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An Analysis Approach to Large-Scale Vehicular Network Simulations

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Abstract

Advances in parallel simulation capabilities are now enabling the possibility of simulating multiple scenarios of large problem configurations. In emergency management applications, for example, it is now conceivable to consider simulating phenomena in large (city- or state-scale) vehicular networks. However, an informed understanding of simulation results is needed for real-time decision support tools that make use a number of simulation runs. Of special interest are insights into trade-offs between accuracy and confidence bounds of simulation results, such as in the quality of predicted evacuation time in emergencies. In some of our emergency management projects, we are exploring approaches that not only aid in making statistically significant interpretations of simulation results but also provide a basis for presenting the inherent qualitative properties of the results to the decision makers. We provide experimental results that demonstrate the possibility of applying our approach to large-scale vehicular network simulations for emergency planning and management.

Keywords

Vehicular Network Simulation, Monte Carlo Simulation, Evacuation/Emergency Planning & Management

1 INTRODUCTION

Simulations are routinely used in emergency planning and management in order to make decisions such as whether to order an evacuation or not[1, 2]. The quality of decisions can greatly depend on the quality of insights into simulation results. When larger geographical regions are considered in such decisions, simulations become more complex in terms of model fidelity and interpretation of simulation results. Also, due to increased execution times incurred by the larger sizes of scenario configurations, tradeoffs often have to be made between accuracy and confidence bounds in the amount of decision time available. An analysis methodology is needed to make an informed decision in such contexts, to execute as few simulation runs as needed, and to use the predicted answers correctly.

To address this analysis problem, we are exploring approaches to incorporate in simulation systems that we are developing in the context of emergency management and planning. In our systems[3], we are incorporating high fidelity models of important underlying phenomena in vehicular traffic-based evacuations. In these systems, with various behaviors to account for, it becomes important to not only take scale and fidelity of models into account but also initiate the simulations in a streamlined fashion.

In the context of predictions based on large-scale vehicular network simulations, multiple questions arise that need to be answered. For example: What is the statistical nature of the effect of the underlying phenomenon on the measure of interest (e.g., effect of evacuation policies on the total evacuation time)? How can we obtain reasonable levels of confidence and acceptable error (e.g., to be able to say that a certain evacuation strategy for a target scenario would take $n \pm e$ hours with a confidence level of c, for some n, e and c)? How can we expose the tradeoff between confidence and accuracy to the user (e.g., trends between n, e and c as real-time elapses during analysis)? How can we best optimize the number of simulation runs in order to minimize the delay of response to the user (e.g., when a certain combination of *n*, *e* and *c* are adequate for the decision of interest)? How can we capture and predict the trends of the tradeoff?

In order to be able to answer such questions, we first need an understanding of the statistical qualities of simulations of the underlying phenomenon. Consequently, we can design an analysis and presentation framework to better conduct simulation runs and interpret simulation results for the end user.

In this document, we present our initial findings towards such an analysis framework. In our approach, we first develop an analysis methodology that could be used to solve the problem of presenting usable metrics to the decision makers and to track the refinement of simulation result quality across multiple runs. We then apply this methodology to the evacuation phenomenon by developing simplified models and observe the evacuation time distributions. This is followed by verification of preservation of the distribution characteristics when more vehicular traffic details are taken into account in the models. We use the high-fidelity vehicular network simulator, SCATTER[4], to simulate the evacuation scenarios under detailed traffic behavior.

The rest of the document is organized as follows. The analysis approach is described in Section 2. The experimental studies and findings are presented in Section 3, followed by a summary and description of future work in Section 4.

2 ANALYSIS APPROACH

Here we focus on the evacuation problem, which we define for the purpose of this document as the problem of predicting the time it takes for a significant fraction of vehicular traffic originating at various parts of the road network to get routed and reach a specified intersection in the road network. While generalizations are possible (with multiple destination points instead of one destination point), for simplicity, we focus here on evacuating all traffic towards one destination point. An important measure of interest in this problem is the expected amount of time for evacuation (e.g., how long it would take for 95% of the traffic to reach the evacuation destination point).

