Optimal Traffic Scheduling Between Roadside Units in Vehicular Delay Tolerant Networks

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***Abstract*— This paper investigates the problem of traffic scheduling between roadside units (RSUs) in a vehicular delay tolerant network. A source RSU needs the help of passing-by vehicles to forward its traffic to a destination RSU. Costs are associated with energy consumption and information loss. When a vehicle arrives, the source RSU needs to decide whether to stop, i.e., transmit its traffic to the vehicle, or skip this vehicle and continue to wait for other vehicles. The source RSU's objective is to achieve the minimal rate of cost. In this paper, we theoretically derive an optimal stopping strategy of the source RSU. Simulation results are presented to show the effectiveness of the derived strategy.**

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

I. INTRODUCTION

Traffic scheduling problems in vehicular delay tolerant networks (VDTNs) have been attracting increasing research interests in the past years. One type of VDTN is installed in less-populated remote areas, which includes a number of roadside units (RSUs), and only a limited number of RSUs have connection to backbone networks [1]. The isolated RSUs (i.e., the RSUs without backbone network connection) are deployed to serve as gateways for sensor networks (for example, sensor networks for monitoring environment or wildlife [2]–[5]) in less-populated remote areas. Since it may be costly to set up direct communication connections from the isolated RSUs to backbone networks, passing-by vehicles may provide a solution: passing-by vehicles can help forward traffic (e.g., sensed data) from isolated RSUs to RSUs that have connection to backbone networks [6]. When a vehicle arrives at a source RSU that is isolated, the source RSU may send its traffic to the vehicle, and then the vehicle stores the traffic in its local buffer and forwards the traffic to a destination RSU with backbone network connection when the vehicle arrives at the destination RSU [7]. The destination RSU then forwards (through backbone networks) the traffic to a data center that processes the data.

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For such RSU-to-RSU communication in a VDTN, in general, delay (the duration from the moment that the traffic arrives at the source RSU until the moment that the traffic is delivered to the destination RSU) can be tolerated to a certain level. However, it is still desirable that the traffic is delivered before it becomes expired [8]–[10]. In other words, there is a delay bound associated with each traffic unit. In RSU-to-RSU communication, the delay of the traffic is composed of two parts: Queueing delay at the source RSU (from the moment that the traffic arrives until the moment that the traffic is sent to a passing-by vehicle) and transit delay (from the moment that the passing-by vehicle receives the traffic until the moment that the vehicle arrives at the destination RSU and forwards the traffic). There is a tradeoff between these two delay components. If each passing-by vehicle is used to forward traffic, then we can keep the smallest queueing delay; however, low-speed vehicles may make the transit delay very large. On the other hand, if only high-speed vehicles are selected to help, then we can keep small transit delay; however, the queueing delay might be out of control since it might take a long time for the next high-speed vehicle to arrive. Therefore, the source RSU should strike a balance between queueing delay and transit delay. In [11], the traffic to be sent is either a finite-size file or an infinite-size file. For the first case, the finite-size file is partitioned into segments, and the tool of Markov decision process is used so as to minimize the time needed by the destination RSU to receive all segments of the file. For the second case, there are an infinite number of segments in an infinite-size file, and thus, the tool of Markov decision process is used to achieve the minimum average delay of a segment. It can be seen that both queueing delay and transit delay are considered in [11]. In [12], when the source RSU is waiting for vehicles, its incoming traffic is aggregated into a bundle. The probability that a passing-by vehicle arrives at the destination later than the next vehicle does is calculated, and upon arrival of a vehicle, the source RSU transits to the vehicle with that probability.

For the isolated RSUs in a VDTN, it is also likely that they are powered by batteries or renewable energy (for example, solar power). Therefore, energy consumption of the RSUs is another important performance measure in VDTNs [13]–[16]. In [13], the objective is to design a scheduling algorithm that achieves minimum energy consumption of the RSUs while satisfying passing-by vehicles' communication requirement. It is shown that vehicles that are closer to the RSU and with higher speeds should be picked up. In [14], each packet has a delay bound deadline, and packets that have not been received at the destination by the deadline will be discarded at the source node. The source node probabilistically sends its traffic to a vehicle, and the optimal probability to send traffic (i.e., the probability that achieves the highest successful delivery probability under a constraint of energy consumption) is obtained. In [15] and [16], in addition to energy used for data transmission, energy used by the source RSU to detect a passing-by vehicle is also taken into account. By distributing available energy for vehicle detection and data transmission, the RSU maximizes the probability of successful traffic delivery prior to a delay bound, for two-hop routing case in [15] and epidemic routing case in [16].

Both queueing delay and energy consumption are taken into account in [17]. Cost is charged 1) for consumed energy to send information, and 2) when there is information loss due to delay bound violation. An optimal scheduling strategy, in which the rate of cost (i.e., the average cost per unit time) is minimized, is derived, and is shown to have a pure-threshold structure, that is, a passing-by vehicle should be picked up if the queueing delay exceeds a threshold whose value can be numerically calculated off-line.

