Metaheuristics Evolutionary Algorithms Vehicular Adhoc Networks

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ABSTRACT: *In the Mobile adhoc networks, the Vehicular adhoc networks are the integral part that helps to transfer information about the nearby vehicles and also between many vehicles and the devices uses in the vehicular networks. In testing the proposed models in VANET there are several constraints such as logistics, higher cost and reproducibility and hence the implementation channels rely on simulation experiments. While designing the models, the VANET simulations are important parts. The vehicular mobility models depend on the data reliability. To ease this testing process, currently the vehicular traces are used. We in this paper use the metaheuristics evolutionary algorithms and the simulations are produced by these algorithms. Besides, in this work, we have studied the benefits and limitations of the EA domains for producing vehicular traces.*

Keywords: VANETs, Vehicular Traces, Traffic Simulation Model, Evolutionary Algorithms, Traffic Network Simulator

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1. Introduction

VANETs are advanced dedicated wireless networks that support cooperative driving among a large number of dynamically moving communicating vehicles on the road. Vehicles perform as communication nodes or relays, forming highly dynamic vehicular networks together with other nearby vehicles or with nearby roadside equipment. VANETs provide both Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) dedicated communication [1]. VANETs have specific characteristics that distinguish them from typical mobile ad hoc networks. Vehicles do not move at random and they are limited to known paths road topology while moving, often in a predictable manner. Additionally, a specific vehicle might have only predictable routes. If the road information is available, it is possible to predict the future position of a vehicle or get information about various risk traffic events and accidents. Generally, variable network traffic density mostly depends on the time and the area, and usually at rush hours the traffic is high and it is low in rural or suburb areas [2].

The majority of applications, protocols and communication algorithms proposed in VANETs are designed to improve active safety in driving, efficiency and travel convenience. Developing vehicular applications and protocols usually requires experimental expensive testbeds and real simulation tools. Real-world simulations for VANETs require realistic network and mobility models. Due to several constrains such as reproducibility, economic costs and lack of scalability, simulation is one of the most often used methods for performance evaluation. The recent challenge in mobility modelling process is the synthetic generation of realistic vehicular traces (at geographical and temporal domain) as an input to a network simulator [3]. The current research trend in realistic vehicular traces modelling is based on evolutionary algorithms (EAs). The EA model uses freely available source data - geographical from online digital maps, and set of traffic volume counts corresponding to the region covered by the digital map. The automatic counting of the vehicle traffic comprises a set of counting roadside devices (induction loops, radars) installed on main roads and highways. Collected data describes the cumulated volume of the traffic flow over a particular spot and can be distinguished regarding time, direction or type of a vehicle.

The rest of the paper organized as follows. Section 2 describes the basic concepts of realistic VANET simulation, while Section 3 focuses on EAs approach used for optimizing vehicular mobility models. Section 4 presents some of the related solutions in the field of EAs vehicular traces optimization, and we finally conclude in Section 5.

2. Realistic VANET Simulations

Vehicular traffic simulators generally can be classified into macroscopic, microscopic and mesoscopic. Macroscopic models consider traffic flow, density and velocity of vehicles. Microscopic approach considers the movement of each individual vehicle (acceleration-deceleration, line change…) and mesoscopic models consider some interactions among vehicles at an individual level.

There are three classes of VANET mobility models: trace based, survey-based and traffic simulator-based [4]. In the first class, mobility patterns are extracted directly from real world mobility movement traces. A collection of datasets can be generated from traces obtained by GPS tracking of vehicles or by commercial vehicles (public busses, taxis). Such traces have a limited availability and are limited to the type of tracked vehicles. In the survey-based models mobility patterns are derived from traffic statistics (arrival times at work, breaks, pedestrian and vehicular dynamics etc.) at the macroscopic level. Traffic simulator-based mobility models based on microscopic traffic simulators. It determines the movement of each vehicle at the microscopic level (breaking, acceleration, energy consumption, noise level monitoring etc.). This class of mobility models can realistically simulate road infrastructure and interactions between vehicles.

