.61	91.90	93.61
	15	93.51	**93.56**	91.80	93.49
	20	93.39	**93.47**	91.68	93.36
	25	**93.49**	93.44	91.78	93.48
E2E	0	**74.83**	74.86	78.40	97.14
	5	73.03	**70.60**	77.85	90.92
	10	71.62	**68.96**	78.26	91.31
	15	74.12	**69.69**	77.73	97.10
	20	73.56	**73.03**	80.78	93.04
	25	73.11	**71.74**	78.87	92.94
OVR	0	8.88	8.85	9.74	**8.75**
	5	8.46	8.49	9.46	**8.33**
	10	8.53	8.56	9.47	**8.51**
	15	8.65	**8.60**	9.64	8.61
	20	8.68	**8.55**	9.71	8.64
	25	8.7	**8.69**	9.75	**8.69**

5.2 Medium Traffic

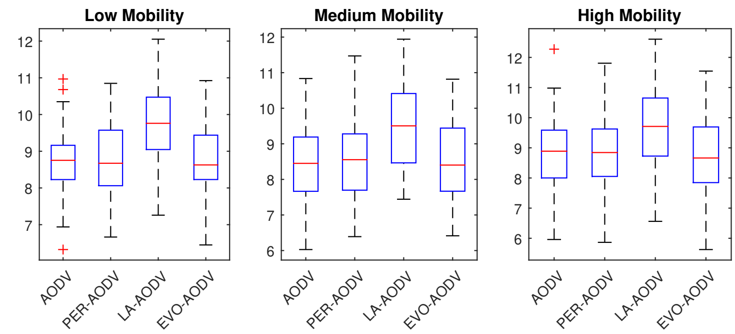
Whereas there is no significant difference among the performance of routing protocols on networks under low traffic in terms of PDR (except for the poor



(a) PDR



(b) E2E



(c) OVR

Fig. 5: Performance of routing protocols on networks under low traffic

performance of LA-AODV), the performance of EVO-AODV is overwhelmingly better than that of its competitors in terms of PDR and OVR on networks under medium data traffic (which corresponds to 60 connections), as shown in Figure 6 and Table 5. Regardless of the mobility level of the networks, it shows the best performance. The metric is also evolved using the networks under the same traffic conditions in the training. A clear performance comparison of routing metrics on the network under medium traffic is given in Fig. 6. Please note that the mobility is not the only factor that affects the results; there can be other factors, such as network topology, traffic, and mobility patterns. This also supports our hypothesis that the solution yielded by AI-based approaches are more suitable for such complex systems than those developed by humans.

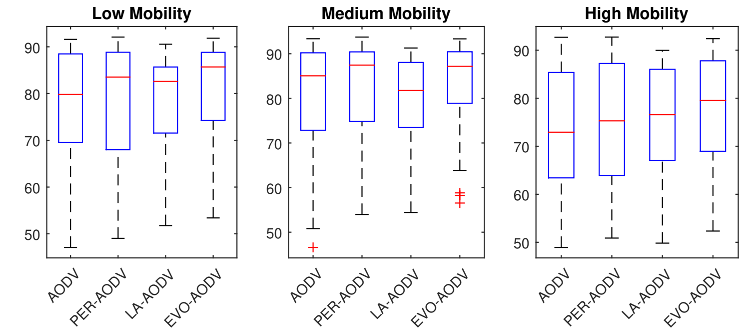
Table 5: Average performance of routing protocols on networks with varying mobility levels under medium traffic

	Pause Time	AODV	PER-AODV	LA-AODV	EVO-AODV
PDR	0	72.27	75.31	75.10	**77.76**
	5	74.59	74.92	76.79	**78.91**
	10	79.85	81.87	79.45	**83.24**
	15	75.81	77.70	78.00	**81.03**
	20	74.19	76.68	77.55	**77.89**
	25	77.32	78.41	78.09	**81.28**
E2E	0	953.86	823.00	**707.53**	713.53
	5	811.40	826.09	**645.27**	674.11
	10	603.14	521.78	542.01	**502.55**
	15	803.11	720.41	586.13	**577.58**
	20	875.43	744.99	**591.83**	721.25
	25	718.36	651.01	568.06	**548.96**
OVR	0	17.49	16.38	16.72	**15.81**
	5	16.73	16.54	16.17	**15.13**
	10	14.67	13.95	15.04	**13.58**
	15	16.38	15.68	15.65	**14.54**
	20	16.67	15.83	15.69	**15.39**
	25	15.95	15.51	15.75	**14.48**