The delay considered in [17] is the queueing delay at the source RSU. However, in a real application, we are more interested in the total delay including the queueing delay and the transit delay. The transit delay depends on the speeds of the passing-by vehicles. As aforementioned, there is a tradeoff between queueing delay and transit delay. So the source RSU's scheduling decision (i.e., upon a vehicle arrival, whether to stop at this vehicle and transmit, or continue to wait for other vehicles) should depend on both the queueing delay and the speed of the passing-by vehicle, to be addressed in this work. Another issue of the work in [17] is that in a forced stop (i.e., when the delay of any traffic unit in the queue of the source RSU is more than the delay bound, the RSU is forced to use the coming vehicle), a fixed penalty is charged regardless of the amount of traffic units whose delay is more than the delay bound. This may not be practical, since it is more reasonable to set up the penalty proportional to the amount of traffic units whose delay is more than the delay bound. This issue is to be addressed in this work. In specific, in this work, costs are assigned for both energy consumption and traffic loss: An amount of cost is associated with each consumed energy unit, and an amount of cost is charged if a traffic unit cannot be delivered (by the selected vehicle) before its delay bound and thus is discarded. We derive an optimal strategy for the source RSU to select passing-by vehicles to help deliver its traffic.

The remainder of this paper is organized as follows. Section II presents the system model and problem formulation. Section III derives an optimal strategy. Section IV shows performance evaluation of the derived optimal strategy. Section V investigates the effect of wireless transmission errors, followed by concluding remarks in Section VI. Appendices include proofs of the theorems. A list of symbols used is given in Table I.

TABLE I
USED SYMBOLS

Symbol	Meaning
A_n	Amount of discarded traffic if vehicle n is selected
a, b	The smallest, largest transit delay
b^*	Convergence point of sequence $\{b_i\}_{i=1,2,...}$ $(b_1 = \phi(b); b_i = \phi(b_{i-1}), i \geq 2)$
B	Cost of discarding one traffic unit
C	Cost of energy used to transmit one traffic unit
D	Distance between source RSU and destination RSU
$F_G(g)$	Cumulative distribution function of transit delay
$F_V(v)$	Cumulative distribution function of vehicle speed
$f_G(g)$	Probability density function of transit delay
$\mathscr{F}_n$	Information of $T_1, T_2, ..., T_n$ and $G_1, G_2, ..., G_n$
G_n	The transit delay of vehicle n
K	Delay bound
$N^\dagger(\lambda)$	Optimal stopping rule of Problem (7)
P	Transmit power level
R	Data transmission rate from source RSU to a vehicle
r	Incoming traffic rate at the source RSU
T_n	The arrival time of vehicle n
V_n	Speed of vehicle n
$V(\lambda)$	Minimal cost of Problem (7)
$v_{\max}$	Maximum vehicle speed
$v_{\min}$	Minimum vehicle speed
W	Cost of energy per Joule
X_n	Duration between arrivals of vehicles $n-1$ and n
Y_n	Total cost of using vehicle n (given in (2))
$Z_n(\lambda)$	Cost function for Problem (7)
μ	Average vehicle inter-arrival duration
κ	Overhead duration for communication
ω	Outcome of $Y_1, Y_2, Y_3, ...$

II. System Model and Problem Formulation

We consider a source RSU, which does not have backbone connection, and a destination RSU with backbone connection. The distance from the source RSU to the destination RSU is D (meters). Traffic arrives at the source RSU at a constant rate r (bits/second) (for example, when the source RSU is used as a gateway of underlying wireless sensor networks, the collected traffic by the source RSU is likely to be with almost constant rate). Each traffic unit should be sent to the destination RSU by a maximal delay of K (seconds) from the moment when the traffic unit arrives at the source RSU. No direct connection is assumed between the two RSUs. Therefore, passing-by vehicles are selected by the source RSU to forward its accumulated traffic to the destination RSU. At the source RSU, the traffic is kept buffered until a passing-by vehicle is selected, at which moment those accumulated traffic units whose delay (including the queueing delay and the transit delay, i.e., the time needed by the vehicle to arrive at the destination RSU) is less than K are sent to the selected vehicle, and other traffic units are discarded by the source RSU. Subsequently the vehicle forwards the traffic to the destination RSU when it arrives at the destination RSU. Assume that wireless transmission between RSUs and vehicles is error free (effects of wireless transmission errors will be investigated in Section V).

Assume that the starting point of the process of observation is $T_0 = 0$ (second). At the source RSU, the arrival instant of the nth vehicle (called vehicle n) is T_n (second). Then $X_n = T_n - T_{n-1}$ ($n = 1, 2, ...$) is the vehicle inter-arrival duration. Since some empirical measurement [18] has shown that the vehicle inter-arrival durations at a roadside point follow independent and identically distributed (i.i.d.) exponential distributions, similar to [11], [12], [19]–[22], we assume X_n's are independent and follow an exponential distribution with parameter μ, i.e., $\mathbb{E}[X_n] = \mu$ (seconds). Here $\mathbb{E}[\cdot]$ means expectation. In other words, vehicle arrivals at the source RSU follow a Poisson process with vehicle arrival rate being $1/\mu$. Similar to [11], [12], [21], we assume that, upon a vehicle arrival, the source RSU can detect the speed of the vehicle and the vehicle's speed does not change from the source RSU to the destination RSU. Denote V_n as the speed of the nth vehicle. Suppose the vehicle speeds are i.i.d. random variables with cumulative distribution function (CDF) being $F_V(v)$ for $v \in [v_{\min}, v_{\max}]$, where $v_{\min}$ (m/s) and $v_{\max}$ (m/s) are the minimum and maximum speeds, respectively. The transit delay of vehicle n is $G_n = D/V_n$ (seconds). So G_n's ($n = 1, 2, ...$) are i.i.d. random variables with CDF $F_G(g) = 1 - F_V\left(D/g\right)$ for $g \in [a, b]$, where $a \triangleq D/v_{\max}$ (seconds) and $b \triangleq D/v_{\min}$ (seconds) are the smallest and the largest transit delay, respectively.

