IMPACT OF BUSY LINES AND MOBILITY ON CALL BLOCKING IN A PCS NETWORK

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SUMMARY

Several analytical models have been proposed to study the blocking probability for personal communications service networks or mobile phone networks. These models cannot accurately predict the blocking probability because they do not capture two important features. First, they do not capture the busy-line effect. Even if a cell has free channels, incoming and outgoing calls must be dropped when the destination portable is already in a conversation. Second, they do not capture the mobility of individual portables. In these models, mobility is addressed by net hand-off traffic to a cell, which results in traffic with a smaller variance to a cell compared with the true situation. We propose a new analytic model which addresses both the busy-line effect and individual portable mobility. Furthermore, our model can be used to derive the portable population distribution in a cell. The model is validated against the simulation experiments. We indicate that the previously proposed models approximate a special case of our model where the number of portables in a cell is 40 times larger than the number of channels.

KEY WORDS: blocking probability; handoff; mobility; personal communications

1. INTRODUCTION

In a personal communications services (PCS) network, the total number of voice radio channels available is limited. Thus, the channels are reused for different conversations, in locations that are sufficiently distant from each other so that their transmissions do not interfere with one another. The service area is partitioned into cells, and a cell signifies the area in which a particular transmitter site is likely to serve portable (i.e., mobile phone) calls. To avoid interference, the channels are partitioned into several channel sets, and every channel set is nominated at exactly one cell, which cannot be used by other cells within the interference distance. Consider a cell with \( c \) channels. Assume that in the steady state, \( N \) customers are in the cell on the average and the incoming calls to a portable are a Poisson process with rate \( \lambda \). The holding time for a call has an exponential distribution with rate \( \mu \).

Several analytic models have been proposed to study call blocking (new call blocking and hand-off call forced termination). In these models, the call arrivals are represented by two aggregated traffics: the new call attempts and the net hand-off calls.

In References 1 and 2, the net hand-off call arrival rate is derived by using the new call rate and some mobility models. In References 3 and 4, both new call rate and hand-off call rate are given input parameters. The aggregate call arrivals imply that there is an infinite number of portables in a cell, and every call arrival is for a different portable in the cell. Such models have two problems:

1. These models do not capture the busy-line effect. Even if a cell has free channels, incoming and outgoing calls must be dropped when the destination portable is already in a conversation. The aggregate call arrivals do not consider individual portable behavior, and the models assume that a call is always connected if there is a free channel.

2. These models do not capture the mobility of individual portables. Suppose that the call arrival rate to a portable is \( \lambda \), and there are \( N \) portables in a cell on the average. The previously proposed models ignore the notation \( N \), and simply consider the net call arrival rate \( NA \). When a portable moves in or out of a cell, the net call arrival rate does not change. This approach does not reflect the real situation. For example, suppose that there are 10 portables in a cell at time \( t \). Then the net call arrival rate to the cell is \( 10\lambda \). If a portable moves in or out of the cell at \( t + \delta \), the net call arrival rate increases or decreases by 10 per cent instantaneously. In other words, assuming the net call arrivals as a Poisson process with a fixed rate is not appropriate.

An open queue model has been proposed to address the mobility of individual portables. Unfortunately, three major equations (2), (4) and (5) in Reference 5 are not consistent, and the results may not be correct. Although the model considered the average number of portables in a cell, the net new call stream and the hand-off stream (see (4) and (5) in Reference 5) were used just like the other models, and the effect of individual portable mobility was
not well treated. Furthermore, the busy-line effect was not considered in this model.

This paper proposes an analytical model to capture both the busy line effect and the individual portable mobility. Our model can also be used to derive the distribution of the portable population in a cell. The model is validated against the simulation experiments. We show that the previously proposed models approximate a special case (i.e., when $N \to \infty$) of our model. When $N$ is not sufficiently large, the previously proposed models underestimate the blocking probability $p_b$ (new call blocking and hand-off call forced termination) for a small offered load because the individual portable movement feature is not captured, and overestimate $p_b$ for a large offered load because the busy-line effect is not captured.