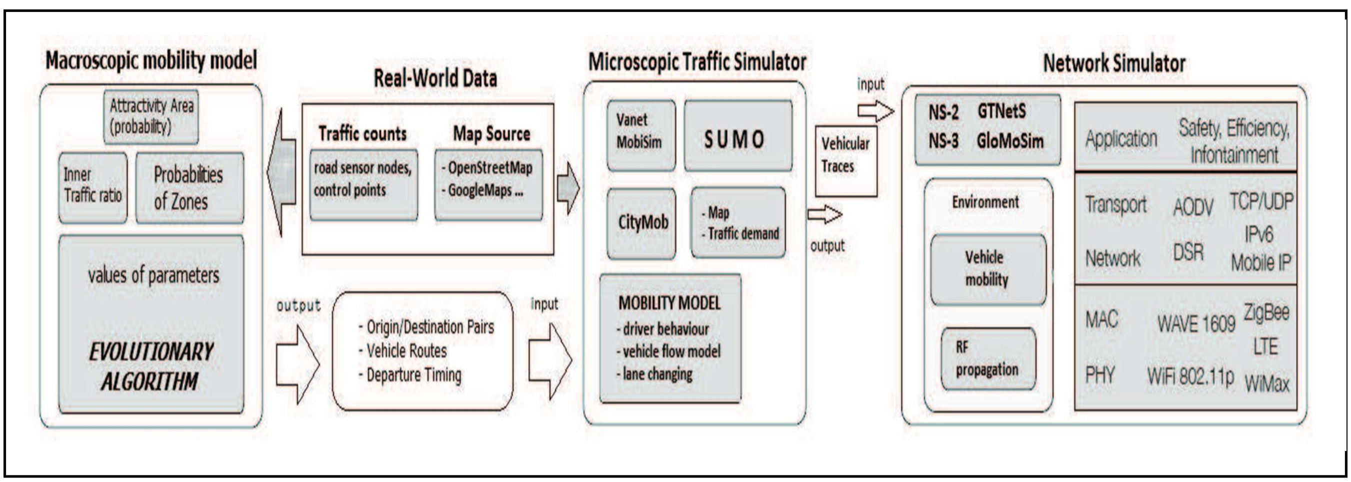

Figure 1. Generation of vehicular traces and bidirectional coupling between microscopic traffic and network simulators

A recent research trend in mobility modelling is to combine real-world information such as digital maps, traffic counters and statistical data together with microscopic simulation. In order to obtain realistic vehicular mobility at macroscopic and microscopic levels, trace information needs to be used in relationship with microscopic traffic simulation. According to the concept picture in Figure 1, the EA model uses two sources of real-world data inputs (geographical map and traffic volume counts). As outputs, microscopic model generates three elements for each time slot: a prediction of the origin/destination (O/D) pairs for vehicles, a set of a routes for all generated O/D pairs and the estimation of the departure time for vehicles moving in the area covered by the digital map. The output data is then processed by a traffic generator that models traffic demand and generates synthetic traces as an input to a traffic simulator [5].

A microscopic traffic simulator moves vehicles in accordance to requested routes and physical rules. A network simulator based on new vehicles position update its own nodes positions and communications links in every time step. Interactions between particular elements present reciprocal impact and further increase the realism of a simulation. Traffic simulator can change vehicle routes as a result of VANET applications. Traffic generator fuses all real-world data that can be useful to determine the traffic demand and can uses feedback from traffic micro simulator. Information about current traffic situation can influence the traffic demand by changing traveler decisions and adjusting activity schedules. The separation of particular steps ensures modularity what makes easier the replacement of each module and testing of different scenarios. Although many microscopic simulators enable to specify traffic demand integrally, researchers tend to implement a separated module to gain the flexibility and modularity of the platform [6].

3. EA Algorithm - Optimization Basics

Evolutionary algorithms (EAs) are a family of nature inspired computational techniques and interactive heuristics that evolve a set of candidate solutions, represented as individuals that are grouped in a population. That candidate solutions are able to reproduce themselves to an additional selection procedure. Implementation of an EA begins with a definition of the search space as a finite bounded domain. Parameters are the population size (α) as well as the number of offspring (β) that have to be created each generation (see Algorithm 1). Additionally, a genotypic search space G must be determined together with a decoding function dec: $G \rightarrow \Omega$ that determines to which phenotypic candidate solution a genotype is mapped. Ideally, a mapping from genotype to phenotype is bijective [7].

