Optimal Traffic Scheduling in Vehicular Delay Tolerant Networks

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***Abstract*— In a vehicular delay tolerant network, the problem of scheduling the traffic from a roadside unit to passing-by vehicles is studied. A cost function is associated with a scheduled transmission. And if a delay bound is violated, a penalty cost is charged. The optimal stopping theory is applied to decide when the roadside unit should schedule its accumulated traffic to a passing-by vehicle such that the rate of cost is minimized. It is shown that the optimal scheduling strategy is a pure-threshold strategy, i.e., upon a vehicle arrival, if the queueing delay at the roadside unit is above a threshold, it is optimal to schedule a transmission via the vehicle. Simulation results validate the effectiveness of the derived optimal rule.**

***Index Terms*— Vehicular delay tolerant networks, optimal stopping, scheduling.**

I. Introduction

Vehicular delay tolerant networks have recently gained much research attention [1]–[4]. A typical vehicular delay tolerant network consists of unconnected stationary RoadSide Units (RSUs) and is deployed along highways in sparsely populated or unpopulated zones. It is very likely that the RSUs in those zones are driven by batteries [3]. Only a few RSUs are connected to the Internet, and other RSUs should send their traffic to those RSUs with Internet connection. There is no direct connection among the RSUs, and passing-by vehicles serve as relays, to help forward traffic among the RSUs. For such networks, delay minimization problem in a Markov decision process framework is studied in [1], while a model is given in [2] to probabilistically decide whether a passing-by vehicle is suitable to carry the traffic of an RSU such that the total transit delay is minimized. Minimizing the energy consumption of the RSUs, under the constraint of satisfying the communication requirements of the passing-by vehicles, is studied in [3].

In this letter, we also consider the problem of traffic scheduling from an RSU. Different from the existing research efforts that consider either delay or energy consumption, we take both into account. In specific, a source RSU is assumed to try to send traffic to a destination RSU (with Internet connection). The source RSU needs to select a passing-by vehicle as a relay to carry and forward its traffic to the destination. It has been shown through empirical measurement [5] that, the inter-arrival times of vehicles at a roadside point are independent and identically exponentially distributed. In other words, if we let $\{\tau_1, \tau_2, \cdots, \tau_n, \cdots\}$ denote the inter-arrival times of consecutive vehicles at the source RSU, then they are i.i.d. exponential random variables with parameter μ. So $E[\tau_n] = 1/\mu$, where $E[\cdot]$ denotes expectation. And we use $t_n = \sum_{i=1}^{n} \tau_i$ to denote the nth vehicle's arrival time at the source RSU. Here we set $t_0 = 0$. At the source RSU, the traffic is generated at a constant rate r, and buffered, waiting for being scheduled to a passing-by vehicle. Our target is to minimize the rate of the overall cost of the system. Since both energy consumption and delay are considered, the overall cost is defined as a weighted sum of costs related to energy consumption and delay, as elaborated in the following. Similar weighted cost structures are also adopted in [4], [6], [7].

Upon a vehicle arrival, the source RSU needs to decide whether it should *stop* waiting and transmit its accumulated traffic to the vehicle. If the RSU decides not to stop, it will continue to buffer traffic and wait for the next vehicle arrival and decide again. If the RSU decides to stop waiting at the nth vehicle arrival, the accumulated traffic with amount $s_n = rt_n$ is sent to the vehicle with a constant transmission power P and a constant data transmission rate R. For the data transmission, there is usually a communication overhead between the RSU and the vehicle (for example, request-to-send [RTS], clear-to-send [CTS], and ACK if IEEE 802.11 medium access control [MAC] protocol is applied. A detailed example is given in Section III). Assume the transmission power of the overhead is also P and the duration of the overhead transmission is T_o. Then total energy consumption in the data and overhead transmission is $wP\left(\frac{s_n}{R} + T_o\right)$, where w (unit: unit of cost per Joule) is the cost weight of energy consumption. On the other hand, it is desired that large queueing delay is avoided even in a delay tolerant network. Let T denote the desired queueing delay bound. Therefore, upon a vehicle arrival, if the RSU's queueing delay (also the RSU's waiting time) is above T, the RSU is forced to transmit its accumulated traffic to the vehicle, and similar to [6], a penalty with amount B is charged for delay bound violation.