2. THE BUSY-LINE EFFECT

This section models the busy-line effect by ignoring the mobility of portables (the mobility will be considered in the next section). That is, we assume that there are $c$ channels and $N > c$ portables in a cell and no portable moves in or out of the cell. (Note that by ignoring the mobility, the hand-off stream does not exist, and the previously proposed model degenerates into an Erlang-B system with a state diagram shown in Figure 1 (a).)

Let $\pi_i$ be the steady state probability that $i$ channels are busy. The state diagram of the used channels which captures the busy-line effect is given in Figure 1 (b). In this model, state $i$ represents that $i$ channels are in use, and a transition from state $i$ to state $i + 1$ is with rate $(N - i)\lambda$ for $i < c$. This transition implies that if $i$ portables are busy in the cell, then the incoming (outgoing) calls to (from) these busy portables are dropped immediately and do not consume any free channels. Several measures are defined for the busy-line model. Let $n_c$ be the number of incoming calls, $n_A$ be the number of completed calls, $n_D$ be the number of lost calls because of busy lines, and $n_L$ be the number of lost calls because no channel is available. It is clear that

$$n_c = n_A + n_D + n_L$$

(1)

The ratio of the effective call arrival rate per portable is defined as

$$\lambda_e = \frac{n_c - n_D}{n_c} \lambda$$

Note that to improve the performance of a PCS network, $\lambda_e$ should be considered to determine the number of channels, not $\lambda$. Let $p_b$ be the blocking probability and $p_b^*$ be the blocking probability which excludes the dropped calls caused by the busy-line effect (this probability is referred to as the effective blocking probability). That is,

$$p_b = \frac{n_l}{n_c}, \quad p_b^* = \frac{n_l}{n_c - n_D}$$

(2)

Note that for the Erlang-B system, $p_b = p_b^*$ is expressed by the Erlang-B equation. In the busy-line model, $p_b \neq p_b^*$. Let $x$ be the expected number of incoming calls arriving during one conversation. Then

$$n_D = xn_A$$

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(a) The state diagram of the used channels (exclude the busy line effect)

(b) The state diagram of the used channels (include the busy line effect)

Figure 1. The state diagram for the number of used channels
Figure 2 illustrates the case when \( i \) calls are dropped during a conversation. Let \( t' = t_0 + t_1 + \ldots + t_{i-1} \). Because the incoming calls form a Poisson process with rate \( \lambda \) and the holding times have an exponential distribution with mean \( 1/\mu \), we have

\[
x = \sum_{i=1}^{\infty} i \Pr[t' \leq t < t' + t_i]
\]

\[
= \sum_{i=1}^{\infty} i \int_{t_i}^{t_i+1} \int_{t_i}^{t} \int_{t_i}^{t} \mu e^{-\mu t} \lambda e^{-\lambda t} dt \, dt \, dt
\]

\[
= \sum_{i=1}^{\infty} \frac{i \lambda e^{-\lambda t} \lambda e^{-\lambda t} dt \, dt}{(i-1)!}
\]

\[
= \frac{\lambda}{\mu} (\lambda + \mu)^{-i}
\]

Thus

\[
n_D = \frac{\lambda n_A}{\mu} \quad (4)
\]

From (1), (2) and (4), we have

\[
p_b = \frac{p_b^*}{1 + (1 - p_b^*)} \quad (5)
\]

Let \( p_a \) be the probability that a call is completed (i.e., accepted) and \( p_d \) be the probability that a call is dropped because of the busy-line effect, then

\[
p_a = \frac{n_A}{n_C} = \frac{1 - p_b}{1 + (1 - p_b^*)} \quad (6)
\]

\[
p_d = \frac{n_D}{n_C} = sp_a = \frac{(1 - p_b^*)}{1 + (1 - p_b^*)} \quad (7)
\]

and

\[
\lambda_c = \lambda(1 - p_d) = \frac{\lambda}{1 + (1 - p_b^*)} \quad (8)
\]