For prediction of evacuation times, the simulation-based decision system is envisioned to be built on Monte Carlo simulation method[5]. A simulator of vehicular movement from origins to the evacuation destination is assumed. Different versions of such a simulator are possible, each taking into account varying levels of behavior fidelity of the vehicular traffic and related factors (we will look at two such simulators in the experimental study section). Multiple runs using this simulator are initiated with different random seed values.

One of the key questions to be answered in such a framework is how many simulation runs are needed to establish a value for the mean evacuation time within a prescribed set of confidence limits. This quantity, in turn, depends on several factors the most important of which is the width of the distribution of evacuation times. To see why this is so consider the simple but commonly encountered case where the random variable of interest, in this case, the evacuation times, has a Gaussian (normal) distribution.

Consider the following illustrative example. Suppose a particular neighborhood evacuation is run N times with a resulting sample mean t = 100. Several difference scenarios are explored each yielding a different value for the sample standard deviation St. The following table can then be constructed to illustrate the dependence on the sample size N for two cases, knowing the mean to within 1% and within 3%. Shown in this table are the numbers N of simulation runs required to achieve a certain precision at the desired confidence level.

Table 1: Number of simulation runs needed to achieve different combinations of error and confidence levels

Confidence Level	*99%*	*98%*	*95%*	*90%*	*80%*
S_t=30, Error = ±1%	5991	4886	3457	2435	1475
S_t=30, Error = ±3%	666	543	384	271	164
S_t=10, Error = ±1%	666	543	384	271	164
S_t=10, Error = ±3%	74	60	43	30	18

Clearly, it is possible to realize the exact levels of error and confidence by running appropriate number of simulation runs. However, if we consider the possibility that we cannot hope to execute as many runs as necessitated by tables such as the above, we need to look for alternative analysis approach.

The alternative approach is to continually monitor the error and confidence levels actually observed at run time as the simulation runs are executed. Then, at some point in time, either the amount of available time for analysis is used up (in which case, the decision maker must use the results at the best combination of error and confidence levels realized at the end of the time), or the decision maker can halt the process at runtime dynamically when the desired combination of error and confidence is reached.

To illustrate with an example, suppose the simulations are time-consuming. Then, only a small number of simulation runs could be executed in the time available for decision making (say, 3-4 hour time window). The number of runs could be less than those required (as in Table 1), for the best results, but the quality of results will be known, albeit with a larger error margin or wider confidence bands than desired. On the other hand, if the simulation runs end up giving the desired combination of, say, error of ±30% with confidence of 90%, the decision maker could indeed be able to make use that information in certain situations despite the large error margin.

Since the exact variation/refinement of error margin over a series of simulation runs is dependent on the problem and scenario, and thus cannot be determined a priori, it can be tracked at execution time and plotted. Figure 1 illustrates the variation of confidence level and z_c (factor of standard deviation from mean for given confidence level) for two different sample evacuation scenarios.

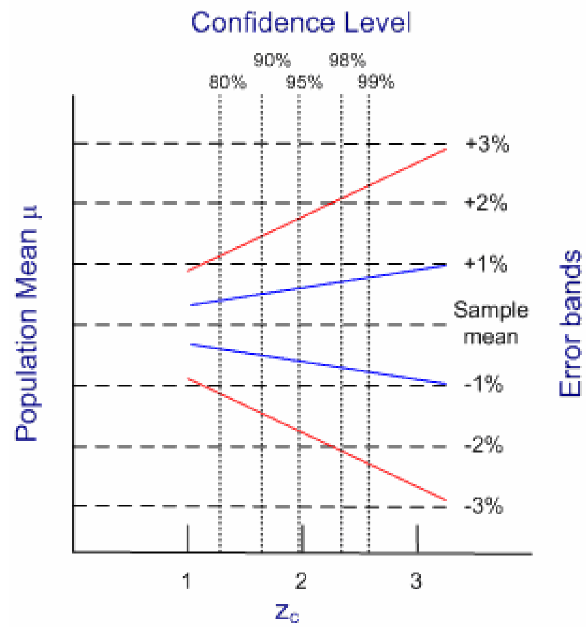

Figure 1: Illustration of tradeoffs between accuracy and confidence levels. Superimposed on this population mean versus z_c plots are the 1, 2 and 3% errors bands and the 80, 90, 95, 98 and 99% confidence levels.

