A General Framework to Construct Stationary Mobility Models for the Simulation of Mobile Networks

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Abstract—Simulation has become an indispensable tool in the design and evaluation of mobile systems. By using mobility models that describe constituent movement, one can explore large systems, producing repeatable results for comparison between alternatives. In this paper, we show that a large class of mobility models—including all those in which nodal speed and distance or destination are chosen independently—have a transient period in which the average node speed decreases until converging to some long-term average. This speed decay provides an unsound basis for simulation studies that collect results averaged over time, complicating the experimental process. In this paper, we derive a general framework for describing this decay and apply it to a number of cases. Furthermore, this framework allows us to transform a given mobility model into a *stationary* one by initializing the simulation using the steady-state speed distribution and using the original speed distribution subsequently. This transformation completely eliminates the transient period and the decay in average node speed and, thus, provides sound models for the simulation of mobile systems.

Index Terms—Computing methodologies, simulation and modeling, mobility model, stationary distribution.

1 Introduction

Simulation has become an indispensable tool in the design and evaluation of mobile systems. It allows study of larger scale systems than can be built practically. Furthermore, it enables the evaluation of systems not amenable to analysis. By carefully controlling the movement of nodes and wireless conditions between them, simulations provide excellent reproducibility across experimental trials.

Typically, simulations of mobile systems rely upon *random mobility models*. Such models are characterized by a collection of nodes, placed within a confined space U, that move according to certain underlying random processes. The behavior of most mobile systems depends heavily on the movement of constituent nodes [1]. Therefore, it is highly desirable to have a mobility model that generates stable nodal movement so that the mobile system maintains a steady level of mobility over time, e.g., a fixed average nodal speed and a fixed speed variance. This is especially critical for simulation studies that present performance metrics as time averages.

Our recent work [2] shows that one of the most widely used, the *random waypoint* model, has a transient period in which the average nodal speed decreases to a steady-state level (below the initial average) as the simulation goes on. Such speed decay can have dramatic influence on measured performance and overhead. Consequently, one cannot present time-averaged metrics during this period of decay as the underlying process is not stationary.

There are a number of ways to mitigate the negative effect of this transient speed decay. For example, narrowing the range from which to select speeds can reduce the degree of decay and the time required to reach a steady state. However, it limits the speed variation and does not remove decay in principle. Another approach [2], [3] is to *warm up* every simulation by running it until steady state is reached and then discarding the initial data. While this is valid, it can be cumbersome, especially because the duration of this settling period is case-dependent in general, rendering the simulation process error prone.

The objective of this study is to develop *stationary* mobility models, i.e., those that do not have such transient speed decay, so that reliable simulation results may be obtained via time-averages without having to discard initial data. In this paper, we give a general derivation of the steady-state average speed distribution for several classes of random mobility models and show that speed decay is not a property exclusive to the random waypoint model, but, rather, a much more common phenomenon. Indeed, *any* random mobility model that chooses speed and destination independently exhibits a similar transient period in which the speed decays. The intuition is that nodes travel for longer times at lower speeds if the destination is chosen independently of the nodal speed. This result is true *independent* of the specific distribution from which speeds are chosen and the mechanism with which destinations are determined. Furthermore, if pause time between successive trips is set to zero, the distribution governing the steady-state average speed is *independent* of the mechanisms used to determine destination; it depends only on the distribution from which speeds are chosen.

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Following this result, we show how this transient period and speed decay can be *completely* eliminated in a fundamental way by constructing a composite random mobility model from any random mobility model that exhibits speed decay. The key is to initialize the simulation in the steady state by selecting the speed of the first trip from the steady-state speed distribution and selecting speeds of subsequent trips from the original speed distribution. It is worth pointing out that this method is orthogonal to any modification to a random mobility model to obtain desired *spatial* distributions of nodes, e.g., uniform distribution within the movement area. Thus, it is equally applicable. Finally, warmup may still be needed if the simulated mobile system starts from a "cold state." However, by having such stationary mobility models, warmup is no longer needed for nodal movement, freeing the experimenter to consider other matters.

The rest of the paper is organized as follows: Section 2 gives an overview of problems and issues. Section 3 presents a taxonomy of random mobility models and derives their steady-state average speed distribution. Section 4 presents the methodology of constructing a stationary mobility model without speed decay from a random mobility model, while Section 5 demonstrates its effectiveness for a variety of mobility models via simulation. Section 6 presents related work. Section 7 discusses the application of the results obtained in this study and concludes the paper.

2 Speed Decay in Mobility Models

As mentioned earlier, the performance of a mobile ad hoc network is highly dependent on the underlying mobility model employed for the study, including experiment, simulation and analysis [3], [4]. As performance measures from experimental or simulation studies are often collected in the form of averages over time, it is highly desirable to have mobility models that provide a steady level of mobility over time. The random waypoint model is one of the most widely used models for mobile ad hoc network simulation. A majority of work in the area is based on simulation results with this model. However, the random waypoint model has a transient period at the beginning of the simulation in which the average node speed decreases before reaching the steady-state level [2]. This poses a serious problem because, with the decrease in average node speed, various performance measures also change over time, leading to unreliable time averages. It was also shown that the speed decay could last for a considerable length of time if the minimum speed is set close to zero in the simulation; it becomes infinitely long when the minimum speed is set to zero, which is the default setting in ns-2 [5].

Fig. 1 shows the simulation results illustrating the speed decay phenomenon and how it affects performance of mobile ad hoc routing protocols in simulation. Using DSR for example, it shows that even when the minimum speed is set to be positive and the steady-state is eventually reached, the time it takes for this to happen may still outlast the system warmup period. As a result, performance evaluation is complicated not only by the system itself, but also by the mobility model.

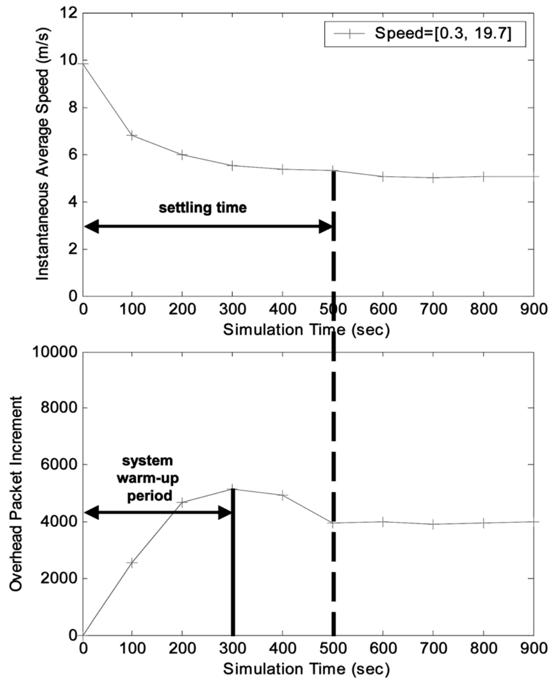

Fig. 1. Speed decay and its effect on overhead packets of mobile ad hoc routing protocols. Fifty nodes, 10 simulation runs, 30 sources, 64 bytes/packet, 4 packets/sec, speed = [0.3, 19.7] m/s.

A natural question to ask is whether this problem is exclusive to the random waypoint model. As will be shown in the next section, this indeed is a problem common to a large class of mobility models.