The probability \( p_b^* \) (i.e., \( \pi_c \)) is derived by considering the state diagram in Figure 1 (b). For \( 1 \leq i \leq c \), we have\(^6\)

\[
\pi_i = \frac{(N-i+1)\lambda}{i\mu} \quad \pi_{i-1} = \frac{\lambda^i \prod_{j=1}^{i} (N-j+1)}{i!\mu^i}
\]

\[
\pi_0 = \left( \frac{N}{i} \right)^e \quad \pi_0
\]

From (9) and the fact that \( \pi_0 + \pi_1 + \ldots + \pi_n = 1 \), we have

\[
p_b^* = \pi_c = \sum_{0 \leq i \leq c} \left( \frac{N}{i} \right) \left( \frac{\lambda}{\mu} \right)^i
\]

Figure 3 (a) illustrates the impact of the busy-line effect. In the figure, \( c = 10 \). Two sets of curves are considered. The dashed curves are for \( N = 200 \), and the solid curves are for \( N = 20 \). In each set of curves, the curve marked \( \circ \) plots the Erlang-B equation, the curve marked \( \bullet \) plots equation (5) for the busy-line model, and the curve marked \( \ast \) plots the simulation results (the simulation setup will be discussed in Section 5). Figure 3 (a) indicates that the busy-line model is consistent with the simulation study. We observe that when \( N \) is small, Erlang-B is not appropriate to predict call blocking for a PCS network with low mobility. Figure 3 (b) plots \( \lambda_c \) against \( \lambda \). When the number of portables in a cell is small, every portable is likely to connect for the first phone call, and the subsequent incoming calls are likely to be blocked as a result of the busy-line effect. Thus, the effective arrival rate per portable is small. When \( N \) is large, it is more likely that a portable is unable to connect to any incoming call (because there is no free channel), and the busy-line effect is less significant, and the effective rate \( \lambda_c \) approaches \( \lambda \).

3. THE MOBILITY MODEL

This section considers the portable mobility as well as the busy-line effect. We assume that in the steady state, there are \( N \) portables in a cell on average. Besides the parameters defined in the busy-line model, two parameters \( \lambda_m \) and \( \alpha \) are introduced. Suppose that the time a portable resides in a cell has an exponential distribution with the expected time \( 1/\lambda_m \). The portable moves to the neighbouring cells with the same probabilities. Thus, in the steady state, the rate \( \lambda_c \) at which portables move to a cell
equals the rate at which portables move out of the cell, where

\[ \lambda_E = N \lambda_m \]

Another parameter, \( \alpha \), represents the probability that a hand-off occurs when a portable moves in a cell. In the mobility model, a state is a pair \((i,j)\) where \(i\) represents the number of used channels \((0 \leq i \leq c)\), and \(j\) represents the number of portables in the cell \((i \leq j \leq \infty; \text{note that the number of portables is no less than the number of used channels})\). Figure 4 illustrates the transitions for state \((i,j)\). The Markov process moves from state \((i,j)\) to \((i,j+1)\) if a new portable not in a conversation arrives at the cell (and no hand-off occurs) when there are \(i\) used channels and \(j\) portables in the cell. The transition rate is \((1-\alpha)\lambda_E\). The Markov process moves from state \((i,j+1)\) to \((i,j)\) if a portable not in a conversation leaves the cell. Since there are \((j-i)\) portables not in a conversation, the transition rate is \((j-i)\lambda_m\). The Markov process moves from state \((i,j)\) to \((i+1,j+1)\) if a new portable in conversation arrives at the cell (and a hand-off occurs) when there are \(i\) used channels and \(j\) portables in the cell. The transition rate is \(\alpha\lambda_E\). The Markov process moves from state \((i+1,j+1)\) to \((i,j)\) if a portable in a conversation leaves the cell. Because there are \((i+1)\) portables in a conversation, the transition rate is \((i+1)\lambda_m\). The Markov process moves from state \((i,j)\) to \((i+1,j)\) if an incoming call arrives for a portable not in conversation. The transition rate is \((j-i)\lambda\). The Markov process moves from state \((i+1,j)\) to \((i,j)\) if a portable completes a conversation. The transition rate is \((i+1)\mu\). The complete state diagram is given in Figure 5. The probability \(\pi_{ij}\) that the