Upon the nth vehicle arrival, define *observations* $X_n = \{t_n, s_n\}, n > 0$. Let $C = \min\{n : t_n \geq T\}$ denote the index of the vehicle to which the accumulated traffic is forced to be released. If it is decided to let the nth vehicle carry the accumulated traffic with amount s_n (i.e., decided to *stop* observations, simplified as "*stop*" in the sequel), then the *cost function* is given as

$$y_n = wP\left(\frac{s_n}{R} + T_o\right) + B\mathbf{I}(n = C),\ n \leq C$$

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where $\mathbf{I}(\cdot)$ is an indicator function. To enforce stopping at the Cth vehicle, define $y_n = \infty$ for $n > C$.

Let N denote the stopping time, i.e., the RSU stops at the Nth vehicle arrival, and the corresponding stopping rule is also denoted N. In this letter, we are interested in deriving the optimal stopping rule of the RSU, such that the rate of cost is minimized. In other words, if the RSU applies a given stopping rule N repeatedly, we have i.i.d. stopping times $\{N_1, N_2, \cdots, N_m, \cdots\}$ (note that once the RSU stops at a vehicle, the next vehicle is called Vehicle 1 again), and i.i.d. costs $\{y_{N_1}, y_{N_2}, \cdots, y_{N_m}, \cdots\}$. So the rate of cost (average cost per unit time) is $\sum_i y_{N_i} / \sum_i t_{N_i}$, which converges to $E[y_N]/E[t_N]$ by the law of large number. Therefore, our objective is to achieve

$$\min_{N>0} \quad \frac{E[y_N]}{E[t_N]}. \tag{1}$$

II. Optimal Scheduling Strategy

Problem (1) is to decide when the RSU should stop and transmit its accumulated traffic to a passing-by vehicle. Note that when $t_n < T$, there does not exist queueing delay penalty B. Thus, it is desired to keep $t_N < T$ and make t_N as close to T as possible. Therefore, an intuitive strategy is: upon arrival of a vehicle (say Vehicle a), if the RSU expects that the queueing delay upon the next vehicle arrival (if the RSU does not stop at Vehicle a) will exceed T, then the RSU should stop at Vehicle a, i.e., transmit its accumulated traffic to Vehicle a. Actually as shown in Section III, this intuitive rule is not optimal.

The theory of optimal stopping [8] is proposed to be applied to optimally solve Problem (1). Note that Problem (1) is not easy to solve directly. Thus, by using the λ-minimization technique [8], we first solve the following ordinary optimal stopping problem

$$\min_{N>0} E[z_N] = \min_{N>0} E[y_N - \lambda t_N], \ \lambda > 0 \tag{2}$$

where $z_N \triangleq y_N - \lambda t_N$ is the cost function, whose expectation is to be minimized. And the physical meaning of λ is rate of cost. Next we first derive the optimal stopping rule of Problem (2) in Section II-A, and then derive the optimal stopping rule of Problem (1) in Section II-B.

A. Optimal Stopping Rule of Problem (2)

The basic idea is to first derive the myopic rule of Problem (2), and then theoretically prove the myopic rule is the optimal stopping rule.

Theorem 1: The myopic stopping rule of Problem (2) is

$$N^\dagger = \begin{cases} 1 & \text{if } 0 < \lambda \le \alpha \\ \min\{n : t_n \ge T_\lambda\} & \text{if } \alpha < \lambda < \beta \\ \min\{n : t_n \ge T\} & \text{if } \lambda \ge \beta \end{cases} \tag{3}$$

where

$$\begin{aligned} \alpha &= \mu B \exp(-\mu T) + \tfrac{wrP}{R} \\ \beta &= \mu B + \tfrac{wrP}{R} \\ T_\lambda &= T - \tfrac{1}{\mu} \ln\left(\tfrac{\mu R B}{\lambda R - wrP}\right). \end{aligned}$$

Proof: According to [8], the myopic stopping rule of Problem (2) is given as

$$N^\dagger = \min\{n : z_n \le E[z_{n+1}|X_n]\}. \tag{4}$$

The physical meaning of the myopic rule in (4) is that, if the cost of the nth vehicle is less than the expectation of the cost of the $(n+1)$th vehicle, we should select the nth vehicle to carry the accumulated traffic.

When $t_n \ge T$, i.e., $n \ge C$, the RSU is forced to stop. So (4) can be simplified as $N^\dagger = C = \min\{n : t_n \ge T\}$.