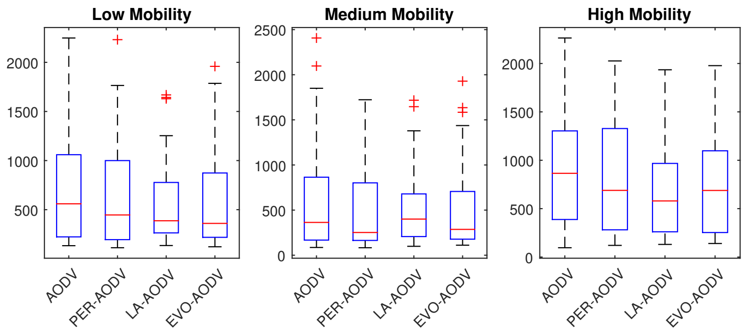
From the viewpoint of E2E, although EVO-AODV and LA-AODV wait for additional RREP packets to arrive for a short time, they cause less delay than PER-AODV and the original AODV protocol, as shown in Table 5. We can state that not only the mechanism of the routing protocol but also the stability/density of the selected routes affect the E2E delay directly. The results also show that while LA-AODV waits for two RREP packets to arrive, EVO-AODV builds better routes waiting for additional RREP packets to arrive.

5.3 High Traffic

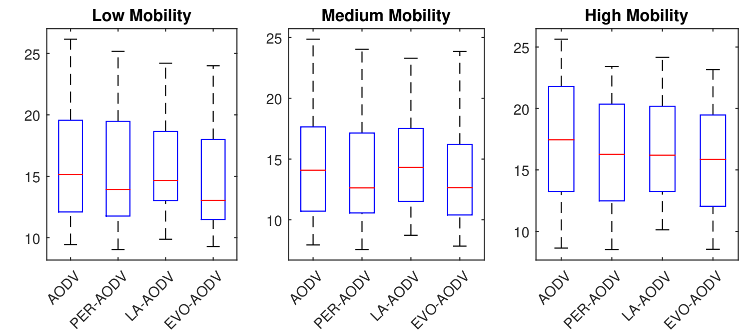
The routing protocols show similar performances on networks under high traffic, as illustrated in Table 6. Although AODV may not be the best choice for high traffic, it is presented here for the sake of completeness. Most routing protocols achieve an approximately 40% PDR. EVO-AODV slightly improves the PDR and OVR.



(a) PDR



(b) E2E



(c) OVR

Fig. 6: Performance of routing protocols on networks under medium traffic

5.4 Statistical Tests

In order to clarify the experimental results and to further investigate any significant difference between EVO-AODV and the competitor protocols, we have employed statistical tests to determine the impact of our proposed EVO-AODV protocol over the competitor protocols. Statistical tests are categorized depending on the data to be examined: *Parametric* and *non-parametric* tests.

Table 6: Average performance of routing protocols on networks with varying mobility levels under high traffic

	Pause Time	AODV	PER-AODV	LA-AODV	EVO-AODV
PDR	0	38.66	38.9	38.14	**39.17**
	5	38.33	38.67	38.13	**39.24**
	10	38.86	39.34	38.67	**39.66**
	15	39.14	39.61	39.08	**40.22**
	20	38.34	38.59	38.06	**39.21**
	25	39.69	40.12	39.6	**40.81**
E2E	0	2070.17	2089.52	**1932.66**	2073.54
	5	2118.77	2106.07	**1916.20**	2069.96
	10	2005.00	2050.33	**1882.63**	2058.01
	15	2038.13	2067.83	**1911.93**	2026.28
	20	2045.74	2056.23	**1871.64**	2024.34
	25	1986.27	2027.23	**1861.22**	1986.32
OVR	0	19.88	**19.69**	19.74	19.71
	5	20.05	19.88	19.82	**19.76**
	10	19.87	**19.61**	19.60	19.69
	15	19.98	19.68	19.67	**19.62**
	20	19.99	19.80	19.83	**19.74**
	25	20.03	19.79	19.72	**19.67**

Parametric test is used when data variables are continuous and come from a normal distribution. However, non-parametric test (also called as *distribution-free* test) is used when data variables are categorical, nominal or do not have normal distribution.