![Figure 3. The impact of the busy-line effect on the effective blocking probability (c = 10. Dashed curves: N = 200; solid curves: N = 20; o: the Erlang-B system; *: the busy-line model; +: simulation)](image)

![Figure 4. The transitions for state \((i,j)\)](image)
Markov process is in state \((i,j)\) is given below. For \(0 < i < c\) and \(j > 0\),

\[
\pi_{ij} = \frac{1}{\lambda_{ij} + (j - i)\lambda + j\lambda_m + i\mu} \\
[(j - i + 1)(\lambda_m\pi_{i,j+1} + \lambda\pi_{i-1,j}) \\
+ (i + 1)(\lambda_m\pi_{i+1,j} + \mu\pi_{i+1,j+1}) \\
+ (1 - \alpha)\lambda_E\pi_{i,j-1} + \alpha\lambda_E\pi_{i-1,j-1}]
\]

(11)

For \(i = 0\) and \(j > 0\),

\[
\pi_{0j} = \frac{(j + 1)\lambda_m\pi_{0,j+1} + \lambda_m\pi_{1,j+1} + \mu\pi_{1,j} + (1 - \alpha)\lambda_E\pi_{0,j-1}}{\lambda_E + j\lambda + j\lambda_m} 
\]

For \(i = c\) and \(j > 0\),

\[
\pi_{cj} = \frac{1}{(1 - \alpha)\lambda_E + j\lambda_m + c\mu} \\
[(j - c + 1)\lambda_m\pi_{c,j+1} \\
+ (1 - \alpha)\lambda_E\pi_{c,j-1} + \alpha\lambda_E\pi_{c-1,j-1} \\
+ (j - c + 1)\lambda\pi_{c-1,j}]
\]

(13)

For \(0 < i = j < c\),

\[
\pi_{ij} = \frac{\lambda_m\pi_{i+1,j+1} + (i + 1)\lambda_m\pi_{i,j+1} + \alpha\lambda_E\pi_{i-1,j} + \lambda\pi_{i-1,j}}{\lambda_E + i\lambda_m + i\mu}
\]

(14)

For \(i = j = c\),

\[
\pi_{cc} = \frac{\lambda_m\pi_{c,c+1} + \alpha\lambda_E\pi_{c-1,c} + \lambda\pi_{c-1,c}}{(1 - \alpha)\lambda_E + c\lambda_m + c\mu}
\]

(15)
For $i = j = 0$,
\[
\pi_{0,0} = \frac{\lambda_m(\pi_{0,1} + \pi_{1,1})}{\lambda_E} \tag{16}
\]