3 Mobility Models and Steady-State Speed Distribution

3.1 Classification of Mobility Models

Mobility models may be classified in many ways. In this section, we will follow the terms used in [3] and categorize them into entity mobility models and group mobility models. In the former, nodes move independently of each other, while, in the latter, nodes move in groups or in a correlated way. Here, we will limit our attention to models under which a node's movement is specified by a sequence of *trips*, where a trip is a miniature movement on a smaller scale in both time and distance compared to the duration of the simulation and the movement area.[1] The node's entire movement trajectory is formed by a sequence of such trips and a node may pause between successive trips. A trip is typically specified by two or more of the following random elements: node speed, travel time, travel distance, destination, and travel direction/angle. Since this study primarily concerns the speed property of a mobility model rather than the spatial property, we will be considering only three elements: speed, time, and distance. This is because a destination or direction can both be translated into travel distance, given a starting point and choices of either speed

1. Often, the movement during a trip is on a straight line with a fixed speed. A notable exception is a model suggested by Bettstetter [6], where accelerations and decelerations are added to select a modal speed.

or time. Since there are only two degrees of freedom, it suffices to specify any two of these three elements for a trip. Furthermore, as speed is almost always directly specified in a mobility model, we will only consider models that are based on the selection `(speed, time)` and `(speed, distance)`. Examples of such models include the random waypoint model [7], [8], [9] and the random direction model [10]. More can be found in the survey [3].

3.2 Entity Mobility Models without Pause

In this section, we consider entity mobility models with no pause in between trips. We will study the steady-state speed distribution of this class of mobility models given different assumptions on the dependence of the underlying random elements.

3.2.1 General Case, Dependence Unknown

We first consider the general case where the dependence of the random elements are not known. The random variables, speed, time, and distance, are denoted by V, S, and R, respectively, and are assumed to be within finite minimum and maximum values, denoted by V_{min}, V_{max}, S_{min}, S_{max}, R_{min}, and R_{max}, respectively. This also implies that the minimum speed, V_{min}, is strictly positive since, otherwise, the maximum travel time S_{max} can be unbounded.[2]

The cumulative distribution function (cdf) of the steady-state speed, V_{ss}, can be obtained as follows when `(speed, time)` are chosen:

$$P(V_{ss} \le v) = \text{fraction of time speed falls below } v = \frac{\int\int_{v' \le v} s f_{S,V}(s, v')\ ds dv'}{\int\int_{S,V} s f_{S,V}(s, v')\ ds dv'}, \quad (1)$$

where $f_{S,V}(s, v)$ is the joint probability density function (pdf) of time and speed.

Similarly, when `speed, distance` are chosen, the steady-state cdf of V_{ss} is

$$P(V_{ss} \le v) = \frac{\int\int_{v' \le v} \frac{r}{v'} f_{R,V}(r, v')\ dr dv'}{\int\int_{R,V} \frac{r}{v'} f_{R,V}(r, v')\ dr dv'}, \quad (2)$$

where $f_{R,V}(r, v)$ is the joint pdf of distance and speed.

From (1) and (2) we can obtain the pdf and expectation of the steady-state speed. Alternatively, the expectation can be obtained through time averages. Since each node moves independently, it suffices to consider a single node. Denoting the long-term time average of node speed by $\bar{V}$, we have

$$\begin{aligned} \bar{V} &= \lim_{t \longrightarrow \infty} \frac{1}{t} \int_0^t v(\tau) d\tau = \lim_{t \longrightarrow \infty} \frac{\sum_{n=1}^{N(t)} v_n s_n}{t} \\ &= \lim_{t \longrightarrow \infty} \frac{\sum_{n=1}^{N(t)} r_n}{\sum_{n=1}^{N(t)} s_n} = \lim_{t \longrightarrow \infty} \frac{\frac{1}{N(t)} \sum_{n=1}^{N(T)} r_n}{\frac{1}{N(t)} \sum_{n=1}^{N(t)} s_n} \\ &= \frac{E[R]}{E[S]}, \end{aligned} \quad (3)$$

where $N(t)$ is the total number of trips taken up to time t, including the last one which may be incomplete. r_n, s_n, and v_n are the travel distance, time, and speed of the nth trip, respectively. Note that $\{r_n\}$ and $\{s_n\}$ are iid random sequences; thus, their averages converge to the ensemble averages as $t \to \infty$ by the strong law of large numbers.

On the other hand, at time 0 when the first trip is determined, the distribution of node speed is simply $f_{V_{init}} = f_V(v)$, the distribution from which random speeds are chosen, and the expected speed is

$$E[V_{init}] = E[V] = \int_V v f_V(v) dv.$$

These quantities will be used to compare with the steady-state values in subsequent sections.

3.2.2 Speed and Time, Independent

We have $f_{S,V}(s, v) = f_S(s) f_V(v)$. Thus, (1) reduces to the following:

$$\begin{aligned} P(V_{ss} \le v) &= \frac{\int\int_{v' \le v} s f_{S,V}(s, v')\ ds dv'}{\int\int_{S,V} s f_{S,V}(s, v')\ ds dv'} \\ &= \frac{\int_{V_{min}}^{v} f_V(v')\ dv' \int_{S_{min}}^{S_{max}} s f_S(s)\ ds}{\int_{V_{min}}^{V_{max}} f_V(v')\ dv' \int_{S_{min}}^{S_{max}} s f_S(s)\ ds} \\ &= \int_{V_{min}}^{v} f_V(v')\ dv'. \end{aligned} \quad (4)$$

Therefore, the pdf of the steady-state speed V_{ss} is simply

$$f_{V_{ss}}(v) = f_V(v), \quad (5)$$

which is identical to the initial speed distribution. It immediately follows that

$$E[V_{ss}] = E[V] = E[V_{init}], \quad (6)$$

which means that the average speed does not change over time. The intuition and significance of this result will be more clearly described in the next section.

3.2.3 Speed and Distance, Independent

Since speed and distance are independent, speed and time are necessarily dependent. Thus, (3) gives

$$E[V_{ss}] = \bar{V} = \frac{E[R]}{E[S]} = \frac{E[VS]}{E[S]} \ne E[V] = E[V_{init}]. \quad (7)$$

This indicates that the steady-state average node speed is *different* from the initial average node speed. To derive this expectation precisely, we proceed using (2). Since speed and distance are independent, $f_{R,V}(r, v) = f_R(r) f_V(v)$. Plugging this in (2) gives

$$\begin{aligned} P(V_{ss} \le v) &= \frac{\int\int_{v' \le v} \frac{r}{v'} f_{R,V}(r, v')\ dr dv'}{\int\int_{R,V} \frac{r}{v'} f_{R,V}(r, v')\ dr dv'} \\ &= \frac{\int_{V_{min}}^{v} \frac{1}{v'} f_V(v')\ dv' \int_{R_{min}}^{R_{max}} r f_R(r)\ dr}{\int_{V_{min}}^{V_{max}} \frac{1}{v'} f_V(v')\ dv' \int_{R_{min}}^{R_{max}} r f_R(r)\ dr} \\ &= \frac{\int_{V_{min}}^{v} \frac{1}{v'} f_V(v')\ dv'}{\int_{V_{min}}^{V_{max}} \frac{1}{v'} f_V(v')\ dv'}. \end{aligned} \quad (8)$$