Upon arrival of a vehicle, the source RSU has two choices: To skip the vehicle and continue to wait for future vehicles (referred to as *continue* in the sequel), or to stop waiting (referred to as *stop* in the sequel) and send its accumulated traffic (that can meet the delay bound requirement) to the vehicle by a constant rate R (bits/second) and a transmit power level P (Watt). Consider that vehicle n is selected to help (which implies that the source RSU does not stop at vehicles $1, 2, ..., n-1$). The amount of accumulated traffic (from moment 0 to moment T_n) is rT_n. Let A_n denote the amount of traffic units that cannot meet their delay requirement (i.e., when queueing delay plus transit delay is more than the delay bound K)[1] and thus are discarded. A_n is given as

$$A_n = \begin{cases} rT_n & \text{if} \quad K < G_n \\ r(T_n + G_n - K) & \text{if} \quad G_n \le K < T_n + G_n \\ 0 & \text{if} \quad K \ge T_n + G_n \end{cases} \tag{1}$$

for the following reason. When $K < G_n$, even the transit delay G_n alone is more than the delay bound K, so all accumulated traffic with amount rT_n will be discarded. When $K \ge T_n + G_n$, it means that even the oldest traffic unit in the source RSU's buffer can meet the delay bound (for the oldest traffic unit, its queueing delay is T_n, and its transit delay is G_n). So no traffic will be discarded. When $G_n \le K < T_n + G_n$, considering that vehicle n needs G_n duration to arrive at the destination RSU, only traffic accumulated in the past $(K - G_n)$ duration can meet delay bound requirement. So the amount of discarded traffic is $rT_n - r(K - G_n) = r(T_n + G_n - K)$.[2]

Similar to the weighted cost structure in [23]–[25], if vehicle n is selected, we have cost values associated with the energy consumption and traffic loss.

- Energy: The total energy consumption for the data transmission from the source RSU to the vehicle is $P(rT_n - A_n)/R$ (Joule). By letting W (unit of cost per Joule) denote the cost weight of energy consumption, the cost of the energy consumption of transmitting data is given by $WP(rT_n - A_n)/R$. For the data transmission, there is also communication overhead to setup the transmission (for example, the information exchanges of request-to-send [RTS] and clear-to-send [CTS]) and to acknowledge the transmission. Assume the overhead also uses power level P, and the total duration of the transmission of the overhead is κ (seconds). Then the energy cost for communication overhead is $WP\kappa$. So the total cost for energy consumption is $WP(rT_n - A_n)/R + WP\kappa = C(rT_n - A_n) + WP\kappa$, where $C \triangleq WP/R$ is the energy cost of sending one traffic unit.
- Traffic loss: When some traffic units are discarded, a penalty of B (unit of cost) is charged for each discarded traffic unit. So the total cost for traffic loss is BA_n.

The total cost of using vehicle n, denoted Y_n, is thus given as[3]

$$Y_n = WP\kappa + C(rT_n - A_n) + BA_n. \tag{2}$$

Y_n's ($n = 1, 2, ...$) are random variables.

For the stopping problem, consider that we observe random variables $Y_1, Y_2, \ldots$, and get one realization of them as $y_1, y_2, \ldots$, corresponding to the costs of using vehicle $1, 2, \ldots$, respectively. In probability theory, a such realization, denoted as ω, is referred to as *one outcome*. And the sample space, denoted as Ω, is the set of all outcomes. An event is defined as a subset of Ω, which is assigned a probability.

For example, consider that we have observed the value of the first random variable Y_1 as y_1. This fact can be defined as an event $\mathcal{E}_1 = \{\omega : Y_1 = y_1\}$. In other words, the event is the set of outcomes that have the first observed value as y_1. We can write $Y_1(\omega) = y_1$ for $\omega \in \mathcal{E}_1$; and $Y_1(\omega) \neq y_1$ for $\omega \in \Omega \backslash \mathcal{E}_1$.

After knowing $Y_1 = y_1$ or the event $\mathcal{E}_1$ happens, if the source RSU decides to stop at vehicle 1, the final cost of the stopping problem is y_1; otherwise, the source RSU continues to observe $Y_2, Y_3, \ldots$, which are unobserved random variables conditioned on the event $\mathcal{E}_1$. What we aim to achieve is to find the right moment to stop so as to minimize the cost.

[1]The total delay is the summation of the queueing delay and the transit delay G_n. The transmission duration from the source RSU to the vehicle is not considered here, since the transmission duration is actually included in the transit delay.

[2]Considering that the delay bound K of a VDTN is usually not more than a few thousand seconds (e.g., 7200 seconds as used in [4]) and that the data coming rate r at the source RSU is usually not more than a few hundred bps [4], [5], it is reasonable to assume that all the traffic that is not discarded, with amount given as $rT_n - A_n$, can be transmitted from the source RSU to the passing-by vehicle within their contact time.

[3]If the source RSU selects vehicle n to help, it is optimal to transmit all $rT_n - A_n$ traffic to vehicle n, for the following reason. Assume an amount x of the $rT_n - A_n$ traffic is not transmitted to vehicle n. If the amount x traffic is transmitted to vehicle n, the extra cost is given as Cx. However, for any future vehicle to carry the amount x traffic, the cost is at least Cx, considering that all or part of the x amount of traffic may become expired when waiting for future vehicles.