The probability $\alpha$ is derived as follows. Assume that $\lambda_m \ll \lambda$ and consider the last conversation of a portable before it leaves the cell. Figure 6 gives the timing diagram when a hand-off occurs. The incoming calls form a Poisson process, and $t_1, t_2, \ldots, t_{l-1}$ have the same exponential distribution. Since the time that a portable resides in a cell is exponentially distributed, the time when the portable leaves the cell is a random observer of the incoming call process and the residual time $t_j$ (1 $\leq j < i$) is also exponentially distributed. Thus, let $t'$ $= t_0 + t_1 + \ldots + t_{i-1}$,
\[
\alpha = \Pr[t > t'] = \sum_{i=1}^{\infty} \Pr[t > t' \text{ and } t' = t_0 + \ldots + t_{i-1}]
\]
\[
= \sum_{i=1}^{\infty} \left[ \int_{t=0}^{\infty} \mu e^{-\mu t} \int_{t'=0}^{\infty} p_0 \rho_{l-1}^{(i-1)} \left( \frac{\lambda t}{i} \right) e^{-\lambda t} dt' dt \right]
\]
\[
= \sum_{i=1}^{\infty} \left[ \int_{t=0}^{\infty} \mu e^{-\mu t} \left( \frac{\lambda t}{i} \right) p_0 \left[ 1 - \sum_{j=1}^{l-1} \left( \frac{\lambda t}{j} \right) e^{-\lambda t} \right] dt \right]
\]
\[
= \sum_{i=1}^{\infty} \left[ \left( \frac{\lambda}{\mu} \right)^{i-1} p_0 - \left( \frac{\lambda}{\lambda + \mu} \right)^{i-1} p_0^{(i-1)} \sum_{j=0}^{l-1} \left( \frac{\lambda}{\lambda + \mu} \right)^j \right]
\]
\[
= \frac{\left( \frac{\lambda}{\mu} \right) p_0}{1 + \left( \frac{\lambda}{\mu} \right) - \left( \frac{\lambda}{\mu} \right)^2 p_0} \tag{17}
\]

The probabilities $\pi_{ij}$ are computed numerically by a two-level iterative procedure. Note that the state space for the mobility model is infinite (because $i \leq j \leq \infty$). In order to compute $\pi_{ij}$ numerically, we select a number, $N_m$, such that $i \leq j \leq N_m$. In the procedure, we iterate by increasing $N_m$ until the output measure converges. Let $N_m(m)$ be the value chosen in the $m$th iteration. In this iteration, the probabilities $p_{ij}, p^*_i$ and $\alpha$ are also computed iteratively. Let $\pi_{ij}(m), p^*_i(m),$ and $\alpha(m)$ be the values computed in the $k$th inner iteration when $N_0 = N_m(m)$. The procedure is described below.

Step 1. $N_0(0) \leftarrow N_0, m \leftarrow 0, p^*_0(0) \leftarrow 0.$ (In this paper, $N_0 = 1000.$)

Step 2. For $0 \leq i \leq c, 0 \leq j \leq N_m(m)$,
\[
p_{ij}(0,m) \leftarrow \frac{i}{0.5(c+1)(c+2) + (c+1)N_m(m)}
\]
\[
p^*_i(0,m) \leftarrow \sum_{c<j<N_m(m)} \pi_{ij}(0,m)
\]
\[
\alpha(0,m) \leftarrow 0 \text{ and } k \leftarrow 1
\]

Step 3. Compute $\pi_{ij}(k,m)$ using equations (11)–(16), and the state probabilities computed in the previous iteration.

Step 4. $p^*_i(k,m) \leftarrow \sum_{c<j<N_m(m)} \pi_{ij}(k,m)$.

Step 5. Compute $\alpha(k,m)$ using $p^*_i(k,m)$ and equations (6) and (17).

Step 6. If the difference of $\pi_{ij}(k,m)$ and $\pi_{ij}(k,m - 1)$ is larger than a threshold for all $c \leq i \leq N_m(m)$, then $k \leftarrow k + 1$ and go to Step 3.

Step 7. If the difference of $p^*_i(k,m) = p^*_i(m,k)$ and $p^*_i(m-1)$ is larger than a threshold then $N_m(m) \leftarrow N_m(m-1) + \delta$ and go to Step 2. (In this paper, $\delta = 10$).

Although we do not have proof of the convergence of the procedure, it does converge for all experiments studied in this paper.