2. Positive minimum speed also prevents the average node speed from asymptotically approaching zero as time goes on [2].

Thus, we obtain the pdf of the steady-state speed

$$f_{V_{ss}}(v) = \frac{\frac{1}{v} f_V(v)}{\int_{V_{min}}^{V_{max}} \frac{1}{v'} f_V(v')\, dv'} \tag{9}$$

and the expectation of steady-state speed

$$\begin{aligned} E[V_{ss}] &= \int_{V_{min}}^{V_{max}} v \cdot f_{V_{ss}}(v)\, dv \\ &= \frac{1}{\int_{V_{min}}^{V_{max}} \frac{1}{v'} f_V(v')\, dv'} = \frac{1}{E[\frac{1}{V}]}. \end{aligned} \tag{10}$$

$E[V_{ss}]$ is always less than or equal to the initial average $E[V]$ by Jensen's inequality [11], which states that if a function $g(X)$ is convex, then $E[g(X)] \geq g(E[X])$. Now, let $g(V) = \frac{1}{V}$ $(V_{min} \leq V \leq V_{max})$, which is convex. It follows that

$$E\left[\frac{1}{V}\right] \geq \frac{1}{E[V]} \Rightarrow E[V] \geq \frac{1}{E[\frac{1}{V}]}. \tag{11}$$

Therefore,

$$E[V_{init}] = E[V] \geq E[V_{ss}], \tag{12}$$

where the equality holds only when $V_{min} = V_{max}$. Thus, the average speed decays with time unless the node speed is constant.

The above results are summarized as follows:

1. The steady-state speed distribution is different from the initial speed distribution.
2. The steady-state speed distribution and expectation of node speed are completely characterized by the initial speed distribution $f_V(v)$, which is usually given.
3. The steady-state speed distribution is determined only by the node speed distribution and not by how distances/destinations are chosen.
4. The steady-state average node speed is lower than the initial average speed. This means that if distance/destination is chosen independently of speed, there will always be speed decay.

Items 3 and 4 further indicate that models that only differ in distance/destination selection are essentially indistinguishable in terms of their speed properties.

An intuitive explanation for 4 is that when speed and distance are chosen independently, a lower speed results in a longer trip. Note that the steady-state speed is weighted by travel time and, thus, is always lower than the initial average speed. To see this more clearly, consider the following intermediate result from (3):

$$E[V_{ss}] = \bar{V} = \lim_{t \longrightarrow \infty} \frac{\sum_{n=1}^{N(t)} v_n s_n}{t}.$$

Note that low speed v_ns are more likely to be weighted by large s_ns, which leads to a lower long-term average node speed. In contrast, when speed and time are selected independently (as in Section 3.2.2), v_n is not correlated with s_n. Thus, the steady state speed distribution remains the same as the initial speed distribution. Alternatively, 4 can be explained using the properties of *harmonic mean* of renewal speed, where the steady-state average speed can be viewed as the average rate in the system performance measure [12]. This phenomenon can also be explained via Palm calculus, see, for example, [13].

Equation (9) is a very general result. It holds regardless of the speed distributions used. It shows that the average node speed of an *arbitrary* mobility model starts from an initial value, decays over time, and then settles to a certain steady-state value, as long as speed and distance are chosen independently.

3.2.4 (Speed and Time) or (Speed and Distance), Correlated

If speed and distance are chosen dependently, e.g., a model that gives higher probability to higher speeds when the distance chosen is larger, one may be able to reduce speed decay by properly correlating the two. In [14], we showed an example where travel time is correlated with travel speed. In this particular example, speed decay exists. However, it is possible to construct a joint distribution of speed/time or speed/distance so that the resulting average speed process is stationary, although, in this case, the derivation of the steady state speed distribution is much more complicated.

3.3 Entity Mobility Models with Pause

3.3.1 General Case, Dependence Unknown

If pause is added between successive trips, a mobility model can be viewed as an alternating renewal process that has two independent renewal processes: a move process and a pause process [15]. Since, during pause, the node has a speed of zero, the pause process essentially has a speed pdf of $f_{V_P}(v) = \delta(v)$, where V_P denotes the "pause speed" (which is zero).

When `(speed, time)` are chosen, the cdf of V_{ss} can be obtained from (1) as follows: Denoting the pause time by P and using the fact that pause time and pause speed are independent, we have

$$\begin{aligned} F_{V_{ss}}(v) &= P(V_{ss} \leq v) \\ &= \frac{\iint_{v' \leq v} s f_{S,V}(s, v') ds dv' + \iint_{v'' \leq v} p f_{P,V_p}(p, v'') dp dv''}{\iint_{S,V} s f_{S,V}(s, v') ds dv' + \iint_{P,V_p} p f_{P,V_p}(p, v'') dp dv''} \\ &= \frac{\iint_{v' \leq v} s f_{S,V}(s, v') ds dv' + E[P] \int_{v'' \leq v} \delta(v'') dv''}{\iint_{S,V} s f_{S,V}(s, v') ds dv' + E[P]}, \end{aligned} \tag{13}$$

where $f_{S,V}(s, v')$, $V_{min} \leq v' \leq V_{max}$, and $f_{P,V_p}(p, v'')$, $v'' = 0$, are corresponding joint pdfs. $E[P]$ is the expectation of pause time.

Similarly, when `(speed, distance)` are chosen, the steady state cdf of V_{ss} is generalized from (2) as

$$\begin{aligned} F_{V_{ss}}(v) &= P(V_{ss} \leq v) \\ &= \frac{\iint_{v' \leq v} \frac{r}{v'} f_{R,V}(r, v') dr dv' + \iint_{v'' \leq v} p f_{P,V_p}(p, v'') dp dv''}{\iint_{R,V} \frac{r}{v'} f_{R,V}(r, v') dr dv' + \iint_{P,V_p} p f_{P,V_p}(p, v'') dp dv''} \\ &= \frac{\iint_{v' \leq v} \frac{r}{v'} f_{R,V}(r, v') dr dv' + E[P] \int_{v'' \leq v} \delta(v'') dv''}{\iint_{R,V} \frac{r}{v'} f_{R,V}(r, v') dr dv' + E[P]}, \end{aligned} \tag{14}$$

where $f_{R,V}(r, v')$ for $V_{min} \leq v' \leq V_{max}$ is the joint pdf of travel distance and speed.

With a slight modification to (3), the long-term time average of node speed with nonzero pause time becomes

$$\bar{V} = \frac{E[R]}{E[S] + E[P]}. \tag{15}$$

As in Section 3.2.1, we would like to determine the initial average speed for comparison purposes. We will consider the case where a node starts in either the move or pause state with a certain probability. From the point of view of using a mobility model for simulation, it is reasonable to assume that these are exactly the probabilities that a node is found to be in either state when the mobility model reaches equilibrium, denoted by P_{move} and P_{pause}, respectively. Then, the initial average speed is simply

$$E[V_{init}] = E[V]P_{move} + 0 \cdot P_{pause} = E[V]P_{move}. \tag{16}$$

3.3.2 Speed and Time, Independent

As in Section 3.2, this independence allows (13) to reduce to

$$\begin{aligned} F_{V_{ss}}(v) &= P(V_{ss} \le v) \\ &= \frac{E[S]\int_{V_{min}}^{v} f_V(v')\, dv' + E[P]\int_{v'' \le v} \delta(v'')dv''}{E[S] + E[P]}. \end{aligned} \tag{17}$$

Then, the probability that a node is in a pause state is

$$P_{pause} = F_{V_{ss}}(v=0) = \frac{E[P]}{E[S] + E[P]} \tag{18}$$

and the probability that a node is in a move state is

$$P_{move} = 1 - P_{pause} = \frac{E[S]}{E[S] + E[P]}. \tag{19}$$

Therefore,

$$f_{V_{ss}}(v) = \begin{cases} \frac{E[S]f_V(v)}{E[S]+E[P]} \\ = f_V(v)\ P_{move}, \quad V_{min} \le v \le V_{max} \\ \frac{E[P]\delta(v)}{E[S]+E[P]} \\ = \delta(v)\ P_{pause}, \qquad v = 0. \end{cases} \tag{20}$$

This pdf indicates that a node either moves at a certain speed selected from the pdf $f_V(v)$ with probability P_{move} or pauses with probability P_{pause}. From (20), the expectation of steady-state node speed is

$$E[V_{ss}] = \frac{E[S]E[V]}{E[S] + E[P]}, \tag{21}$$

which indicates that there is no speed decay, because $E[V_{ss}]$ is the same as the initial average speed $E[V_{init}] = E[V]P_{move}$ in (16).