As the performance of the EVO-AODV protocol as well as its competitor protocols fit left-skewed distribution rather than normal distribution, we have employed the following three well-known non-parametric statistical tests for comparison: *Friedman* [17], *Friedman Aligned* [22], and *Quade* [45]. These tests could detect significant differences between two or more algorithms (protocols in this study) by analyzing the median values. Null hypothesis (H_0) for these tests states the equality of medians between data populations. Therefore, the rejection of H_0 is required to prove a significant difference between protocols. If there is a significant difference between protocols, the post-hoc procedures could be applied in order to characterize the difference at the protocol basis.

The CONTROLTEST package, a package developed to compute the rankings [12], is used for the application of Friedman, Friedman Aligned, and Quade tests as well as for the application of post-hoc procedures. These statistical procedures are applied on networks under *medium* mobility and *medium* traffic, which is the setting employed in the training.

Table 7 presents the Friedman, Friedman Aligned, and Quade test results for the PDR. Lower ranks indicate a protocol with a better performance. The last two rows present statistic and p-values of each test. The p-values, which are computed through the statistics of each test, reject H_0 with a significance level $\alpha = 0.05$ and thus strongly suggest the existence of significant differences between protocols. The rank values reveal that the EVO metric is the best metric representing the network characteristics.

Table 7: Friedman, Friedman Aligned and Quade ranks (PDR)

Protocol	Friedman	Friedman Aligned	Quade
EVO-AODV	1.96	72.74	1.97
PER-AODV	2.30	92.26	2.31
AODV	2.62	110.16	2.78
LA-AODV	3.12	126.84	2.92
Statistic	21.91	40.95	15.31
p-value	6.80E-5	6.71E-9	1.00E-5

The adjusted p-values with different post-hoc procedures of the Friedman, Friedman Aligned, and Quade tests are provided in Table 8. EVO-AODV is taken as the control protocol, and thus, it is compared with others. It is reported that the adjusted p-value is more suitable for multiple comparison [12]. Hence, the adjusted p-values are also evaluated and given in the table. These results also support that there is a significant difference between EVO-AODV and the rest of the protocols. As the Quade test takes the relative difficulties of problems into account [12], the adjusted p-values of the the Quade test present that EVO-AODV achieves better results on relatively tough problems than other protocols.

Table 8: Results of post-hoc procedures over all algorithms with EVO-AODV as control method at α=*0.05*

Procedure	i	Protocol	z-value	p-value	p_{Holl} [23]	p_{Rom} [47]	p_{Finn} [16]	p_{Li} [33]
Friedman	1	PER-AODV	1.316	0.187	0.050	0.050	0.050	0.050
	2	AODV	2.556	0.010	0.025	0.025	0.033	0.042
	3	LA-AODV	4.492	7.03E-6	0.016	0.016	0.016	0.042
Aligned Friedman	1	PER-AODV	1.686	0.091	0.050	0.050	0.050	0.050
	2	AODV	3.232	0.001	0.025	0.025	0.033	0.047
	3	LA-AODV	4.673	2.96E-6	0.016	0.016	0.016	0.047
Quade	1	PER-AODV	0.932	0.351	0.050	0.050	0.050	0.050
	2	AODV	2.242	0.024	0.025	0.025	0.033	0.034
	3	LA-AODV	2.605	0.009	0.016	0.016	0.016	0.034

To conclude, we would like to emphasize the strengths and weaknesses of each protocol for the sake of clarity. HOP is the poorest metric among all metrics. However, it could be used on networks under low traffic, in which scenarios the recently proposed metrics do not show an important improvement on AODV. While the PER-AODV metric shows results comparable with those of AODV on networks under low traffic, it is not suggested to use LA-AODV and EVO-AODV for such networks. EVO-AODV causes an unnecessary delay because of the waiting mechanism in its route discovery procedure. LA-AODV results in a decrease in the PDR without any improvements in the E2E delay and OVR. When the traffic density increases, the LA-AODV metric shows a better performance, especially in terms of the E2E delay. It could be preferred on network applications where the delivery time is the primary target. The EVO metric shows the best performance on networks under medium traffic and improves all the performance metrics considerably. PER-AODV presents a performance comparable with that of EVO-AODV, especially on networks under medium mobility and medium traffic.

6 Discussion

In this study, we investigate the use of evolutionary computation techniques for the generation of a routing metric that can represent the dynamic features of mobile ad hoc networks well. Although the proposed approach outperforms other metrics recently proposed in the literature on networks under medium traffic, we would like to discuss the additional advantages of each metric.