When $t_n < T$, we have

$$\begin{aligned} z_n &= wP(\tfrac{s_n}{R} + T_\text{o}) - \lambda t_n \\ z_{n+1} &= wP(\tfrac{s_{n+1}}{R} + T_\text{o}) + B\mathbf{I}(n+1 = C) - \lambda t_{n+1}. \end{aligned}$$

Recall that $t_n = \sum_{i=1}^n \tau_i$ and $s_n = r t_n$. Then $z_n \le E[z_{n+1}|X_n]$ is equivalent to

$$\begin{aligned} & wP\left(\frac{r\sum_{i=1}^n \tau_i}{R} + T_\text{o}\right) - \lambda \sum_{i=1}^n \tau_i \\ & \quad \le wP\left(\frac{r(\sum_{i=1}^n \tau_i + E[\tau_{n+1}|X_n])}{R} + T_\text{o}\right) \\ & \quad + BE[\mathbf{I}(n+1=C)|X_n] - \lambda\left(\sum_{i=1}^n \tau_i + E[\tau_{n+1}|X_n]\right) \end{aligned}$$

which leads to

$$BE[\mathbf{I}(n+1=C)|X_n] + \left(\frac{wrP}{R} - \lambda\right) E[\tau_{n+1}|X_n] \ge 0. \tag{5}$$

Further we have $E[\tau_{n+1}|X_n] = \frac{1}{\mu}$ and

$$\begin{aligned} & E[\mathbf{I}(n+1=C)|X_n] = \text{Prob}(n+1 = C|X_n) \\ & = \text{Prob}(t_{n+1} \ge T|X_n) = \text{Prob}(t_{n+1} - t_n \ge T - t_n) \\ & = \text{Prob}(\tau_{n+1} \ge T - t_n) = \exp\left(-\mu(T - t_n)\right). \end{aligned}$$

So (5) is rewritten as

$$B \exp\left(-\mu(T - t_n)\right) \ge \frac{\lambda R - wrP}{\mu R}. \tag{6}$$

It can be seen that, when $0 < \lambda \le \alpha$, (6) always holds. So the myopic stopping rule of Problem (2) is $N^\dagger = 1$. When $\lambda \ge \beta$, (6) never holds. This means the RSU will wait until it is forced to stop. So the myopic stopping rule of Problem (2) is $N^\dagger = \min\{n : t_n \ge T\}$. When $\alpha < \lambda < \beta$, (6) leads to $t_n \ge T_\lambda$, where $T_\lambda < T$. So the myopic stopping rule of Problem (2) is $N^\dagger = \min\{n : t_n \ge T_\lambda\}$. ∎

Theorem 2: The myopic rule $N^\dagger$ is the optimal stopping rule of Problem (2).

Proof: According to Theorem 2 and Corollary 2 in Chapter 5 of [8], $N^\dagger$ is the optimal stopping rule for Problem (2) if the following conditions are satisfied:

- i) The problem is monotone;
- ii) z_n can be written as $z_n = u_n + w_n$, where $E[\sup_n |u_n|] < \infty$ and w_n is nonnegative and nondecreasing a.s.;
- iii) $\lim_{n\to\infty} z_n = z_\infty$ a.s..

Firstly, Condition i) means if $N^\dagger$ calls for stopping at the nth vehicle, then it will also call for stopping at the $(n+1)$th vehicle (assuming it does not stop in previous n vehicles). This is apparent, since t_n is nondecreasing.

Secondly, z_n can be written as $z_n = (-\lambda t_n) + y_n$, where y_n is nonnegative and nondecreasing from its definition. So next we focus on proving $E[\sup_n |-\lambda t_n|] < \infty$. Because of the fact that the problem is forced to be stopped when $n = C$, we can equivalently set $t_n = t_C$ if $n > C$. Thus, we have

$$t_n = t_n \mathbf{I}(n \le C) + t_C \mathbf{I}(n > C) \le t_C \tag{7}$$

which leads to

$$E[\sup_n |-\lambda t_n|] \le \lambda E[t_C] = \lambda \left(T + \frac{1}{\mu}\right) < \infty.$$

Thus, Condition ii) is satisfied, and we have $t_C < \infty$ a.s..