Clearly, such analysis is easy to apply if the distribution of the metric of interest follows a known distribution, such as the Normal (Gaussian) distribution. If indeed the evacuation time follows a Gaussian distribution, it becomes readily possible to present such an error-confidence interface to the decision maker, and even continually update the relationship as more simulation runs are executed. To ascertain if the Gaussian distribution holds for evacuation time, we undertake experimental study under different vehicular traffic behavior conditions. Such a study is described next.

3 EXPERIMENTAL STUDY

We employ two simulation systems in our experimental study to determine the evacuation time distribution. The first is a simplified simulator that predicts evacuation time without much vehicular movement behavior aside from simple transitions across road intersections. The other is a detailed vehicular network simulator that includes many vehicular movement effects, including traffic light controllers, car-following and lane-changing behaviors, and queuing/congestion effects.

3.1 Simplified Vehicular Network Benchmark

The evacuation problem is modeled in this simplified simulator as a neighborhood depicted in Figure 2. Shown in this diagram are a number of cells. Each cell is characterized by a number of evacuees (vehicles) that will move from cell to cell during the simulation. They are free to enter or leave any cell except the one shown in red that is designated as a global attractor. This cell represents the exit from the neighborhood (e.g., an expressway up-ramp). Vehicles will enter this cell but not leave.

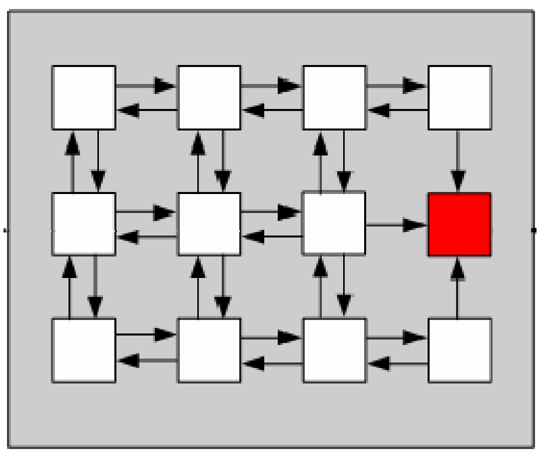

Figure 2: Simplified evacuation benchmark

The simulation model is completed by organizing the vehicles in each cell into a queue. At each time step, each cell is polled. The vehicle at the head of the queue is given a direction, randomly chosen that enables it to move to the next cell. When entering the new cell the vehicle goes to the back of the queue. The vehicles keep moving from cell to cell until all vehicles have entered the red cell whence the neighborhood is considered as evacuated. The number of time steps required for this to happen is recorded. The simulation is reinitialized and run *N* times. The distribution of evacuation times is output and analyzed. This is done for a fixed total population in the neighborhood that has been randomly distributed among the cells at the start of each simulation run.

Table 2: Evacuation times of 1000 vehicles to an exit cell (i,j) on a 10×10 grid network

Exit: i,j	**Low**	**High**	**Median**	**Mean**	**StdDev**
Center: 5,4	1937	2317	2074	2084	102
Edge: 9,5	3373	4358	3830	3855	221
Corner: 9,9	5908	6879	6379	6385	238

The simulated scenario consists of 10×10 grid of cells with 1000 vehicles (uniformly randomly assigned at initial time to the cells) being routed to an evacuation cell (i,j), where (i,j) is experimented with an exterior cell (9,9) or (9,5) and interior cell (5,4). Table 2 shows the distribution of evacuation times with 30 Monte Carlo runs. Figure 3 shows the evacuation time distribution with 3000 Monte Carlo runs. The top distribution corresponds to evacuation to a corner cell (9,9), and the bottom figure is for evacuation to an interior cell (5,4).