First, the PER and HOC metrics do not depend on any specific routing protocols. They can both be implemented on any proactive and reactive routing protocols. The HOC metric is already employed in a proactive routing protocol (DSDV) and improves the PDR significantly [1]. However, our metric is specific to AODV. The metric generated by using GP consists of features specific to AODV, as shown in Eq. 2. However, this study shows the potential of evolutionary computation techniques to solve complex problems in MANETs. The same approach could easily be applied to other routing protocols to evolve a routing metric. The development of a routing metric by using only non-specific features could also be explored in the future.

Moreover, in addition to the stability of routes, their sustainability in terms of power could be taken into account in the fitness function. A variety of devices can be included in MANETs, ranging from laptop computers to handheld devices, such as PDAs and mobile phones. Since these nodes in MANETs are generally resource-constrained, power consumption is an important objective that should also be considered in a routing protocol design. Additional criteria could be the trustfulness of nodes in the route. Since most of the routing protocols assume that nodes are cooperative and non-malicious, this is another area that should be investigated. Hence, a routing metric could be generated by optimizing two or more objectives simultaneously. Multi-objective evolutionary computation techniques are good candidates for such problems, allowing two or more frequently conflicting objectives to be optimized. Similarly, the metrics such as the E2E delay and OVR could also be taken into account in the evolution by using such techniques. While the networks under medium traffic and medium mobility are employed in the training, networks with different characteristics in terms of mobility and traffic could be employed for evaluating the fitness function. For this purpose, the number of networks used in the training could be increased. However, it should be noted that this could also increase the running time of the GP algorithm.

While the PER metric monitors the changes in the neighborhood, the HOC metric considers the changes in the hop count. Both metrics are simple and low cost in terms of computation and communication. They calculate their values based on a single feature. While our metric relies on more than one feature related to routing, it achieves a better performance with a negligible computation cost. However, all the metrics have a similar communication cost when a new entry is added to RREP packets.

In this study, we have developed a metric automatically, which is then used to select suitable routes for communication. Different metrics could be evolved for different applications, since different metrics are shown to be more suitable for different applications [29]. Since the training phase can be conducted off-line, and each node evaluates only the output of the same evolved metric periodically in real life, this off-line approach is believed to be more suitable than on-line, dynamic learning systems for such a resource-constrained environment.

7 Conclusion

In this paper, we propose a new routing metric called EVO, which is generated automatically using GP. The modified AODV protocol using the EVO metric, EVO-AODV, is also introduced. The results show that the performance of AODV is noticeably improved by using the EVO metric instead of the well-known HOP metric. The proposed metric is also compared with the metrics recently proposed in the literature that improve considerably on AODV. Each metric is evaluated on 900 networks with varying mobility and traffic levels. To the best of our knowledge, this constitutes a more comprehensive comparison of routing metrics than those already existing in the literature. The extensive simulation results show that the evolved metric presents the properties of such dynamic networks well, since it takes into account mobility- and traffic-related features in the evolution. It especially shows the best performance on networks under medium traffic and medium mobility, which is also the setting used for the evolution of the metric. In the future, different metrics could be generated for different types of networks/network applications, having different settings and performance targets.

As has been previously suggested, the routing metric that should be used depends on the application. The results of the extensive simulation conducted in this study provide some guidelines for the selection of a routing protocol. While the HOP metric could be preferable for networks having low traffic, HOC metrics could be used for applications in which the packet delivery time is more important than the PDR. The PER and EVO metrics are the two best metrics, showing a comparable performance on networks under medium traffic and medium mobility. Moreover, the EVO metric improves all the performance metrics considerably, namely the PDR, E2E delay, and OVR, on networks under medium traffic, regardless of the mobility level.

A Feature Set [50]

Table 9: Feature set used in the generation of *EVO metric*.