Consider a *stopping rule* such that for each outcome $\omega \in \Omega$, the moment to stop is denoted $N(\omega)$ where $N(\omega) \in \{1, 2, \dots\}$ is the index of the vehicle that the source RSU stops at. $N(\omega)$ is also used to denote the stopping rule. We can think of a stopping rule as a function in the domain Ω, which maps each $\omega \in \Omega$ to one positive number. So $N(\omega)$ (a stopping rule) is a random variable and is often written in short form as N. A simple example of stopping rules is $N = 1$ ($N(\omega) = 1$) for $\omega \in \Omega$, i.e., always stop at the first vehicle. To solve an optimal stopping problem is to find an optimal stopping rule that maps each outcome to a stopping moment to minimize the cost.

In this paper, we consider stopping problems that are repeated in time. For the moment when the source RSU completes information exchange with a selected vehicle, this moment is considered as the end of the old stopping problem and also the beginning of a new stopping problem. If the source RSU stops at vehicle $N(\omega)$, whose cost is $Y_{N(\omega)}(\omega)$ and stopping time is $T_{N(\omega)}(\omega)$, then starting from the moment $T_{N(\omega)}(\omega)$, a new stopping problem begins with starting point denoted $T_0 = 0$ and the next arrival vehicle called vehicle 1. For such repeated stopping problems with stopping rule $N(\omega)$, denote the independent outcomes as $\omega_1, \omega_2, \dots$, etc. Then we have i.i.d. stopping vehicle indices $\{N(\omega_1), N(\omega_2), \dots, N(\omega_n), \dots\}$, i.i.d. stopping moments $\{T_{N(\omega_1)}(\omega_1), T_{N(\omega_2)}(\omega_2), \dots, T_{N(\omega_n)}(\omega_n), \dots\}$, and i.i.d. costs $\{Y_{N(\omega_1)}(\omega_1), Y_{N(\omega_2)}(\omega_2), \dots, Y_{N(\omega_n)}(\omega_n), \dots\}$. The total cost is $\sum_i Y_{N(\omega_i)}(\omega_i)$ and the total amount of traffic that arrives at the source RSU is $\sum_i rT_{N(\omega_i)}(\omega_i)$. So the rate of cost (average cost per traffic unit) is $\sum_i Y_{N(\omega_i)}(\omega_i) / \sum_i rT_{N(\omega_i)}(\omega_i)$, which converges to $\mathbb{E}\left[Y_{N(w)}(w)\right] / \mathbb{E}\left[rT_{N(w)}(w)\right]$, or in short form $\mathbb{E}[Y_N]/\mathbb{E}[rT_N]$, by the law of large numbers [26]. Here $\mathbb{E}[\cdot]$ means expectation. Therefore, our objective is to find a stopping rule N to minimize the rate of cost $\mathbb{E}[Y_N]/\mathbb{E}[rT_N]$. The optimal rate of cost is given as

$$\begin{aligned} Q^* &\triangleq \inf_{N\geq 1} \frac{\mathbb{E}[Y_N]}{\mathbb{E}[rT_N]} \\ &= \inf_{N\geq 1} \frac{WP\kappa + C\mathbb{E}[rT_N - A_N] + B\mathbb{E}[A_N]}{\mathbb{E}[rT_N]} \\ &= \inf_{N\geq 1} \frac{WP\kappa + C\mathbb{E}[rT_N] + (B-C)\mathbb{E}[A_N]}{\mathbb{E}[rT_N]} \end{aligned} \quad (3)$$

where $\{N \geq 1\}$ is the set of stopping rules that observe at least one vehicle.[4]

III. AN OPTIMAL STOPPING RULE

We make three comments here.

- We assume $a \leq K$, because otherwise the minimum transit delay a alone is more than the delay bound K, and thus, no vehicle can meet the delay requirement of any traffic unit.
- If $b > K$, which means the maximum transit delay b is greater than the delay bound K, then those vehicles whose transit delay are greater than K should be skipped, since they cannot meet the delay bound requirement of any traffic unit. Recall that the vehicle arrivals follow a Poisson process with rate $1/\mu$. Upon a vehicle arrival, it is with probability $1 - F_G(K)$ that the vehicle is skipped. Thus, the arrivals of considered (not skipped) vehicles follow a Poisson process with rate $F_G(K)/\mu$ [27]. Then the original stopping problem is equivalent to the case when vehicle arrivals follow a Poisson process with rate $F_G(K)/\mu$, the transit delay of a vehicle is within range $[a, K]$, and the CDF of transit delay is

$$\begin{cases} 0 & \text{if} \quad g < a \\ F_G(g)/F_G(K) & \text{if} \quad a \leq g \leq K \\ 1 & \text{if} \quad g > K. \end{cases}$$

  Therefore, without loss of generality, we assume $K \geq b$ in the sequel. And thus, from (1), A_n now takes the form of

$$A_n = r(T_n + G_n - K)^+ \quad (4)$$

  in which $(x)^+ = \max(x, 0)$.
- We should have

$$B > C + \frac{WP\kappa}{r(K-a)}. \quad (5)$$

  The reason is as follows. First we have $B > C$ (this is because, if $B \leq C$, it means the cost of discarding a traffic unit is not more than the energy cost of sending a traffic unit, then all traffic units should be discarded). Next we use proof by contradiction. Suppose $B \leq C + WP\kappa/\big(r(K-a)\big)$, which means $WP\kappa - r(B-C)(K-a) \geq 0$. Since the maximal amount of traffic that a vehicle can carry is $r(K-a)$,[5] then for any amount of traffic $x \in (0, r(K-a)]$ carried by a selected vehicle, we have $WP\kappa - (B-C)x \geq WP\kappa - r(B-C)(K-a) \geq 0$, which leads to $WP\kappa + Cx \geq Bx$. This means that $WP\kappa + Cx$, the cost of energy consumption in sending the carried traffic, is not less than Bx, the cost of discarding the carried traffic. Thus, the source RSU should discard all traffic. Therefore, we should not have $B \leq C + WP\kappa/\big(r(K-a)\big)$.