Several conclusions are immediately apparent. The first and most important is even for a small number (just 30) of Monte Carlo events the resulting distributions are remarkably well behaved. The variations from low to high are small; the distributions are quite symmetric – the mean and median are near one another, and the standard deviations are modest. A separate Chi-Square test also confirmed good fit to Gaussian distribution.

The experiments for this evacuation behavior (random self-determined routing) show that (a) the evacuation time follows a Gaussian, and (b) it is possible to run as few as 30 simulation runs to determine reasonable statistical properties for error and confidence levels on evacuation time.

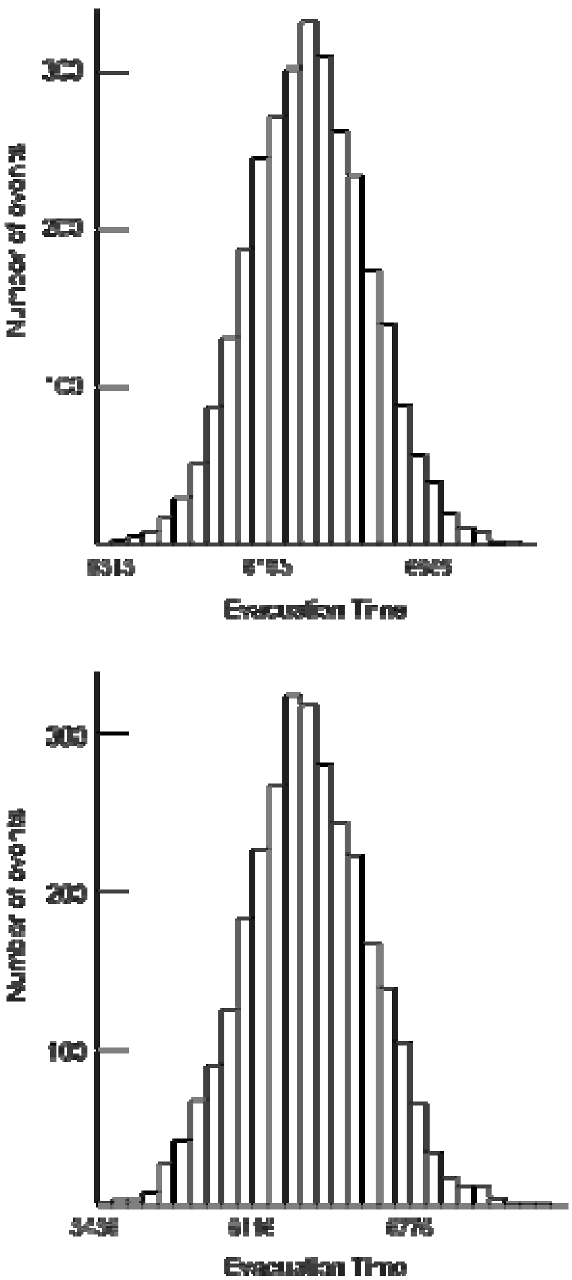

Figure 3: Histograms from Monte Carlo simulations of evacuation times of 1000 vehicles using the simplified simulator on a 10×10 grid

3.2 Vehicular Traffic with Kinetics and Queuing

While the simplified model of the evacuation vehicular traffic shows the statistical properties that we could use, it remains to be seen if and how they change when more movement behavior is taken into account in a detailed vehicular network simulator. To address this, we developed evacuation experiments using a high-fidelity vehicular network simulator, SCATTER[4]. There exist several vehicular network simulators that are commonly used, such as CORSIM[6, 7], TRANSIMS[8-10] and OREMS[1, 2]. We use the SCATTER tool as it is designed for parallel execution, and consequently, can be used to experiment with larger scale network scenarios in the future, which we plan to exercise in our future.