Features	Explanation
routes	No. of active routes
added_neighbors	No. of added neighbors
added_repairedroutes	No. of added routes under repair
addedroutes_disc	No. of added routes by route discovery mechanism
addedroutes_notice	No. of added routes by overhearing
avg_hopcount	No. of hop counts (average) of active routes
dropped_data	No. of data packets not forwarded by the next node
frw_aodv	No. of forwarded total routing protocol packets by this node
frw_rrep	No. of forwarded route reply packets from this node
frw_rreq	No. of forwarded route request packets from this node
invalidated_routes	No. of invalidated routes
invroutes_other	No. of routes invalidated for other reasons
invroutes_timeout	No. of routes invalidated because of expiry
neighbors	No. of neighbors
recv_aodv	No. of received total routing protocols packets
recv_rrep	No. of received route replay packets destined to this node
recv_rreq	No. of received route request packets destined to this node
recvb_rerr	No. of received broadcast route error packets
recvf_aodv	No. of received total routing protocol packets to be forwarded
recvf_rrep	No. of received route replay packets to be forwarded by this node
recvf_rreq	No. of received route request packets to be forwarded by this node
removed_neighbors	No. of removed neighbors
repaired_routes	No. of routes under repair
send_aodv	No. of initiated total routing protocol packets from this node
send_err	No. of broadcasted route error packets from this node
send_rrep	No. of initiated route replay packets from this node
send_rreq	No. of initiated route request packets from this node
updated_routes	No. of updated routes

References

1. Abri, R., Sen, S.: A lightweight threshold-based improvement on dsdv. In: International Conference on Ad Hoc Networks, Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol. 129, pp. 135–145. Springer (2013)
2. Adya, A., Bahl, P., Padhye, J., Wolman, A., Zhou, L.: A multi-radio unification protocol for ieee 802.11 wireless networks. In: Broadband Networks, 2004. BroadNets 2004. Proceedings. First International Conference on, pp. 344–354 (2004). DOI 10.1109/BROADNETS.2004.8
3. Aschenbruck, N., Ernst, R., Gerhards-Padilla, E., Schwamborn, M.: Bonnmotion: A mobility scenario generation and analysis tool. In: Proceedings of the 3rd International ICST Conference on Simulation Tools and Techniques, SIMUTools '10, pp. 51:1–51:10. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), ICST, Brussels, Belgium, Belgium (2010)
4. Barolli, L., Koyama, A., Shiratori, N.: A qos routing method for ad-hoc networks based on genetic algorithm. In: Database and Expert Systems Applications, 2003. Proceedings. 14th International Workshop on, pp. 175–179 (2003). DOI 10.1109/DEXA.2003.1232019
5. Boukerche, A., Turgut, B., Aydin, N., Ahmad, M.Z., Bölöni, L., Turgut, D.: Routing protocols in ad hoc networks: A survey. Computer networks **55**(13), 3032–3080 (2011)
6. Broch, J., Maltz, D.A., Johnson, D.B., Hu, Y.C., Jetcheva, J.: A performance comparison of multi-hop wireless ad hoc network routing protocols. In: Proceedings of the 4th annual ACM/IEEE international conference on Mobile computing and networking, pp. 85–97. ACM (1998)
7. Camp, T., Boleng, J., Davies, V.: A survey of mobility models for ad hoc network research. Wireless Communications and Mobile Computing **2**(5), 483–502 (2002). DOI 10.1002/wcm.72. URL http://dx.doi.org/10.1002/wcm.72
8. Chen, W., Rao, N., Liang, D., Liao, R., Huang, W.: An ad hoc routing algorithm of low-delay based on hybrid particle swarm optimization. In: Communications, Circuits and Systems, 2008. ICCCAS 2008. International Conference on, pp. 394–397 (2008). DOI 10.1109/ICCCAS.2008.4657800
9. Chettibi, S., Chikhi, S.: Dynamic fuzzy logic and reinforcement learning for adaptive energy efficient routing in mobile ad-hoc networks. Applied Soft Computing **38**, 321 – 328 (2016). DOI http://dx.doi.org/10.1016/j.asoc.2015.09.003. URL http://www.sciencedirect.com/science/article/pii/S1568494615005736
10. Cramer, N.L.: A representation for the adaptive generation of simple sequential programs. In: Proceedings of the First International Conference on Genetic Algorithms, pp. 183–187 (1985)
11. De Couto, D.S.J., Aguayo, D., Bicket, J., Morris, R.: A high-throughput path metric for multi-hop wireless routing. In: Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, MobiCom '03, pp. 134–146. ACM, New York, NY, USA (2003). DOI 10.1145/938985.939000. URL http://doi.acm.org/10.1145/938985.939000
12. Derrac, J., Garcia, S., Molina, D., Herrera, F.: A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. Swarm and Evolutionary Computation **1**(1), 3 – 18 (2011)
13. Di Caro, G., Ducatelle, F., Gambardella, L.M.: Anthocnet: an adaptive nature-inspired algorithm for routing in mobile ad hoc networks. European Transactions on Telecommunications **16**(5), 443–455 (2005)
14. Draves, R., Padhye, J., Zill, B.: Comparison of routing metrics for static multi-hop wireless networks. In: ACM SIGCOMM Computer Communication Review, vol. 34, pp. 133–144. ACM (2004)
15. ECJ: A java-based evolutionary computation research system. https://www.cs.gmu.edu/ eclab/projects/ecj/ (2017)
16. Finner, H.: On a monotonicity problem in step-down multiple test procedures. Journal of the American Statistical Association **88**(423), 920–923 (1993). URL http://www.jstor.org/stable/2290782