A. Transformation of Problem (3)

We consider a transformation of Problem (3). For $\lambda > 0$, define a cost function

$$\begin{aligned} Z_n(\lambda) &\triangleq Y_n - \lambda r T_n \\ &= WP\kappa + C(rT_n - A_n) + BA_n - \lambda r T_n \\ &= WP\kappa + r\,(C - \lambda)\,T_n + (B-C)\,A_n \end{aligned} \quad (6)$$

[4] In the expression of the optimal rate of cost in (3), we use "inf" instead of "min" because for a general stopping problem, it is possible that no optimal stopping rule N exists such that $\frac{\mathbb{E}[Y_N]}{\mathbb{E}[rT_N]} = Q^*$. Nevertheless, in Section III we will show that in our Problem (3), there exists an optimal stopping rule that has a rate of cost being Q^*.

[5] Considering that the transit delay of any vehicle is not less than a, a vehicle can take at most the traffic accumulated in the past $K - a$ duration. So the maximal amount of traffic that a vehicle can carry is $r(K-a)$.

in which the physical meaning of λ is rate of cost.

Based on the cost function $Z_n(\lambda)$, we formulate a new stopping problem as

$$V(\lambda) \triangleq \inf_{N\geq 1} \mathbb{E}\left[Z_N(\lambda)\right] = \inf_{N\geq 1} \mathbb{E}\left[WP\kappa + r\left(C-\lambda\right)T_N + \left(B-C\right)A_N\right]. \quad (7)$$

Theorem 1: For Problem (7) with $\lambda \in (0, B]$, there exists an optimal stopping rule, denoted $N^{\dagger}(\lambda)$, such that $\mathbb{E}\left[Z_{N^{\dagger}(\lambda)}(\lambda)\right] = V(\lambda)$.

Proof: See Appendix A. ■

Theorem 2: If i) there exists a λ^* such that $V(\lambda^*) = \inf_{N\geq 1}\mathbb{E}\left[Z_N(\lambda^*)\right] = 0$; and ii) for Problem (7) with λ^*, there exists an optimal stopping rule $N^{\dagger}(\lambda^*)$ such that $\mathbb{E}\left[Z_{N^{\dagger}(\lambda^*)}(\lambda^*)\right] = V(\lambda^*) = 0$, then $N^{\dagger}(\lambda^*)$ is an optimal stopping rule for Problem (3) and the optimal rate of cost (i.e., the optimal objective function of Problem (3)) is λ^*.

Proof: See Appendix B. ■

The next theorem shows that the first condition in Theorem 2 is satisfied for Problem (7).

Theorem 3: There exists a $\lambda^* \in (C, B]$ such that $V(\lambda^*) = 0$.

Proof: See Appendix C. ■

From Theorem 1, it can be concluded that the second condition in Theorem 2 is also satisfied. Therefore, an optimal stopping rule for Problem (3) is in the form of $N^{\dagger}(\lambda^*)$. So if $N^{\dagger}(\lambda)$ and $V(\lambda)$ can be obtained for any $\lambda \in (C, B]$, then the value of λ^* can be obtained numerically such that $V(\lambda^*) = 0$, and thus $N^{\dagger}(\lambda^*)$ is an optimal stopping rule of Problem (3). Therefore, next we focus on derivation of $N^{\dagger}(\lambda)$ and $V(\lambda)$ for $\lambda \in (C, B]$ in Problem (7). For Problem (7) with a specific λ, we first derive an optimal strategy for vehicles arriving after moment $K-a$ in Section III-B, and based on the result, we derive an optimal stopping rule for vehicles arriving before moment $K-a$ in Section III-C. Then as a summary of Sections III-B and Section III-C, in Section III-D we give an overall optimal stopping rule, i.e., $N^{\dagger}(\lambda)$, for Problem (7) with a specific λ, as well as its optimal cost $V(\lambda)$. In Section III-E, we find λ^* such that $V(\lambda^*) = 0$, and thus, $N^{\dagger}(\lambda^*)$ is an optimal stopping rule of Problem (3).

B. Optimal stopping rule for Problem (7) (with a specific λ) when $T_n \geq K-a$

First we consider that the source RSU does not stop before moment $K-a$, i.e., we consider Problem (7) when $T_n \geq K-a$. For presentation simplicity, in Section III-B, when we say "Problem (7)", it means "Problem (7) when $T_n \geq K-a$".