Thirdly, to prove Condition iii) we define $z_\infty \triangleq +\infty$. Since y_n is nondecreasing, we have

$$\lim_{n\to\infty} y_n = \liminf_{n\to\infty} y_n = \limsup_{n\to\infty} y_n. \tag{8}$$

We also have

$$\begin{aligned} \liminf_{n\to\infty} z_n &\overset{(a)}{\ge} \liminf_{n\to\infty} y_n - \lambda t_C \overset{(b)}{=} \lim\nolimits_{n\to\infty} y_n - \lambda t_C \\ &= \lim\nolimits_{n\to\infty} [y_n \mathbf{I}(n \le C) + \infty \mathbf{I}(n > C)] - \lambda t_C \\ &= \infty - \lambda t_C = z_\infty \text{ a.s.} \end{aligned} \tag{9}$$

where (a) is from (7) and (b) is from (8). Considering (9) and $\limsup_{n\to\infty} z_n \le \limsup_{n\to\infty} y_n = \lim_{n\to\infty} y_n = z_\infty$ a.s., it can be concluded that $\limsup_{n\to\infty} z_n = \liminf_{n\to\infty} z_n = z_\infty$, which leads to $\lim_{n\to\infty} z_n = z_\infty$ a.s.. Thus, Condition iii) is satisfied. ■

Theorem 3: With the myopic stopping rule (3), the minimum cost of Problem (2), denoted $V_{N^\dagger}(\lambda)$, is

$$V_{N^\dagger}(\lambda) = \begin{cases} wPT_\text{o} + B\exp(-\mu T) - \frac{\lambda R - wrP}{\mu R} & \text{if } 0 < \lambda \le \alpha \\ wPT_\text{o} - (\lambda - \frac{wrP}{R})T_\lambda & \text{if } \alpha < \lambda < \beta \\ wPT_\text{o} + B - (\lambda - \frac{wrP}{R})(T + \frac{1}{\mu}) & \text{if } \lambda \ge \beta. \end{cases} \tag{10}$$

Proof: The minimum cost of Problem (2) is

$$\begin{aligned} &V_{N^\dagger}(\lambda) = E[y_{N^\dagger} - \lambda t_{N^\dagger}] \qquad (11) \\ &= wPT_\text{o} + B\text{Prob}(N^\dagger = C) - \left(\lambda - \frac{wrP}{R}\right) E[t_{N^\dagger}]. \end{aligned}$$

When $0 < \lambda \le \alpha$, the optimal stopping rule is $N^\dagger = 1$. Thus we have

$$\begin{aligned} \text{Prob}(N^\dagger = C) &= \text{Prob}(t_1 \ge T) = \exp(-\mu T), \\ E[t_{N^\dagger}] &= E[t_1] = \tfrac{1}{\mu}. \end{aligned}$$

Then from (11) we have

$$V_{N^\dagger}(\lambda) = wPT_\text{o} + B\exp(-\mu T) - \frac{\lambda R - wrP}{\mu R}. \tag{12}$$

When $\alpha < \lambda < \beta$, the optimal stopping rule is $N^\dagger = \min\{n : t_n \ge T_\lambda\}$. To express $V_{N^\dagger}(\lambda)$ we need to calculate $\text{Prob}(N^\dagger = C)$ and $E[t_{N^\dagger}]$. We have

$$\begin{aligned} \text{Prob}(N^\dagger = C) &= \text{Prob}(t_{N^\dagger} \ge T | t_{N^\dagger} \ge T_\lambda) \\ &= \text{Prob}(t_{N^\dagger} - T_\lambda \ge T - T_\lambda). \end{aligned} \tag{13}$$

Note that $t_{N^\dagger} - T_\lambda$ is actually the interval from the moment when waiting time is equal to T_λ to the moment when the next vehicle arrives. Due to memoryless feature of exponentially distributed inter-arrival times of vehicles, we have

$$\text{Prob}(t_{N^\dagger} - T_\lambda \ge T - T_\lambda) = \exp(-\mu(T - T_\lambda)) = \frac{\lambda R - wrP}{\mu RB}$$

and $E[t_{N^\dagger} - T_\lambda] = \frac{1}{\mu}$, i.e., $E[t_{N^\dagger}] = T_\lambda + \frac{1}{\mu}$. Then from (11), we have

$$V_{N^\dagger}(\lambda) = wPT_\text{o} - \left(\lambda - \frac{wrP}{R}\right) T_\lambda. \tag{14}$$

Next consider $\lambda \ge \beta$, when the optimal stopping rule is $N^\dagger = \min\{n : t_n \ge T\}$, i.e., $N^\dagger = C$, and thus $\text{Prob}(N^\dagger = C) = 1$. Similar to the above derivation of $E[t_{N^\dagger}]$, we have $E[t_C - T] = \frac{1}{\mu}$, i.e., $E[t_C] = T + \frac{1}{\mu}$, which leads to

$$V_{N^\dagger}(\lambda) = wPT_\text{o} + B - \left(\lambda - \frac{wrP}{R}\right)\left(T + \frac{1}{\mu}\right). \tag{15}$$

This completes the proof. ■

It can be seen that $V_{N^\dagger}(\lambda)$ given in (10) is a continuous and strictly decreasing function of λ.