17. Friedman, M.: The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association **32**(200), 675–701 (1937). DOI 10.1080/01621459.1937.10503522. URL https://www.tandfonline.com/doi/abs/10.1080/01621459.1937.10503522
18. Ghaffari, A.: Real-time routing algorithm for mobile ad hoc networks using reinforcement learning and heuristic algorithms. Wireless Networks **23**(3), 703–714 (2017)
19. Goswami, M., Dharaskar, R., Thakare, V.: Fuzzy ant colony based routing protocol for mobile ad hoc network. In: Computer Engineering and Technology, 2009. ICCET '09. International Conference on, vol. 2, pp. 438–444 (2009). DOI 10.1109/ICCET.2009.168
20. Gouda, M., Schneider, M.: Maximizable routing metrics. IEEE/ACM Transactions on Networking **11**(4), 663–675 (2003). DOI 10.1109/tnet.2003.815294
21. Haas, Z.J.: A new routing protocol for the reconfigurable wireless networks. In: Universal Personal Communications Record, 1997. Conference Record., 1997 IEEE 6th International Conference on, vol. 2, pp. 562–566. IEEE (1997)
22. Hodges, J.L., Lehmann, E.L.: Rank methods for combination of independent experiments in analysis of variance. The Annals of Mathematical Statistics **33**(2), 482–497 (1962). URL http://www.jstor.org/stable/2237528
23. Holland, B.S., Copenhaver, M.D.: An improved sequentially rejective bonferroni test procedure. Biometrics **43**(2), 417–423 (1987). URL http://www.jstor.org/stable/2531823
24. Huang, J., Liu, Y.: Moeaq: A qos-aware multicast routing algorithm for {MANET}. Expert Systems with Applications **37**(2), 1391 – 1399 (2010). DOI http://dx.doi.org/10.1016/j.eswa.2009.06.086. URL http://www.sciencedirect.com/science/article/pii/S0957417409006526
25. Hussein, O., Saadawi, T.: Ant routing algorithm for mobile adhoc networks (arama). In: Performance, Computing, and Communications Conference, 2003. Conference Proceedings of the 2003 IEEE International, pp. 281–290 (2003). DOI 10.1109/PCCC.2003.1203709
26. Hussein, O.H., Saadawi, T.N., Lee, M.J.: Probability routing algorithm for mobile ad hoc networks' resources management. Selected Areas in Communications, IEEE Journal on **23**(12), 2248–2259 (2005)
27. Johnson, D.B., Maltz, D.A.: Dynamic source routing in ad hoc wireless networks. In: Mobile computing, pp. 153–181. Springer (1996)
28. Kaliappan, M., Augustine, S., Paramasivan, B.: Enhancing energy efficiency and load balancing in mobile ad hoc network using dynamic genetic algorithms. Journal of Network and Computer Applications **73**, 35 – 43 (2016). DOI https://doi.org/10.1016/j.jnca.2016.07.003. URL http://www.sciencedirect.com/science/article/pii/S1084804516301473
29. Karkazis, P., Trakadas, P., Leligou, H.C., Sarakis, L., Papaefstathiou, I., Zahariadis, T.: Evaluating routing metric composition approaches for qos differentiation in low power and lossy networks. Wireless networks **19**(6), 1269–1284 (2013)
30. Khelil, A., Marron, P.J., Rothermel, K.: Contact-based mobility metrics for delay-tolerant ad hoc networking. In: 13th IEEE International Symposium on Modeling, Analysis, and Simulation of Computer and Telecommunication Systems, pp. 435–444. IEEE (2005)
31. Kout, A., Labed, S., Chikhi, S., et al.: Aodvcs, a new bio-inspired routing protocol based on cuckoo search algorithm for mobile ad hoc networks. Wireless Networks pp. 1–11 (2017)
32. Koza, J.R.: Genetic programming: on the programming of computers by means of natural selection, vol. 1. MIT press (1992)
33. Li, J.D.: A two-step rejection procedure for testing multiple hypotheses. Journal of Statistical Planning and Inference **138**(6), 1521 – 1527 (2008). DOI https://doi.org/10.1016/j.jspi.2007.04.032. URL http://www.sciencedirect.com/science/article/pii/S0378375807002960
34. Macone, D., Oddi, G., Pietrabissa, A.: Mq-routing: Mobility-, gps- and energy-aware routing protocol in {MANETs} for disaster relief scenarios. Ad Hoc Networks **11**(3), 861 – 878 (2013). DOI http://dx.doi.org/10.1016/j.adhoc.2012.09.008. URL http://www.sciencedirect.com/science/article/pii/S1570870512001667