3.3.3 Speed and Distance, Independent

As in the previous section, we can proceed from (14) and obtain

$$\begin{aligned} F_{V_{ss}}(v) &= P(V_{ss} \le v) \\ &= \frac{E[R]\int_{V_{min}}^{v} \frac{1}{v'} f_V(v')\, dv' + E[P]\int_{v'' \le v} \delta(v'')dv''}{E[R]E[\frac{1}{V}] + E[P]}. \end{aligned} \tag{22}$$

In the same manner as in Section 3.3.2, the probability that a node is in a pause state is

$$P_{pause} = F_{V_{SS}}(v=0) = \frac{E[P]}{E[R]E[\frac{1}{V}] + E[P]} \tag{23}$$

and

$$P_{move} = 1 - P_{move} = \frac{E[R]E[\frac{1}{V}]}{E[R]E[\frac{1}{V}] + E[P]} \tag{24}$$

and the pdf of the steady-state speed V_{ss} is

$$f_{V_{ss}}(v) = \begin{cases} \frac{E[R]\frac{1}{v}f_V(v)}{E[R]E[\frac{1}{V}]+E[P]} \\ = \frac{\frac{1}{v}f_V(v)}{E[\frac{1}{V}]}\ P_{move}, \quad V_{min} \le v \le V_{max} \\ \frac{E[P]\delta(v)}{E[R]E[\frac{1}{V}]+E[P]} \\ = \delta(v)\ P_{pause}, \qquad v = 0. \end{cases} \tag{25}$$

The steady-state pdf in (25) is interpreted in exactly the same way as in (20): A node moves at a certain speed according to the pdf $\frac{\frac{1}{v}f_V(v)}{E[\frac{1}{V}]}$ with probability P_{move} or pauses with probability P_{pause}.

From the pdf in (25), the expectation of steady-state speed is

$$E[V_{ss}] = \frac{E[R]}{E[R]E[\frac{1}{V}] + E[P]}. \tag{26}$$

In the case of nonzero pause times, it can also be shown that the steady-state average $E[V_{ss}]$ is less than or equal to the initial average $E[V_{init}]$. Recall that, from (16),

$$E[V_{init}] = E[V]P_{move} = E[V]\frac{E[R]E[\frac{1}{V}]}{E[R]E[\frac{1}{V}] + E[P]}. \tag{27}$$

Then, using (26) and $1 \le E[V]E[\frac{1}{V}]$ from (12), we have

$$E[V_{ss}] \le \frac{E[V]E[\frac{1}{V}]E[R]}{E[R]E[\frac{1}{V}] + E[P] = E[V_{init}]}. \tag{28}$$

This means that the average node speed decays with time no matter what pause time is unless the node speed is constant.

3.4 Group Mobility Models

Unlike in entity mobility models where nodes move independently, in a group mobility model, nodes within the same group move in a coordinated way. However, if the movement of an entire group is specified (e.g., via a leader node) in ways similar to those used in entity models, then groups as a whole may again exhibit speed decay when the speed and distance of the group movement are chosen independently. In the remainder of this section, we will examine the speed property of two commonly used group mobility models: the *pursue* model and the *reference point group mobility* (RPGM) model. In the following analysis, we will not consider pause times since analysis with pause time can be easily obtained using similar methods.

3.4.1 Pursue Mode

The main feature of the pursue model is that there is a target (or leader) node followed/tracked by other nodes [3], [16], [17]. The framework was presented in [16], which allows different implementations. We consider the following implementation of the pursue model: Mobile nodes are divided into several groups and each group consists of a single target node and a number of follower nodes. The

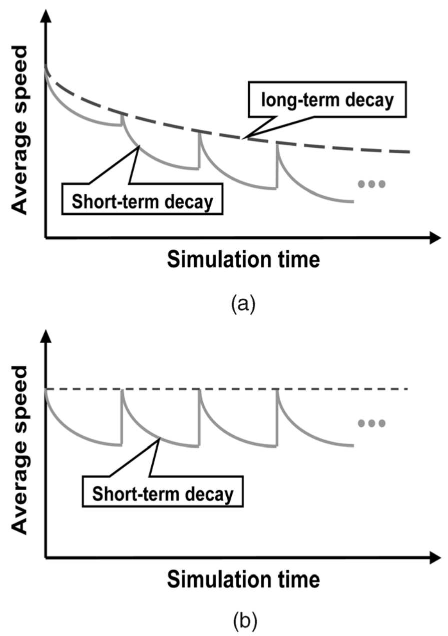

Fig. 2. Two types of speed decays in pursue model: a long-term decay and a short-term decay. (a) Illustration of pursue model simulation result. The dotted line shows a long-term decay. (b) The desired result with the long-term decay eliminated.

target node moves around in a rectangular space, according to the random waypoint model, without pause and with speed range $[V_{min}, V_{max}]$ in m/s. Every T seconds, the follower nodes choose their speed uniformly from $[V_{min}, V_{max}]$, pick the current location of the target node as their destination, and move to the destination. If a follower node arrives at the destination before the next updating instance (i.e., within T seconds), it stays there until the next update. Thus, every T seconds, the follower nodes update their speeds and destinations while continuously tracking a target node. This repeats until the simulation ends. Since each group moves independently of the others, it suffices to look at a single group without loss of generality.

Suppose there are M nodes in a group with a single target node and $M-1$ follower nodes. Since the target node follows the random waypoint model where its speed and distance are chosen independently, its average speed will decrease over time before reaching the equilibrium. Its steady-state distribution $f_{V_{ss}}(v)$ is given by (9). A follower node also chooses its speed and destination independently, but its speed is updated every fixed T seconds. Thus, a follower's speed is not time-weighted as opposed to the case of the target node. However, there could be a "short-term" speed decay *during* an interval, since a node would remain at the location when it arrives there before the next update. So, there are two types of speed decay phenomena: a long-term decay of a target node and a short-term decay of follower nodes, as shown in Fig. 2a. The long-term decay is exactly the same as observed in the entity mobility models due to the independent selection of speed and distance, whereas the short-term decay is a result of the nature of this particular model. Fig. 2b shows the desired result with the decay eliminated.

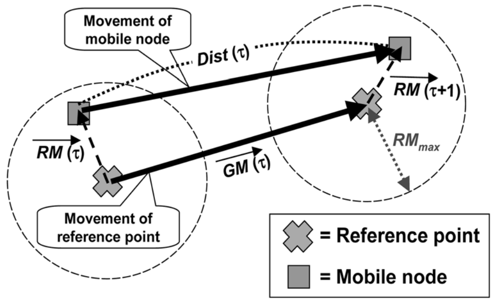

Fig. 3. Reference point group mobility model.