Here we introduce the notion of *myopic stopping rule*. The myopic stopping rule is the rule that calls for stopping at vehicle n if the cost of vehicle n [6] is not greater than the expected cost of vehicle $n+1$. For Problem (7), its myopic rule is to stop at $\min\left\{n \geq 1 : Z_n(\lambda) \leq \mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right]\right\}$. Here $\mathscr{F}_n$ means information of $T_1, T_2, ..., T_n$ and $G_1, G_2, ..., G_n$, which is available at the source RSU when it decides whether or not to stop at vehicle $n+1$. Note that, upon arrival of vehicle n, if the myopic rule calls for continuation[7] (i.e., $Z_n(\lambda) > \mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right]$, and thus, the myopic rule decides not to stop at vehicle n), it is also optimal for Problem (7) to continue since $Z_n(\lambda) > \mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right]$ means that the expected cost of vehicle $n+1$ is smaller than the cost of vehicle n and thus, continuing to observe vehicle $n+1$ is optimal. On the other hand, if the myopic rule calls for stopping at a vehicle, generally it may not be optimal for Problem (7) to stop at the vehicle. However, if a stopping problem is *monotone*, under some mild conditions, if the myopic rule calls for stopping at a vehicle, it is also optimal for the stopping problem to stop at the vehicle (in other words, the myopic rule is an optimal stopping rule). Therefore, next we introduce the concept of *monotone problem*, and when Problem (7) is not monotone, we transform it to a monotone problem, for which we prove that its myopic rule is optimal.

[6]Cost of a vehicle is the cost of stopping at the vehicle.

Definition 1: Let $\mathcal{B}_n$ denote the event $\left\{\omega : Z_n(\lambda) \leq \mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right]\right\}$. Problem (7) is monotone if $\mathcal{B}_1 \subseteq \mathcal{B}_2 \subseteq \mathcal{B}_3 \subseteq \ldots$ almost surely (a.s.) [28].

$\mathcal{B}_n$ is the set of outcomes that the myopic rule calls for stopping at the vehicle n.[8] $\mathcal{B}_n \subseteq \mathcal{B}_{n+1} \subseteq \mathcal{B}_{n+2} \subseteq \ldots$ means that: If for one specific outcome ω the myopic rule calls for stopping at vehicle n, then the myopic rule will also call for stopping at vehicle $n+1$ (for whatever realization of T_{n+1} and G_{n+1}); and in general, the myopic rule will call for stopping at any future vehicle for whatever realization of $\{T_{n+1}, T_{n+2}, ...\}$ and $\{G_{n+1}, G_{n+2}, ...\}$ (a.s.).

Next we will try to transform Problem (7) into a monotone problem (if it is not a monotone problem), derive the myopic rule for the monotone problem and prove that the myopic rule is optimal for Problem (7).

Recall that in this subsection we consider $T_n \geq K-a$, which means $T_n + G_n \geq K$ since $G_n \geq a$. Then from (4) we have $A_n = r(T_n + G_n - K)$. Since $T_{n+1} > T_n \geq K-a$ and $G_{n+1} \geq a$, we also have $A_{n+1} = r(T_{n+1} + G_{n+1} - K)$. $Z_n(\lambda)$ in (6) can be rewritten as

$$\begin{aligned} Z_n(\lambda) =& WP\kappa + r(C-\lambda)T_n + r(B-C)(T_n + G_n - K) \\ =& WP\kappa + r(B-\lambda)T_n + r(B-C)(G_n - K). \quad (8) \end{aligned}$$

From (8), the expectation of $Z_{n+1}(\lambda)$ conditioned on that the source RSU has observed the first n vehicles but has not stopped at them is

$$\begin{aligned} &\mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right] \\ =& WP\kappa + r(B-\lambda)\mathbb{E}\left[T_{n+1}|\mathscr{F}_n\right] \\ &+ r(B-C)\mathbb{E}\left[G_{n+1} - K|\mathscr{F}_n\right] \\ =& WP\kappa + r(B-\lambda)\mathbb{E}\left[T_n + X_{n+1}|\mathscr{F}_n\right] \\ &+ r(B-C)(\mathbb{E}\left[G_{n+1}|\mathscr{F}_n\right] - K) \\ =& WP\kappa + r(B-\lambda)(T_n + \mu) + r(B-C)\left(\mathbb{E}\left[G_{n+1}\right] - K\right) \end{aligned} \quad (9)$$

[7]When we say a stopping rule calls for continuation (which means the source RSU continues to observe other vehicles) or stopping at vehicle n, it implies that the source RSU does not stop at vehicles $1, 2, ..., n-1$.

[8]For presentation simplicity, here vehicle n means the nth vehicle arriving after moment $K-a$ (recalling that in Section III-B we only consider vehicles arriving after the moment $K-a$).

where the last equality comes from the following fact. $\mathscr{F}_n$ does not carry information regarding X_{n+1} and G_{n+1}. In other words, if we know $\mathscr{F}_n$, we know the values of $\{X_k, k = 1, \ldots, n\}$ and $\{G_k, k = 1, \ldots, n\}$, but not X_{n+1} or G_{n+1}. Thus, we have $\mathbb{E}\left[T_n|\mathscr{F}_n\right] = T_n$, $\mathbb{E}\left[X_{n+1}|\mathscr{F}_n\right] = \mathbb{E}\left[X_{n+1}\right] = \mu$, and $\mathbb{E}\left[G_{n+1}|\mathscr{F}_n\right] = \mathbb{E}\left[G_{n+1}\right]$.