35. Marwaha, S., Srinivasan, D., Tham, C.K., Vasilakos, A.: Evolutionary fuzzy multi-objective routing for wireless mobile ad hoc networks. In: Evolutionary Computation, 2004. CEC2004. Congress on, vol. 2, pp. 1964–1971 Vol.2 (2004). DOI 10.1109/CEC.2004.1331137
36. Misra, S., Dhurandher, S.K., Obaidat, M.S., Gupta, P., Verma, K., Narula, P.: An ant swarm-inspired energy-aware routing protocol for wireless ad-hoc networks. Journal of Systems and Software **83**(11), 2188 – 2199 (2010). DOI http://dx.doi.org/10.1016/j.jss.2010.06.025. URL http://www.sciencedirect.com/science/article/pii/S016412121000172X. Interplay between Usability Evaluation and Software Development
37. Moussaoui, A., Boukeream, A.: A survey of routing protocols based on link-stability in mobile ad hoc networks. Journal of Network and Computer Applications **47**, 1–10 (2015)
38. Naimi, S., Busson, A., Veque, V., Ben Hadj Slama, L., Bouallegue, R.: Mobility management in ad hoc networks using routing metrics. In: Communications and Networking (ComNet), 2014 International Conference on, pp. 1–6 (2014)
39. Ns-2: The network simulator
40. Oh, S., Ahn, C., Ramakrishna, R.S.: Neural Information Processing: 13th International Conference, ICONIP 2006, Hong Kong, China, October 3-6, 2006. Proceedings, Part III, chap. A Genetic-Inspired Multicast Routing Optimization Algorithm with Bandwidth and End-to-End Delay Constraints, pp. 807–816. Springer Berlin Heidelberg, Berlin, Heidelberg (2006)
41. Perkins, C., Belding-Royer, E., Das, S.: Ad hoc on-demand distance vector (aodv) routing, rfc 3561. Tech. rep. (2003)
42. Perkins, C.E., Bhagwat, P.: Highly dynamic destination-sequenced distance-vector routing (dsdv) for mobile computers. In: ACM SIGCOMM Computer Communication Review, vol. 24, pp. 234–244. ACM (1994)
43. Perkins, C.E., Royer, E.M.: Ad-hoc on-demand distance vector routing. In: Mobile Computing Systems and Applications, 1999. Proceedings. WMCSA'99. Second IEEE Workshop on, pp. 90–100. IEEE (1999)
44. Poli, R., Langdon, W.B., McPhee, N.F.: A Field Guide to Genetic Programming. Lulu Enterprises, UK Ltd (2008)
45. Quade, D.: Using weighted rankings in the analysis of complete blocks with additive block effects. Journal of the American Statistical Association **74**(367), 680–683 (1979). URL http://www.jstor.org/stable/2286991
46. Reina, D.G., Ruiz, P., Ciobanu, R., Toral, S., Dorronsoro, B., Dobre, C.: A survey on the application of evolutionary algorithms for mobile multihop ad hoc network optimization problems. International Journal of Distributed Sensor Networks **12**(2), 2082,496 (2016)
47. Rom, D.M.: A sequentially rejective test procedure based on a modified bonferroni inequality. Biometrika **77**(3), 663–665 (1990). URL http://www.jstor.org/stable/2337008
48. Sen, B., Guo, J., Zhao, X., Jha, S.: Ectx: A high-throughput path metric for multi-hop wireless routing exploiting mac-layer cooperative retransmission. In: World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2012 IEEE International Symposium on a, pp. 1–9. IEEE (2012)
49. Sen, S.: A survey of intrusion detection systems using evolutionary computation. Bio-Inspired Computation in Telecommunications pp. 73–94 (2015)
50. Sen, S., Clark, J.A.: Evolutionary computation techniques for intrusion detection in mobile ad hoc networks. Computer Networks **55**(15), 3441 – 3457 (2011). DOI http://dx.doi.org/10.1016/j.comnet.2011.07.001. URL http://www.sciencedirect.com/science/article/pii/S1389128611002477
51. Son, T.T., Le-Minh, H., Aslam, N.: Msar: A metric self-adaptive routing model for mobile ad hoc networks. Journal of Network and Computer Applications **68**, 114–125 (2016)
52. Son, T.T., Le Minh, H., Sexton, G., Aslam, N.: Self-adaptive proactive routing scheme for mobile ad-hoc networks. IET Networks **4**(2), 128–136 (2015)
53. Son, T.T., Le Minh, H., Sexton, G., Aslam, N., Boubezari, R.: A new mobility, energy and congestion aware routing scheme for manets. In: Communication Systems, Networks & Digital Signal Processing (CSNDSP), 2014 9th International Symposium on, pp. 771–775. IEEE (2014)