Figure 7 plots $p^*_i$ for the mobility model for $c = 8$ and $N = 80$. The solid curves represent $\lambda_m = 0.02 \mu$. The dashed curves represent $\lambda = 0.01 \mu$. The plain curves represent the analytical results. The curves marked $\circ$ represent simulation. In these two sets of experiments, the procedure converges at $N_m < 4000$ in all cases. Figure 7 indicates that the mobility model is consistent with the simulation study.

Our model can also be used to derive the distribution of the portable population in a cell. Consider the state diagram in Figure 5. Let $\pi_i$ be the steady state probability that there are $i$ portables in a cell. Then $P_i = \sum_{j=i}^{\infty} p_{ij}.$ If we only consider the aggregate probability $\pi_i$, then the model degenerates into an $M/M/m$ queue with arrival rate $\lambda_E$ and completion rate $\lambda_m$. From the standard technique,
\[
P_i = \frac{N_i e^{-N}}{i!} \tag{18}
\]

Figure 8 plots (18) and validates the equation against the simulation experiments. The population distribution has been used to study portable registration and deregistration for a PCS network.
4. SIMULATION

This section presents the simulation results. To simulate a very large PCS network, we proposed a wrap-around hexagonal topology for simulation. This approach eliminates the boundary effect which occurs in an un-wrapped topology. Study indicated that the wrapped topology yields better accuracy with less computing resources compared with the un-wrapped topology (to achieve the same output accuracy for a 37-node wrapped topology, at least 169 nodes are required in an un-wrapped topology). An 8 x 8 wrapped mesh topology is considered in this paper (see Figure 9). The mobility behaviour of portables in the simulation is described by a two-dimensional random walk proposed in Reference 9. In this model, a portable stays in a cell for a period of time which has an exponential distribution with mean $1/\lambda_m$. Then the portable moves to one of the four neighbouring cells with the same routing probabilities 0.25. Initially, every cell has $N = 80$ portables. Four hundred thousand incoming calls are simulated to ensure that the confidence interval of the 95 per cent confidence level of $p_f$ is less than 3 per cent of the mean value $E[p_f]$. Figures 10 and 11 plot $p_b$, $p_a$, $p_d$, and $\alpha$ against $\lambda$. In these figures, $c = 8$, $N = 80$, $\lambda_m = 0.01\mu$ and $0.02\mu$. Figure 10 (a) plots $p_b$ for $\lambda_m = 0.01\mu$, $\lambda_m = 0.02\mu$, and Erlang-B. Figure 10 (b) plots $p_d$ against $\lambda$. The figure indicates that by doubling the mobility from $0.01\mu$ to $0.02\mu$, the call completion probability dropped from 1 per cent to 7 per cent when $\lambda$ increases from 0.1$\mu$ to 0.7$\mu$. Figure 11 (a) plots $p_d$ against $\lambda$. The probability $p_d$ decreases as the
Increasing the mobility has the effect of increasing the randomness of the incoming call traffic to a cell, which has the similar effect of increasing the portable population in the busy-line model. Note that $P_d$ and $P_a$ measured from the simulations are consistent with the equation

$$P_d = \frac{\lambda P_a}{\mu}$$

derived in our analytical model (see Equation (3)). For example, consider $\lambda = 0.7\mu$, $\lambda_m = 0.01\mu$, and $P_a = 0.4456$. From the simulation, $P_d = 0.3107$ (see Figure 11 (a)), and from the analytical analysis, $P_d = 0.3112$, figure 11 (b) plots $\alpha$, the probability of hand-off, against $\lambda$. Note that when $\lambda$ is large (e.g., $\lambda > 0.4$), changing the $\lambda$ value does not have a significant impact on $\alpha$ as when $\lambda$ is small (e.g., $\lambda < 4$). The $\alpha$ values measured from the simulations are consistent with equation (17) derived from our analytical model (see Figure 11 (b)).