Since the speeds of the follower nodes are chosen from distribution $f_V(v)$, there is no speed decay caused by follower nodes at update points. Therefore, at every update point in the steady state, there exists a single target node with $f_{V_{ss}}(v)$ and $M-1$ follower nodes with $f_V(v)$. Since the target node and the follower nodes select speeds independently, the steady-state average speed is simply

$$E[V_{ss}]_{update} = \frac{1}{M} E[V_{ss}] + \frac{M-1}{M} E[V]. \tag{29}$$

This shows that the long-term decay diminishes as the total number of nodes in a group, M, increases. The steady-state distribution is rather complicated to compute in this case. Denoting by Z the average speed of all nodes, we have $Z = \frac{1}{M} X + \frac{1}{M} \sum_{i=1}^{M-1} Y_i$, where X and Y_i, $i = 1, \cdots, M-1$ are the speeds of the target node and the follower nodes, respectively. Then, the pdf of Z can be obtained using convolution integrals [18].

3.4.2 Reference Point Group Mobility (RPGM) Model

Instead of specifying a target node, the RPGM model [3], [4], [19], [20] has an implicit and insubstantial tracking point or reference point. Based on the current position and speed of the reference point, each mobile node selects its own speed, time, or destination. RPGM is also a framework which allows different implementations. Here, we will examine an implementation based on [19].

Suppose that a reference point is following some predefined group motion. Without loss of generality, suppose an update interval T is one second, as is commonly assumed. Then, we can define a vector of group motion $\overrightarrow{GM(\tau)}$ at time τ by subtracting the current position of reference point at τ from the expected next position at $\tau+1$, as shown in Fig. 3. Next, we define a vector of random motion $\overrightarrow{RM(\tau+1)}$ from the position of reference point at $\tau+1$, by randomly selecting a distance between 0 and a predefined maximum value, RM_{max}, and an angle between 0 and 360 degrees. Thus, the next position of mobile node is determined by $\overrightarrow{GM(\tau)}$ and $\overrightarrow{RM(\tau+1)}$ as shown in Fig. 3. Since the movement distance of the mobile node, $Dist(\tau)$, is easily computed from the location of a mobile node at each time instance and travel time is assumed to be $T=1$ second, the speed of the mobile node automatically becomes $\frac{Dist(\tau)}{T}$.

One may think that, since this model selects distance and time independently and updates parameters every fixed interval, it may not have speed decay. However, if the reference point moves according to the random waypoint model, for example, then the average speed of the reference point decays. This in turn will cause the average length of $\overrightarrow{GM(\tau)}$ in Fig. 3 to gradually decrease. Since $Dist(\tau)$ is correlated with $\overrightarrow{GM(\tau)}$, $Dist(\tau)$ also decreases while the speed decay occurs. The simulation result in Section 5 also illustrates this.

4 Eliminating Decay

Speed decay during the transient period is undesirable because simulation results collected during this period (before the steady state is reached) will not be reliable. Methods of reducing such a negative effect have been suggested and used in the literature [21]. One way is to reduce the range of allowed speed by setting the maximum speed and minimum speed to be within a certain percentage of a set value, e.g., $\pm$ 10 percent of 15 miles per hour [3]. This significantly reduces both the magnitude and the duration of speed decay, but also heavily limits the variation of nodal speed within the same experiment. Another method is to warm up the simulation by discarding a certain portion of the initial data or simply to run the simulation long enough and collect results averaged over time so that the effect of the initial decay is diluted. The problem with this method is that it is not always clear how much one should discard or how long is indeed long enough. If we do not warm up enough, then the effect of speed decay still exists; on the other hand, discarding too much results in waste. In order to do this appropriately, we may need to prerun the mobility model, which adds inconvenience and wastes resources required for simulation studies. In short, none of these methods *eliminate* the speed decay inherent to such mobility models in a fundamental way.

In Section 3, we presented a method of deriving the steady-state speed distribution. In [14], we have shown examples of calculating these distributions for a variety of mobility models. This naturally leads us to question whether we can start the mobility model directly from the steady state and construct a stationary process that is free of the transient speed decay period.

It is important to note that this does not mean we can use the distribution derived in (9) or (25) for the selection of node speed *throughout* simulation. We restate the same equation here, assuming a zero pause time for now:

$$f_{V_{ss}}(v) = \frac{f_V(v)}{\text{constant}}\left(\frac{1}{v}\right). \quad (30)$$

The above result essentially indicates that the steady-state speed distribution $f_{V_{ss}}(v)$ is different from any nontrivial distribution $f_V(v)$ from which node speeds are chosen. The former is the distribution observed at arbitrary points in time, whereas the latter is the distribution observed at the waypoints or the points between successive trips. This is illustrated in Fig. 4, where speed distribution observed at points A and C is $f_V(v)$, and $f_{V_{ss}}(v)$ is observed at some arbitrary point B. Therefore, to start the simulation in steady state means to start the simulation from points like B after the system has reached steady state rather than waypoints A and C. This is also equivalent to *resuming* a simulation which is suspended at an arbitrary point in the steady state. This discussion naturally leads us to the following method of constructing a stationary mobility model: Start the simulation by using $f_{V_{ss}}(v)$ to select the speed of the first trip of a moving node as if we are resuming a simulation suspended at an arbitrary point in steady state. After the first trip ends, we use $f_V(v)$ to select node speed for all subsequent trips. We call this a *composite* random mobility model as it consists of two different speed distributions.

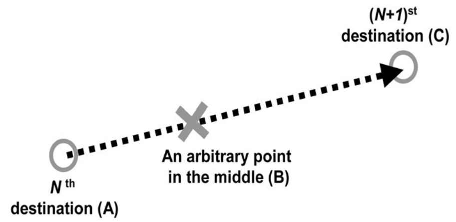

Fig. 4. Different points where distributions are observed in the steady state.

The same argument applies to the initial pause time selection. That is, if a node starts from a pause state, the first pause time should be selected from the steady-state distribution of pause time, which is known to be (the limiting distribution of forward recurrence time using renewal theory) [15]:

$$f_{P_{ss}}(p) = \frac{1 - F_P(p)}{E[P]}, \quad (31)$$

where $F_P(p)$ is the cdf of pause time. This enables us to start a simulation directly from the steady state, which is again equivalent to resuming a simulation suspended at an arbitrary point during some pause period in steady state.

To summarize, we construct a composite stationary random mobility model as follows:[3]

1. Determine whether a node starts from a move state or a pause state, with probability P_{move} and P_{pause}, respectively. These are calculated using methods shown in Section 3.
2. If a node starts from a move state, use $f_{V_{ss}}(V_{min} \leq v \leq V_{max})$ to select the travel speed.
3. If a node starts from a pause state, use $f_{P_{ss}}(p)$ to choose the pause time.
4. After the first trip (either move or pause) of a node, use $f_V(v)$ and $f_P(p)$ to select all subsequent travel speeds and pause times, respectively.

Technically, there are other ways to construct a stationary process by modifying the initial part of the mobility model. For example, if pause is not inserted between successive trips, we could find and use the stationary starting *time* of nodes' first trips, which may seem more intuitive. This method involves the derivation of the distribution of the initial starting time. This may or may

3. This modification has been implemented and included in the latest ns-2 version 2.27.

not be desirable, depending on the mobile system being simulated in that a significant portion of the network may not be moving for some period of time.