B. Optimal Stopping Rule of Problem (1)

From Theorem 1 in Chapter 6 of [8], the optimal stopping rule of Problem (1), N^*, is in form of $N^\dagger$ given in (3) with $\lambda = \lambda^*$, where λ^* satisfies $V_{N^\dagger}(\lambda^*) = 0$. Therefore, to obtain N^*, we need to find the root of $V_{N^\dagger}(\lambda) = 0$. Note that according to (10), $V_{N^\dagger}(\lambda)$ has three different expressions in three regions, $0 < \lambda \le \alpha$, $\alpha < \lambda < \beta$, and $\lambda \ge \beta$, respectively.

Consider the first region $0 < \lambda \le \alpha$. By setting $V_{N^\dagger}(\lambda) = 0$ in (12), we have

$$\lambda^* = \mu wPT_\text{o} + \mu B\exp(-\mu T) + \frac{wrP}{R} = \mu wPT_\text{o} + \alpha$$

which contradicts the fact that $\lambda \le \alpha$. Therefore, no root of $V_{N^\dagger}(\lambda) = 0$ exists when $0 < \lambda \le \alpha$.

When λ changes from α to $+\infty$, $V_{N^\dagger}(\lambda)$ continuously and strictly decreases from $V_{N^\dagger}(\lambda)|_{\lambda=\alpha} = wPT_\text{o} > 0$ to $-\infty$. Therefore, there exists a unique root of $V_{N^\dagger}(\lambda) = 0$ for $\lambda > \alpha$. If $V_{N^\dagger}(\lambda)|_{\lambda=\beta} < 0$, i.e., $wPT_\text{o} < \mu BT$, the root is in region $\alpha < \lambda < \beta$, which (based on (14)) means λ^* is the root of

$$wPT_\text{o} = \left(\lambda - \frac{wrP}{R}\right)\left[T - \frac{1}{\mu}\ln\left(\frac{\mu RB}{\lambda R - wrP}\right)\right]. \tag{16}$$

On the other hand, if $V_{N^\dagger}(\lambda)|_{\lambda=\beta} \ge 0$, i.e., $wPT_\text{o} \ge \mu BT$, the root is in region $\lambda \ge \beta$, which (based on (15)) means

$$\lambda^* = \frac{wrP}{R} + \frac{\mu(wPT_\text{o} + B)}{\mu T + 1}. \tag{17}$$

Overall, if $wPT_\text{o} < \mu BT$, the optimal stopping rule of Problem (1) is $N^* = \min\{n : t_n \ge T_{\lambda^*}\}$ with λ^* being the root of (16), and the rate of cost is λ^*. If $wPT_\text{o} \ge \mu BT$, the optimal stopping rule of Problem (1) is $N^* = \min\{n : t_n \ge T\}$ and the rate of cost is given in (17). In either case, the optimal stopping rule is a pure-threshold strategy, i.e., upon a vehicle (say Vehicle n) arrival, if t_n exceeds a fixed threshold, the RSU should stop and transmit its traffic to the vehicle.

III. Performance Evaluation

In this section we provide numerical and simulation results. IEEE 802.11 MAC protocol is applied to coordinate the transmission between the RSU and vehicles, and we consider energy consumption of both the RSU and vehicles. Note that the case when energy consumption of the RSU only is considered can be treated similarly. The data transmission rate is $R = 11$ Mbps. The overhead duration $T_{\rm o}$ includes RTS time ($\frac{\text{RTS size}}{\text{Basic rate}}$ plus preamble time), CTS time ($\frac{\text{CTS size}}{\text{Basic rate}}$ plus preamble time), ACK time ($\frac{\text{ACK size}}{R}$ plus preamble time), MAC header time ($\frac{\text{MAC header size}}{R}$), and preamble time for data information transmission. The size of RTS, CTS, ACK, and MAC header are 20 bytes, 14 bytes, 14 bytes, and 34 bytes, respectively. The basic rate is 2 Mbps, and each preamble time is 192 μs. Other parameters are: $P = 15.5$ dBm = 35.5 mW, $r = 5$ bits/second, $\mu = 1/400$ vehicles/second, $T = 30$ minutes, and $w = 1$ unit of cost/μJoule. We vary the penalty cost B for delay bound violation. For any B value, the simulation statistics are collected as average for 10000 stops. Two heuristic stopping rules are simulated for comparison: $N_{h1} = \min\{n : t_n \geq T - \frac{1}{\mu}\}$ (actually the intuitive rule discussed at the beginning of Section II) and $N_{h2} = \min\{n : t_n \geq T - \frac{2}{\mu}\}$. Recall that $E[\tau_n] = \frac{1}{\mu}$. Thus, N_{h1} (or N_{h2}) is to stop at the moment by expecting that, if not stopping, the arrival of the next vehicle (or the one after the next vehicle) will make the RSU's waiting time, also the queueing delay, exceed T.