The crucial step is determining a fitness function. The value of the fitness function indicates the amount of closeness to the optimal solution. Using EA implementation is as good as the fitness or evaluation function. Generally, the fitness of an individual determines the probability of its survival to the next generation. The next step is the initialization or selection of the initial

ALGORITHM 1

GENERAL EVOLUTIONARY ALGORITHM EA (PSEUDOCODE)

INPUTS: parameters α, β **...** quality function $f: \Omega \rightarrow R$

PARAMETERS: population size α, number of offspring β, genotype G, decoding function *decod*

t $\leftarrow$ 0

PPL(t) **//**create a population of size α

evaluate individuals in PPL(t) using *decode* and *f*

while termination criteria not fulfilled **do**

E **//**select parents for β offspring from PPL(t)

PPL**'** **//**create offspring by recombination of individuals in E

PPL**''** **//**mutate individuals in PPL**'**

evaluate individuals in PPL**''** using *dec* and *f*

t $\leftarrow$ t + 1

PPL(t) **//**select α individuals from PPL**''** (and P(t **-**1))

end while

OUTPUT: best individual in PPL(t)

population PPL(t). Through the next generations of the population, the existing solution is iteratively improved. This iterative process is called generation and stops after some termination condition is met (e.g. predefined number of iterations). Two basic operators are crossover and mutation. Crossover operator takes two individuals (parents), which are combined to form new chromosomes or offspring (PPL', PPL"). Iteratively applying the crossover operator, genes of good chromosomes appear more frequently in the population, leading to convergence to the optimal solution. The mutation operator alters one individual to produce a single new solution and introduces random changes into the characteristics of chromosomes. Reproduction involves the selection of chromosomes for the next generation [7]. The processing scheme of the general EA is shown in Algorithm 1 in pseudocode.

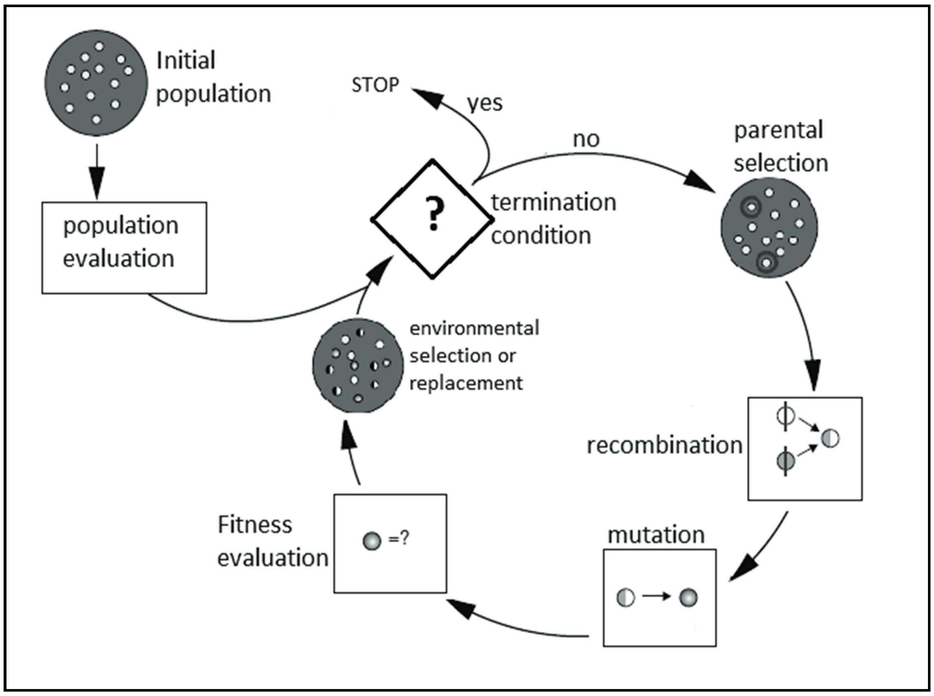

Figure 2. Schematic description of the fitness evaluation in EAs

Figure 1 shows the evolutionary cycle of EA algorithm. In this section we review standard algorithms and paradigms that are relevant in the remainder of this paper, namely genetic algorithms (GAs), developed by Holland [8] and evolution programming (EP) [9].