On the other hand, modification through the steady-state speed distribution provides a very effective way of eliminating speed decay and producing a stationary process. We emphasize that the above composition methodology can be applied to *any* random mobility models that choose speed and distance/destination independently and that employ a single speed distribution, in order to obtain a decay-free random mobility model. For example, as described in Section 3.4, we can identify speed-decaying nodes in a group mobility model and replace their first trip distribution by the steady-state distribution. In doing so, we can also build a stationary composite group mobility model as well as a composite entity mobility model. The effectiveness of this methodology is demonstrated in the next section.

5 Simulation Results

In this section, we show via simulation the evolution of instantaneous average node speed over time for a few entity mobility models and a couple of group mobility models examined in Section 3. As a metric, we use the instantaneous average speed $\bar{v}(t)$, which is defined as

$$\bar{v}(t) = \frac{\sum_{i=1}^{N} v_i(t)}{N}, \qquad (32)$$

where N is the total number of nodes in the simulation scenario and $v_i(t)$ is the speed of node i at time t.

5.1 Entity Mobility Models

Here, we adopt three examples of entity mobility models for simulation: 1) a model using a uniform speed and a uniform destination (i.e., the random waypoint model), 2) a model using a uniform speed and uniform distance distribution, and 3) a model choosing speed correlated with travel time (see [14] for details). Fig. 5 depicts the behavior of each of the original mobility models both with and without pause, while Fig. 6 shows the behavior of the composite models. As described in Section 4, each node in these composite models chooses either its speed or pause time only for the first trip from the computed steady-state distributions of speed and pause time, respectively, depending on the probabilities P_{move} and P_{pause}. Thereafter, each node alternately chooses its speed and pause time from the original distributions. Each graph also plots the steady-state average node speed predicted by analysis.

In this set of simulation results, each curve is the average over 10 different scenarios. Each scenario contains 50 mobile nodes moving independently in a movement space of $1{,}500\ \mathrm{m} \times 500\ \mathrm{m}$, according to the specified mobility model. The speed range for all scenarios is from 1 m/s to 19 m/s, which results in the initial average node speed of 10m/s with zero pause time. When nonzero pause is applied, pause time is randomly selected from the uniform distribution from 0 to 60 seconds.

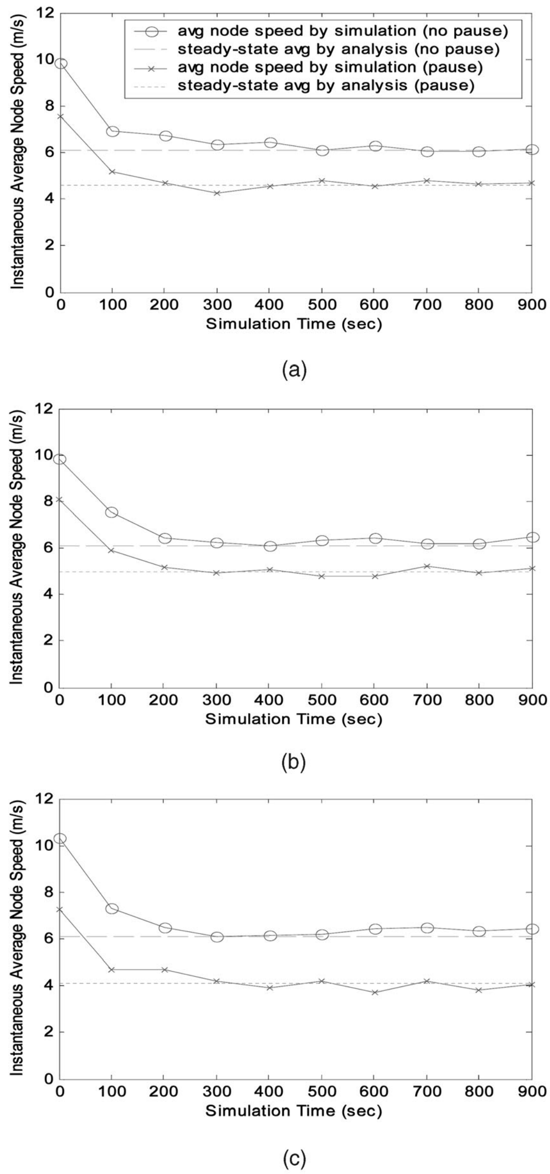

Fig. 5. Average speed decays in a few examples of models examined in Section 3 with and without pause. Speed = [1,19] m/s. Pause = [0,60] sec. (a) Speed = uniform, destination = uniform (i.e., random waypoint model). (b) Speed = uniform, distance = uniform. (c) Speed = uniform, time = bounded exponential.

As shown in Fig. 5, speed decay exists in all cases. We see from Fig. 6 that the constructed composite models successfully eliminated such decay in all cases, including that with speed correlated with time. Thus, this construction methodology is effective, regardless of the dependency between travel speed and distance or time, as long as the steady-state speed distribution can be characterized. Furthermore, analysis in our previous version of this paper [14] showed that average node speed settles to 6.1 m/s in all cases above with the corresponding parameters. As expected, the unmodified models converge to the predicted values, while the composite models start and remain there. Such composite models greatly simplify the evaluation process in a simulation study.

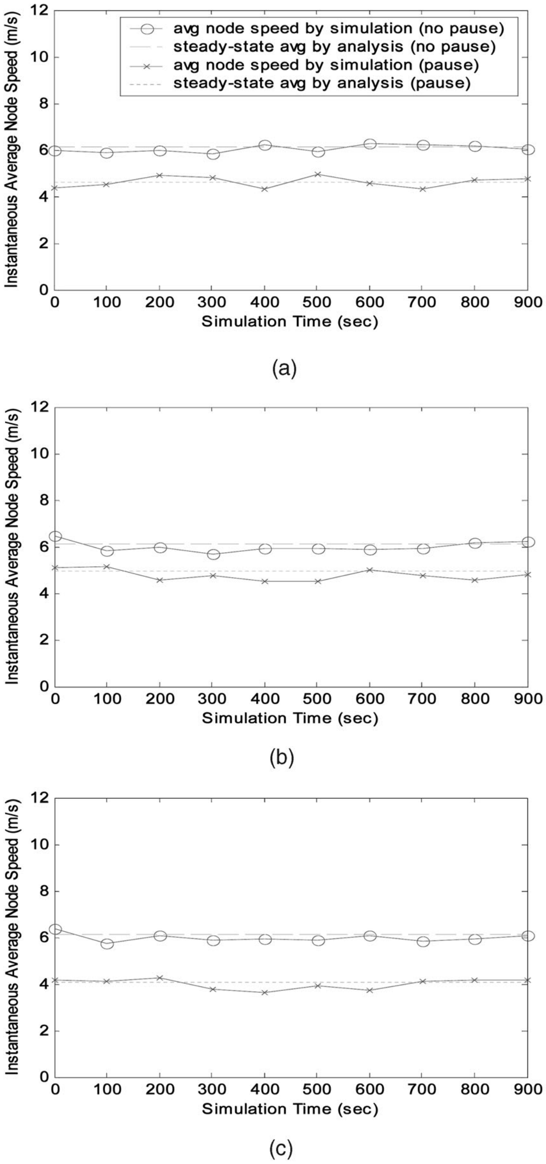

Fig. 6. No speed decays by using a steady-state pdf for the first trip. Speed = [1,19] ms. Pause = [0,60] sec. (a) Speed = uniform, destination = uniform (i.e., random waypoint model). (b) Speed = uniform, distance = uniform. (c) Speed = uniform, time = bounded exponential.