Fig. 1 shows the thresholds of waiting time used in the three stopping rules. The threshold value in our optimal stopping rule N^* is obtained numerically. It can be seen that, when B is small ($B \leq \frac{wPT_{\rm o}}{\mu T}$ according to discussion in the preceding section), it is optimal for the RSU to wait until being forced to stop, i.e., the threshold is 1800 seconds (30 minutes). This is because, although there is a penalty cost for a forced stopping, the penalty cost is dominated by the cost saving that comes from the fact that the communication overhead in a transmission serves more accumulated traffic. When B increases beyond $\frac{wPT_{\rm o}}{\mu T}$, the penalty cost becomes dominant and the threshold of stopping decreases with B. When B goes to infinity, the optimal threshold approaches 0, i.e., the RSU should stop at the first vehicle arrival. Fig. 2 shows the theoretically analyzed (i.e., λ^*) and simulated rate of cost in our optimal stopping rule. It can be seen that the analytical and simulation results closely match, thus validating our analysis. Fig. 2 also shows simulated rates of cost in the two heuristic stopping rules. Our optimal stopping rule outperforms the two heuristic rules.

IV. Conclusion

The problem of traffic scheduling in vehicular delay tolerant networks is studied, by taking into account the transmission energy consumption and the queueing delay. Cost functions are defined, and the rate of overall cost is minimized. Our analytical results show that the RSU should transmit its traffic to the passing-by vehicle if its queueing delay is above a threshold. The optimal threshold and the corresponding minimal rate of cost can be derived analytically, and are validated by simulation.

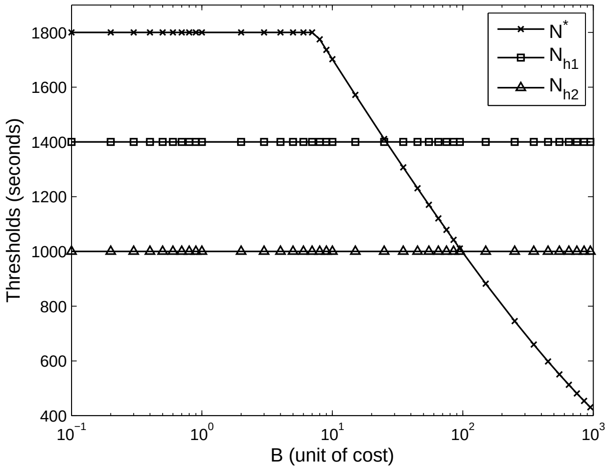

Fig. 1. Thresholds in the optimal and heuristic stopping rules

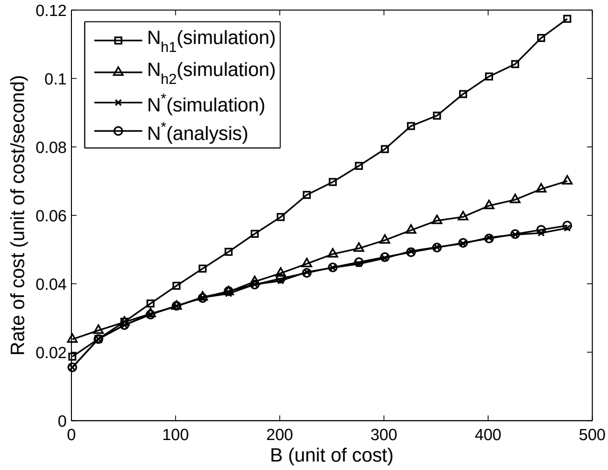

Fig. 2. Rates of cost in the optimal and heuristic stopping rules

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