Figure 12 shows the impact of $N$ (where $\lambda_m = 0.25\mu$ and $c = 5$). In Figure 12 (a), $p_b^*$ for a PCS system with a small $N$ is much larger than a PCS system with a large $N$. This phenomenon is caused by the mobility of individual portables ($p_b^*$ is not directly affected by the busy-line effect because the drops as a result of busy lines are excluded from this measure). For a small $N$, a portable movement will significantly change the net call arrival rate to a cell. In other words, the individual portable moment effect significantly increases the variance of call arrival rate to a cell for a small $N$. In Figure 12 (b), $p_b$ is affected by the individual portable

$$\begin{align*}
N\lambda/\mu & \\
\lambda_m = 0.02\mu & \\
\lambda_m = 0.01\mu & \\
\end{align*}$$

$$(a) \text{ The blocking probability (Simulation results)} \quad \begin{align*}
N\lambda/\mu & \\
\lambda_m = 0.02\mu & \\
\lambda_m = 0.01\mu & \\
\end{align*}$$

$$(b) \text{ The call completion probability (Simulation results)}$$

Figure 10. The probabilities $p_b$ and $p_a$
Figure 11. The probabilities $p_d$ and $\alpha$

Figure 12. The effect of $N (\lambda_m = 0.25\mu, c = 5)$
movement when the offered load \((\lambda N / \mu)\) is small (and \(p_b\) for a small \(N\) is larger than \(p_b^*\) for a large \(N\), as explained above). When the offered load is large (e.g., \(\lambda N / \mu > 4.8\) in Figure 12 (b)), \(p_b\) for a small \(N\) is smaller than \(p_b^*\) for a large \(N\). This phenomenon is explained as follows. For the same (large) offered load, the call arrival rate to a portable is larger for a smaller \(N\), and more calls are dropped as a result of busy lines. These dropped calls do not contribute to the numerator of \(p_b\) (note that the busy lines are counted in the denominator). On the other hand, when \(N\) is very large, the call arrival rate to a portable is small. Thus, the busy-line effect is insignificant, and most call arrivals should be connected if there are free channels. In other words, the effective call arrivals are not reduced by the busy-line effect for a large \(N\). The consequence is that the probability that all channels are busy increases, and \(p_b\) is large compared with the case when \(N\) is small. Note that \(p_b^* \gg p_b\) for \(N < 50\) and \(p_b^* \approx p_b\) for \(N > 400\). In other words, the busy-line effect can be ignored only if the number of portables is much larger than the number of channels. Theoretically, the \(p_b\) curves for the previously proposed models\(^{1-4}\) approaches our model when \(N \rightarrow \infty\). Figure 12 indicates that these models are appropriate only if \(N\) is 40 times larger than \(c\). If \(N\) is not sufficiently large, the previously proposed models underestimate \(p_b\) for a small offered load, and overestimate \(p_b^*\) for a large offered load. The previously proposed models always underestimate \(p_b^*\).

5. CONCLUSIONS

Several analytical models\(^{1-4}\) have been proposed to study the blocking probability of a PCS network. These models consider an aggregate new call arrival stream to a cell. The portable mobility is modelled by an extra aggregate hand-off call arrival stream to the cell. These models do not capture two important features of a PCS network: the busy-line effect and the movement of individual portables. This paper proposed a new analytical model to address these two features by considering \(N\), the average number of portables in a cell as an input parameter. With this input parameter, we have also derived the distribution of the portable population in a cell. The model was validated against the simulation experiments. Our study indicated that the previously proposed models approximate a special case (i.e., \(N \rightarrow \infty\)) of our model. When \(N\) is not sufficiently large, the previously proposed models underestimate the blocking probability \(p_b\) (new call blocking and hand-off call forced termination) for small offered load because the individual portable movement feature is not captured; and overestimate \(p_b^*\) for a large offered load because the busy-line effect is not captured.

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Authors’ biographies:

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