From (8) and (9), the difference between the cost of vehicle n and the expected cost of vehicle $n+1$ is

$$\begin{aligned}
&\mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right] - Z_n(\lambda)\\
=&r(B-\lambda)(T_n+\mu) + r(B-C)\left(\mathbb{E}\left[G_{n+1}\right]-K\right)\\
&-r(B-\lambda)T_n - r(B-C)(G_n-K)\\
=&r(B-\lambda)\mu + r(B-C)\left(\mathbb{E}\left[G_{n+1}\right]-G_n\right)\\
=&r(B-C)\left(\frac{(B-\lambda)\mu}{B-C} + \int_a^b x f_G(x)\,\mathrm{d}x - G_n\right) \qquad (10)
\end{aligned}$$

where $f_G(x)$ is the probability density function of the transit delay of the vehicles. We define a function

$$\phi(g) \triangleq \frac{1}{F_G(g)}\left(\frac{(B-\lambda)\mu}{B-C} + \int_a^g x f_G(x)\,\mathrm{d}x\right) \quad a \le g \le b, \qquad (11)$$

and define $b_1 \triangleq \phi(b)$.[9] Since $F_G(b) = 1$, we can re-write (10) as

$$\mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right] - Z_n(\lambda) = r(B-C)(b_1 - G_n). \qquad (12)$$

We consider two scenarios: $b_1 \ge b$ and $b_1 < b$. For each scenario, we get a monotone problem, obtain its myopic rule, and prove that the myopic rule is optimal for Problem (7), as follows.

1) Scenario with $b_1 \ge b$: Since b_1 is not less than the largest transit delay b, it is not less than G_n. So for any vehicle n, expression (12) is always nonnegative. Thus, for any n, ignoring vehicle n and stopping at vehicle $n+1$ is expected to involve more cost than that of stopping at vehicle n. Therefore, the myopic rule for Problem (7) will require the source RSU to stop at the first vehicle (arriving after $K-a$), given as

$$N^{\mathrm{m}}_{K-a}(\lambda) = \min\{n : T_n \ge K-a\} \qquad (13)$$

in which superscript 'm' means 'myopic' and subscript '$K-a$' means we start observation from moment $K-a$. And Problem (7) is a monotone problem for reason as follows. From (12), we always have $Z_n(\lambda) \le \mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right]$ for any n. Recalling that $\mathcal{B}_n$ denotes the event $\left\{\omega : Z_n(\lambda) \le \mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right]\right\}$, we have $\mathcal{B}_1 = \mathcal{B}_2 = \mathcal{B}_3 = \ldots$, and thus, from Definition 1, Problem (7) is a monotone problem.

Theorem 4: When $T_n \ge K-a$ and $b_1 \ge b$, the myopic rule (13) is an optimal stopping rule for Problem (7) with $\lambda \in (0, B]$.

Proof: See Appendix D. ∎

So when $T_n \ge K-a$, the expected optimal stopping time is

$$\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda)}\right] = K - a + \mu \qquad (14)$$

due to the fact that: Since the Poisson arrival process (of vehicle arrivals) is memoryless, starting from moment $K-a$, the expected waiting time for the next vehicle is μ (the average vehicle inter-arrival time).

Denote the optimal cost of Problem (7) when we start observation from moment $K-a$ as $V_{K-a}(\lambda)$. Then we have

$$\begin{aligned}
V_{K-a}(\lambda) =&\mathbb{E}\left[Z_{N^{\mathrm{m}}_{K-a}(\lambda)}(\lambda)\right]\\
=&WP\kappa + r(B-\lambda)\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda)}\right]\\
&+ r(B-C)(\mathbb{E}\left[G_n\right]-K)\\
=&WP\kappa + r(C-\lambda)K - r(B-\lambda)(a-\mu)\\
&+ r(B-C)\int_a^b x f_G(x)\,\mathrm{d}x \qquad (15)
\end{aligned}$$

where the second equality comes from (8) and the third equality comes from (14).

2) Scenario with $b_1 < b$: We consider a sequence of values $\{b_i\}_{i=1,2,\ldots}$, in which $b_i = \phi(b_{i-1})$ for $i \ge 2$ (recall that $b_1 = \phi(b)$). The following theorem will be useful in subsequent investigation.

Theorem 5: When $b_1 < b$, the sequence $\{b_i\}_{i=1,2,\ldots}$ has the following properties: 1) $b_i < b_{i-1}$ for $i \ge 2$; 2) $\{b_i\}_{i=1,2,\ldots}$ converges to a value denoted b^*; 3) b^* is the unique root of $\phi(g) = g$ for $g \in (a, b]$; 4) for $g \in (a, b]$, $g = b^*$ minimizes $\phi(g)$.

Proof: See Appendix E. ∎

Next we show that when $b_1 < b$, Problem (7) is not a monotone problem, and then transform Problem (7) into a monotone problem. Upon arrival of vehicle n, if $G_n \le b_1$, then from (12) we have $\mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right] - Z_n(\lambda) \ge 0$, and the myopic rule will call for stopping at vehicle n; otherwise, the myopic rule will ask for continuation. This means the decision for any vehicle depends on the transit delay of the vehicle. So Problem (7) is not a monotone problem when $b_1 < b$. To transform Problem (7) into a monotone problem, we have the following iterations.