4. Evolutionary Algorithms For VANETS

Evolutionary algorithms have been applied to vehicular networks for the last decade. There are still many optimization problems in these complex networks that can be solved using a suitable EA. New architecture of EAs are continuously proposed such as coevolutionary and parallel evolutionary algorithms. During this section, we followed the optimization solution proposed in [10, 11, 12] which defines a EAs generic framework for generating realistic mobility vehicular traces using real-world input traffic data.

The current trend in vehicular traces generation is to combine many approaches into a single process in order to obtain the required level of realism. EA model proposed in [10] generates a set of vehicular traces that consider temporal and spatial aspects of traffic distribution. Mobility model uses freely available source data - from digital OSM (Open Street Maps) maps [13], and set of traffic volume counts obtained from roadside control points. This model relies on probabilistic geographical zone surface and attraction points used to select the destination of each vehicle. The residential, commercial and industrial zone types are defined and extracted from OSM maps. Each of them is assigned with a probability of being selected as a destination type. EA model requires the following parameters: zone type, location of zones belonging to each type and location of attractivity areas. The probability for choosing a zone is influenced by the weight of its zone type or the weight of its attractivity area. In the first step

EA selects probability of a zone type and then in second step selects the probability of an attractivity area for the selected zone. The third step is applied if within the selected attractivity area more than one zone of selected type exists. This EA model uses simple weighted Dijkstra shortest path algorithm for the route generation between origin destination vehicle pair. EAs are iterative heuristics that evolve a set of candidate solutions. Two individuals (parents) are chosen in the population using a given criteria. In the evolutionary cycle they are then recombined with fitness dependent probability to produce an offsprings. The obtained offsprings are mutated and they are evaluated and inserted back into the population following a given criteria [14]. As presented in Figure 3, after procedure for selection of a destination zone, next step is optimization of EA parameters (fitness function, encoding and genetic operators).

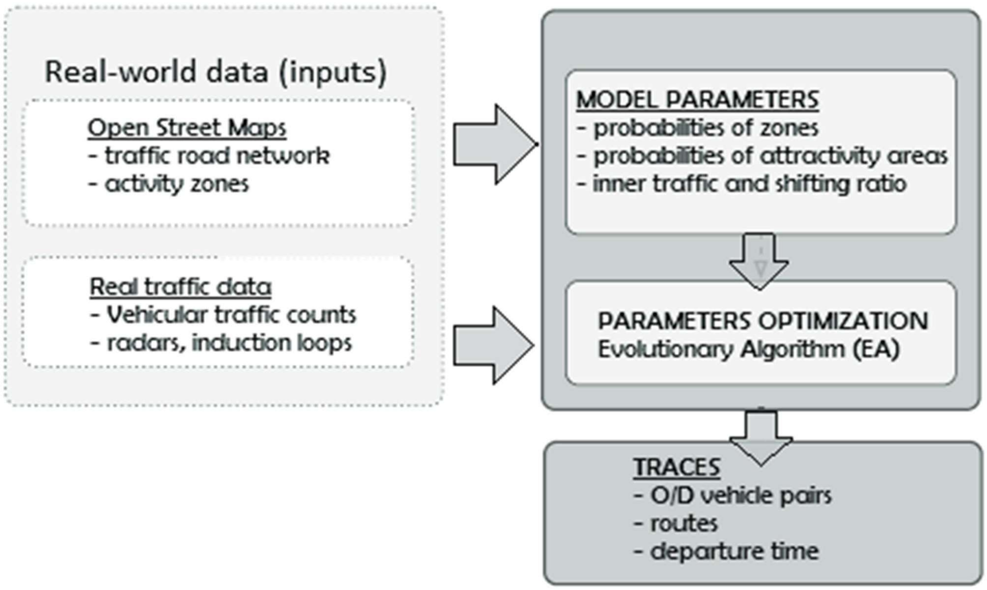

Figure 3. Schematic EA model of the vehicle trace generation

The fitness of the individuals is the basis for the environmental selection, where for each individual a decision is met whether it will survive and be a potential parent in the next iteration (see Figure 2). In this EA model fitness is a quality metric and indicates how the generated traces are consistent with real traffic volume counts. We can conclude that the best fitness is able to reproduce such a realistic traffic vehicle behaviour. The EA fitness function F is computed according to the following equation:

$$F = \sum_{c=1}^{C} \sum_{t=1}^{T} \left| r_c(t) - c_c(t) \right|$$

Here, C is the number of control points and T is the number of time slots. Parameter $r_c(t)$ is the real traffic volume count at control point c in time slot t, and $c_c(t)$ is the number vehicles at control point c derived from the generated traffic flows in time slot t. Generally, the objective is to minimize this sum F of absolute differences between the real traffic volume counts and the estimated ones for all the control points for the simulated period [11, 12].