5.2 Group Mobility Models

Figs. 7 and 8 show the pursue model and RPGM model, respectively. As in the entity model simulations above, all results are the average over 10 scenarios. In the RPGM model, there are one reference point moving by the random waypoint model and 10 mobile nodes moving around in a space. For the pursue model described in Section 3.4.1, we implemented it with 20 groups consisting of a single target and two follower nodes each, a total of 60 nodes. The target node moves around according to the random waypoint model during the entire simulation time. In addition, parameters are updated every five seconds. So, here, M is 3 and T is 5. The original speed distribution for both models is the same as that in the entity models above: $f_V(v)$ is a uniform distribution from 1 to 19 m/s. However, we did not consider pause times for simplicity. Even if pause time is added, the main principle does not change and, thus, we can apply the same framework to the nonzero pause cases.

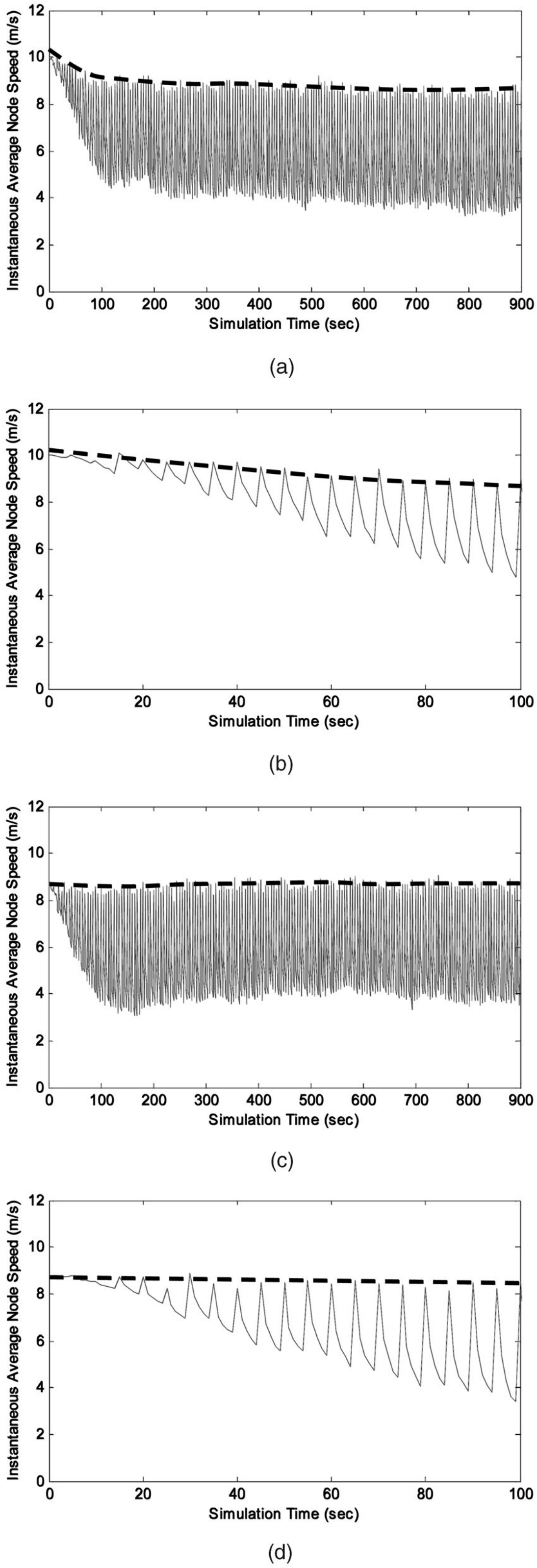

Fig. 7. Pursue model with and without improvement. (a) Pursue model. (b) First 100-second result of (a) magnified. (c) Pursue model with steady-state distribution. (d) First 100-second result of (c) magnified.

Fig. 7a is the average speed over all nodes for 900 seconds and Fig. 7b is a magnified version of Fig. 7a for the first

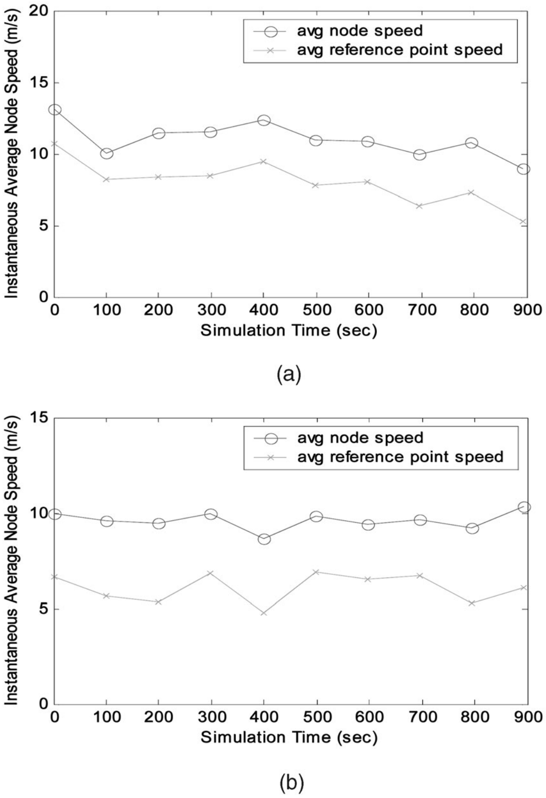

Fig. 8. RPGM model with and without improvement. (a) RPGM model. (b) RPGM model with the speed decay eliminated.

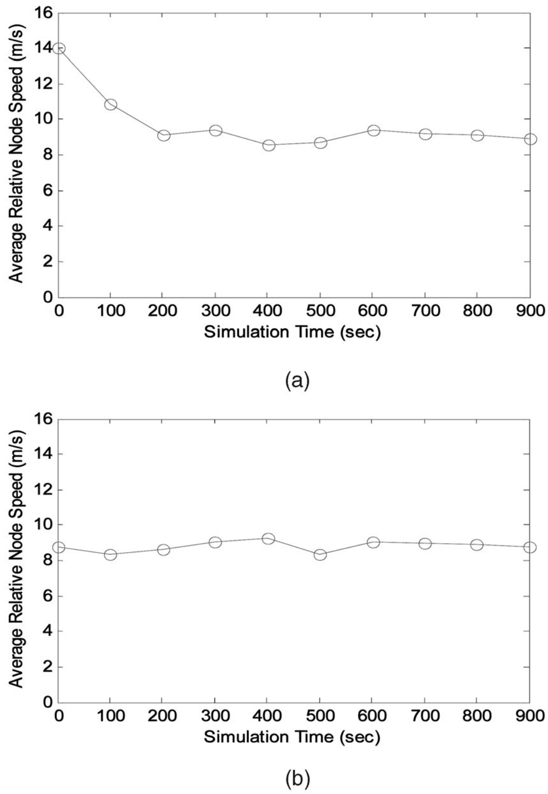

Fig. 9. Relative speed. Speed = [1,19] m/s. (a) Relative speed in the random waypoint model. (b) Relative speed in the composite model.