The same scenario as used in the simplified simulator is used, except for addition of detailed road network properties such as traffic light controllers, road link distances, speed limits and vehicle driving characteristics such as car-following nature. The 10x10 grid is configured with links, each 160 meters in length, 30 mile per hour speed limit and 1 lane in each direction, and with 15-second on time for green signals and 3-second yellow signal time for traffic lights at each intersection. A graphical snapshot of the network in SCATTER animation system is shown in Figure 4, with the small colored dots representing vehicles moving on the network.

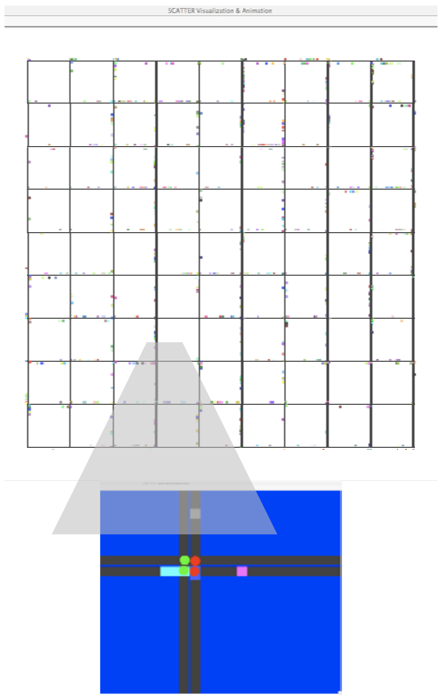

Figure 4: The 10×10 grid benchmark network in SCATTER

The frequency distribution of evacuation time for 1000 vehicles moving to a corner destination is shown in Figure 5. The frequencies represent results from 100 Monte Carlo runs of the scenario. It is observed that the evacuation time follows a Gaussian, allowing the use of the analysis methodology presented earlier.

4 SUMMARY AND FUTURE WORK

Simulation-based decision support for emergency planning and management requires analysis of simulation results to deal with real-time constraints and complexity of the modeled phenomena. We have presented an approach to support an informed analysis of simulation runs in a Monte Carlo-based simulation of vehicular traffic evacuation. Our experimental study demonstrates the use of the analysis approach in an evacuation scenario, by using two different simulators. The results show that it is possible to help the decision maker utilize the simulations under different combinations of desired/observed levels of confidence and error on the measure of interest.

We are investigating the resilience of the observed Gaussian distribution under even wider range of behaviors, namely, under capacity constraints and globally-optimized routing. We are also currently investigating the effect of network topology on the evacuation time distribution, especially using SCATTER to simulate scenarios with real-life networks, such as that of Washington D.C. The possibility of applying this methodology to identifying the sources of bottlenecks and measures of interest other than aggregate evacuation time remains to be investigated as well.

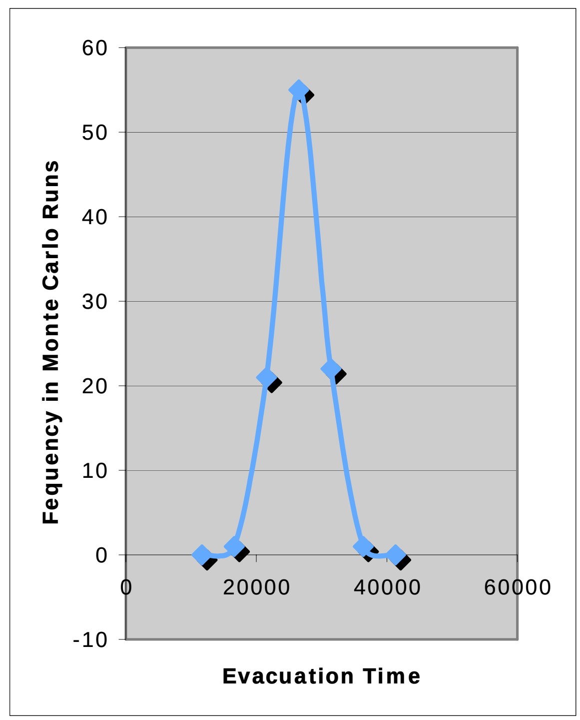

Figure 5: Histograms from Monte Carlo simulations of evacuation times on a 10×10 grid

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