54. Son, T.T., Minh, H.L., Sexton, G., Aslam, N.: A novel encounter-based metric for mobile ad-hoc networks routing. Ad Hoc Networks **14**, 2 – 14 (2014). DOI http://dx.doi.org/10.1016/j.adhoc.2013.10.012. URL http://www.sciencedirect.com/science/article/pii/S1570870513002345
55. Suraj, R., Tapaswi, S., Yousef, S., Pattanaik, K., Cole, M.: Mobility prediction in mobile ad hoc networks using a lightweight genetic algorithm. Wireless Networks **22**(6), 1797–1806 (2016)
56. Taha, A., Alsaqour, R., Uddin, M., Abdelhaq, M., Saba, T.: Energy efficient multipath routing protocol for mobile ad-hoc network using the fitness function. IEEE Access **5**, 10,369–10,381 (2017)
57. Turky, A., Sabar, N.R., Song, A.: A multi-population memetic algorithm for dynamic shortest path routing in mobile ad-hoc networks. In: 2016 IEEE Congress on Evolutionary Computation (CEC), pp. 4119–4126 (2016). DOI 10.1109/CEC.2016.7744313
58. Walikar, G.A., Biradar, R.C.: A survey on hybrid routing mechanisms in mobile ad hoc networks. Journal of Network and Computer Applications **77**, 48–63 (2017)
59. Wu, C., Kumekawa, K., Kato, T.: A manet protocol considering link stability and bandwidth efficiency. In: Ultra Modern Telecommunications Workshops, 2009. ICUMT '09. International Conference on, pp. 1–8 (2009). DOI 10.1109/ICUMT.2009.5345608
60. Yang, S., Cheng, H., Wang, F.: Genetic algorithms with immigrants and memory schemes for dynamic shortest path routing problems in mobile ad hoc networks. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on **40**(1), 52–63 (2010). DOI 10.1109/TSMCC.2009.2023676
61. Yang, Y., Wang, J.: Design guidelines for routing metrics in multihop wireless networks. In: INFOCOM 2008. The 27th conference on computer communications. IEEE. IEEE (2008)
62. Younes, A.: Multicast routing with bandwidth and delay constraints based on genetic algorithms. Egyptian Informatics Journal **12**(2), 107 – 114 (2011). DOI http://dx.doi.org/10.1016/j.eij.2011.04.004. URL http://www.sciencedirect.com/science/article/pii/S1110866511000235
63. Zangabad, R.A.: A new metric for adaptive routing in mobile ad hoc networks. Master's thesis, Hacettepe University (2014)
64. Zhang, H., Wang, X., Memarmoshrefi, P., Hogrefe, D.: A survey of ant colony optimization based routing protocols for mobile ad hoc networks. IEEE Access **5**, 24,139–24,161 (2017)
65. Zhou, J., Tan, H., Deng, Y., Cui, L., Liu, D.D.: Ant colony-based energy control routing protocol for mobile ad hoc networks under different node mobility models. EURASIP Journal on Wireless Communications and Networking **2016**(1), 105 (2016)