100 seconds. As described in Section 3.4.1, there exist both long-term and short-term decay and the dotted curve represents a long-term decay of average node speed at every update point. Since $M = 3$ and $T = 5$, according to (29) in Section 3.4.1, the average speed at every update point starts from $E[V_{init}] = 10 \text{ m/s}$, decays over time, and settles to

$$E[V_{ss}]_{update} = \frac{1}{M}E[V_{ss}] + \frac{M-1}{M}E[V] = \frac{1}{3}(6.1) + \frac{2}{3}(10) = 8.7 \text{ m/s},$$

as shown in Fig. 7a. Since target nodes suffer from speed decay, we can replace the first distribution of target nodes by the steady-state speed distribution and, thus, can construct a stationary model, as shown in Fig. 7c and its magnified version Fig. 7d. Note that the fluctuation of short-term decay increases in the beginning because it should *indispensably* take all follower nodes some time to come close to a target node from the initial uniformly random location, and to start tracking it.

Fig. 8 shows the RPGM model examined in Section 3.4.2 with update interval $T = 1 \text{ sec}$ and maximum random motion value $RM_{max} = 10 \text{ m}$. As explained, the RPGM model also exhibits speed decay because the speed of mobile nodes is affected by the speed decay of the reference point. Fig. 8a presents this result. That is, both speeds of reference point and mobile nodes decay over time. But, since the decay of reference point is the only source of speed decay for all nodes, if it is fixed, other mobile nodes consequently must not have the speed decay problem. Thus, we can again apply the steady-state distribution to the reference point to remove the decay, and Fig. 8b clearly verifies this.

5.3 Relative Speed of Mobile Nodes

In addition to the average node speed, relative speed is also widely used as a criterion for comparison in simulations (e.g., [4]). Relative speed between a pair of nodes is defined as

$$V_{rel}(i,j,t) = |\overrightarrow{v_i(t)} - \overrightarrow{v_j(t)}|, \tag{33}$$

where $\overrightarrow{v_i(t)}$ and $\overrightarrow{v_j(t)}$ are speed vectors of nodes i and j at time t, respectively. Thus, the average relative speed can be defined as

$$\overline{V_{rel}}(t) = \frac{\sum_{i=1}^{N}\sum_{j=i+1}^{N} V_{rel}(i,j,t)}{\binom{N}{2}}, \tag{34}$$

where N is the total number of nodes and $\binom{N}{2} = \frac{N(N-1)}{2}$ is the total number of distinct node pairs. Since relative speed is directly related to the individual node speed, if the individual node speed decreases over time, so does relative speed, as shown in Fig. 9. Here, we measured relative speed of the random waypoint model with speed range from 1 to 19 m/s. As expected, speed decay in relative speed is observed if speed decay in average speed occurs. Thus, if we eliminate speed decay in average speed, speed decay in relative speed also disappears, as shown in Fig. 9b.

6 Related Work

Mobility models are essential to the study of mobile systems and, consequently, they have been extensively studied. One can find a thorough and insightful survey by Camp et al. in [3]. It includes not only a variety of entity random mobility models used in ad hoc network simulations, but also group mobility models such as RPGM [19], [22].

Among commonly used mobility models, the *random waypoint model* is perhaps the most extensively used [1], [7], [17], [23], [24]. It is implemented and widely distributed with the ns-2 [5] simulator. Most of the studies on this model have focused on its *spatial* properties such as node distribution within the simulated area U. Bettstetter [6], [25] showed by simulation that the random waypoint model does not have a uniform spatial distribution of nodes. Chu and Nikolaidis [26] mathematically proved it and also showed that there is a relationship between node distribution and node speed. Due to the boundary effect, nodes are more likely to be near the center of U and, thus, the node distribution becomes bell-shaped. Royer et al. [10] pointed out that the boundary effect not only causes a nonuniform node distribution but also causes the node density to fluctuate with time. To eliminate both problems, they proposed a *random direction model* and showed satisfactory results. Bettstetter et al. further obtained the steady-state node spatial distribution of the random waypoint model by analysis and verified by simulation in [9]. In addition, some stochastic properties of the random waypoint model also have been analyzed in [8]: epoch length (i.e., travel distance), direction distribution, and cell change rate of mobile nodes.

In [2], we studied the temporal properties of nodal movement/speed under the random waypoint model. We showed that the average node speed decreases with time before reaching a steady state. The settling time it takes to reach the steady state increases as the minimum speed decreases. In particular, if the minimum speed is zero, this transient period becomes infinitely long. Simulation results showed how such speed decay affects ad hoc routing protocols such as DSR [7] and AODV [27]. A simple solution suggested was to use a positive minimum speed, combined with simulation warmup or initial data deletion to remove the negative effect of speed decay. This nevertheless does not remove the speed decay in an essential manner. In a follow-up study [14], we developed a general framework to determine whether speed decay occurs in a specific mobility model and to construct a stationary composite model by using the steady-state distribution of node speed. Navidi and Camp independently and concurrently developed a method for constructing a stationary process for the random waypoint model [28]. Our work presented here is more general as it applies to multiple classes of mobility models including the random waypoint model. Lin et al. in [29] and Le Boudec in [13] recently proposed similar methods to build a stationary version of the random waypoint model by using renewal theory and palm calculus, respectively.

The study presented in this paper does not concern whether a mobility model is realistic; rather, it concerns how to construct mobility models so that they are more suitable for simulation studies. Significant effort has been made in the literature toward developing more realistic mobility models. Hong et al. [19] proposed a group mobility model to reflect a realistic scenario of group movement and Bettstetter [6], [25] developed an enhanced model by avoiding the impossible changes of speed or direction in reality. A recent paper by Jardosh et al. [30] considered obstacles to constructing a more realistic mobility model and showed the effect of them on the performance of ad hoc routing protocols.

There are also studies on characterizing the effect mobility models have on the performance of the mobile system. Examples include Bai et al. [4], which analyzed mobility models by factors and showed the impact of each factor on performance of ad hoc routing protocols, and Kwak et al. [20], which proposed a general metric to characterize mobility models based on link change rate of mobile nodes.

It has to be noted that the random mobility models considered in this paper are more commonly used for the study of mobile ad hoc networks rather than infrastructured networks that may involve (static or mobile) base stations. This is especially the case with entity mobility models where each node moves independently. Certain group mobility models may describe the movement of a network with mobile base stations, but the two examples considered in this paper are again designed for ad hoc networks.

7 Discussion and Conclusion

This paper examined a number of random mobility models that are based on the selection of node speed, travel distance or destination, travel time, or pause time from probability distributions. A large class of these models—including all those that select node speed and distance independently—exhibit a transient period in which the average node speed decreases before before reaching steady-state. Such decay poses potential problems for simulation studies that collect results averaged over time, complicating the experimental process. This decay is easily explained with a general analytical framework, which allows one to transform a given random mobility model into a stationary one by selecting initial speeds from the steady-state distribution and subsequent speeds from the original speed distribution.

It has to be mentioned that the focus of this study is on constructing mobility models that are suited for simulation studies of mobile networks. The construction presented in this paper does not make a mobility model more or less realistic. Developing realistic mobility models is a challenging research area on its own and is out of the scope of this paper. Rather, the study here aims at fixing certain hidden problems in a model. Similar problems should also be avoided in a more realistic mobility model, however constructed. Thus, by such studies, we hope that a similar analysis may be applied to the development or evaluation of more realistic models, which would ultimately lead to better, more efficient models.

Acknowledgments

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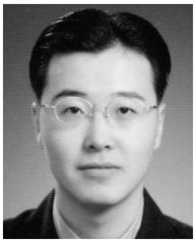

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