Figure 4 shows how the basic parameters of the model are encoded. This model uses integer gene representation where each gene represents one parameter. Zone probabilities are noted as P_T where $T \in \{R, C, I\}$ denotes the zone type. The length of the chromosome depends on the numbers of zone types and attractivity areas. The sum of probabilities of each group must be 100 and it is basic constraint. For the fitness evaluation F (see equation) all of the values for each gene are scaled and must be in the range from 0 to 1. This model uses a modified uniform mutation operator which replaces the value of the chosen gene with a random value selected between 0 and 100. As Figure 4 shows, the gene with value 88 is mutated and replaced by 42. Therefore, gene with value 12 is also changed to 58. [10]

In order to obtain more realistic traffic distribution, Cooperative Coevolutionary GA (CCGA) gives more efficient optimization. CCGA proposed and discussed in [15] uses Gawron's algorithm [16]. Model modifications include timeframe reduction, geo graphical model decomposition and additional attractivity areas. CCGA consists of splitting the whole population into several subpopulations. Instead of evolving a population of similar individuals representing in classical EAs, CCGAs consider the coevolution of subpopulations of individuals representing different species. Each subpopulation runs a genetic algorithm.

The output of the proposed EA and CCGA mobility models is a set of vehicles with their route and ready to be used as an input for SUMO [17] traffic simulator. Finally, the newly generated traces will be compared to the original model accuracy.

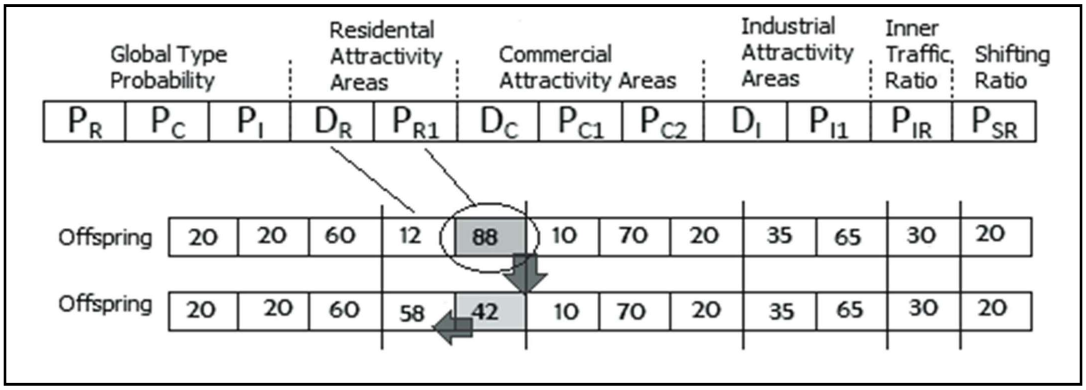

Figure 4. EA encoding scheme and uniform mutation operator

5. Trends and Conclusion

This paper presented that realistic vehicular simulation is one of the biggest promising challenges in a VANETs research. We have acknowledged the need of realism in every aspect of simulation in order to obtain reliable results. The paper indicated that the future direction in research of intervehicle communication and applications is based on mobility traces. We have presented the main features and restrictions that should be taken into consideration for the use of evolutionary algorithms in generating traces for citywide area for which traffic volume counts exist. Additionally, we have reviewed the main works found in the research literature and we believe that the use of EAs in generating of realistic traces for vehicular mobility simulations is in a very dynamically stage of research.

The major concern of generating realistic vehicular traces is how to select the values of the probabilities associated with attraction points. A genetics operators and fitness function are proposed to model the problem, but in some cases the results notably deviate from real traffic count data. This is due to the route generation process of the EA model. The future research can be EAs expanding with the more tunable and time-variant probabilistic model of areas and zones.

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