Iteration 1: By observing (12), we notice that $\mathbb{E}\left[Z_{n+1}(\lambda)|\mathscr{F}_n\right] - Z_n(\lambda)$ depends only on G_n. Upon arrival of vehicle n, if $G_n > b_1$, then for whatever value of T_n, the myopic rule always asks for continuation and thus it is optimal for Problem (7) to skip this vehicle and continue to wait for other vehicles (recalling that if myopic rule calls for continuation, it is optimal for the source RSU to continue). So we can ignore those slow vehicles with transit delay larger than b_1, and only consider those vehicles whose transit delay is smaller than or equal to b_1. After ignoring those slow vehicles, the arrival rate of *considered* vehicles is $F_G(b_1)/\mu$. We use superscript '[1]' to denote the case when vehicles with transmit delay more than b_1 are not considered. The transit delay of the nth considered vehicle, denoted $G^{[1]}_n$, is in the range of $[a, b_1]$ with CDF $F_{G^{[1]}}(g) = F_G(g)/F_G(b_1)$

[9]Note that b_1 is a function of λ. For presentation simplicity, we do not show it in form of $b_1(\lambda)$. The subsequent $b_2, b_3, \ldots$ and b^* are treated similarly.

for $g \in [a, b_1]$. And similar to (10), we have

$$\begin{aligned}
&\mathbb{E}\left[Z^{[1]}_{n+1}(\lambda)|\mathscr{F}^{[1]}_n\right] - Z^{[1]}_n(\lambda)\\
=&r(B-\lambda)\mu/F_G(b_1) + r(B-C)\left(\mathbb{E}\left[G^{[1]}_{n+1}\right] - G^{[1]}_n\right)\\
=&r(B-\lambda)\mu/F_G(b_1) + r(B-C)\left(\frac{\int_a^{b_1} x f_G(x)\,\mathrm{d}x}{F_G(b_1)} - G^{[1]}_n\right)\\
=&r(B-C)\left(\frac{1}{F_G(b_1)}\left(\frac{(B-\lambda)\mu}{B-C} + \int_a^{b_1} x f_G(x)\,\mathrm{d}x\right) - G^{[1]}_n\right)\\
=&r(B-C)(\phi(b_1) - G^{[1]}_n)\\
=&r(B-C)(b_2 - G^{[1]}_n) \qquad (16)
\end{aligned}$$

where the last two equalities come from the definition of $\phi(\cdot)$ in (11) and $b_2 = \phi(b_1)$, respectively.

From Theorem 5, we have $b_2 < b_1$.

Iteration 2: Upon arrival of the nth considered vehicle, if $G^{[1]}_n > b_2$, then $\mathbb{E}\left[Z^{[1]}_{n+1}(\lambda)|\mathscr{F}^{[1]}_n\right] - Z^{[1]}_n(\lambda) < 0$, and thus, it is optimal to continue since continuing to stop at vehicle $n+1$ expects to incur less cost than that of stopping at vehicle n. So we can ignore those slow vehicles with transit delay $G^{[1]}_n > b_2$, and only consider the remaining vehicles. After ignoring those slow vehicles, the arrival rate of considered vehicles is $F_G(b_2)/\mu$. And the transit delay of the nth considered vehicle, denoted $G^{[2]}_n$, is in the range of $[a, b_2]$ with CDF $F_{G^{[2]}}(g) = F_G(g)/F_G(b_2)$ for $g \in [a, b_2]$. Here superscript '[2]' means that those vehicles with transmit delay more than b_2 are not considered. And similar to (16), we have

$$\mathbb{E}\left[Z^{[2]}_{n+1}(\lambda)|\mathscr{F}^{[2]}_n\right] - Z^{[2]}_n(\lambda) = r(B-C)(b_3 - G^{[2]}_n).$$

Similarly, we can have Iterations 3, 4,...,etc. And in Iteration l ($l = 1, 2, ...$), vehicles with transit delay more than b_l should not be considered. Since sequence $\{b_i\}_{i=1,2,...}$ converges to b^* (from Theorem 5), it can be concluded that, as an overall result after all iterations, vehicles with transit delay more than b^* should not be considered. The arrival rate of considered vehicles is $F_G(b^*)/\mu$. And the transit delay of the nth considered vehicle, denoted $G^{[o]}_n$, is in the range of $[a, b^*]$ with CDF $F_{G^{[o]}}(g) = F_G(g)/F_G(b^*)$. Here superscript '$[o]$' means the overall effect of the iterations (i.e., vehicles with transit delay more than b^* are not considered).

With only those considered vehicles, Problem (7) is a monotone problem. This is because for any considered vehicle $n = 1, 2, ...$, we have $G^{[o]}_n \le b^*$, and similar to (16), we have $\mathbb{E}\left[Z^{[o]}_{n+1}(\lambda)|\mathscr{F}^{[o]}_n\right] - Z^{[o]}_n(\lambda) = r(B-C)(b^* - G^{[o]}_n) \ge 0$. Similar to the scenario with $b_1 \ge b$, Problem (7) with only those considered vehicles is monotone.

For Problem (7) with only those considered vehicles, since $\mathbb{E}\left[Z^{[o]}_{n+1}(\lambda)|\mathscr{F}^{[o]}_n\right] - Z^{[o]}_n(\lambda) \ge 0$ for any n, its myopic rule will call for stopping at the first considered vehicle after moment $K-a$ (recalling that we consider $T_n \ge K-a$ in this subsection). The myopic rule is expressed as

$$N^{\mathrm{m}}_{K-a}(\lambda) = \min\left\{n : T^{[o]}_n \ge K-a\right\}. \qquad (17)$$

Theorem 6: When $T_n \ge K-a$ and $b_1 < b$, the myopic rule (17) is an optimal stopping rule for Problem (7) when only vehicles with transmit delay less than b^* are considered.
The proof is similar to the proof of Theorem 4, and is omitted here.

As aforementioned, for Problem (7) when the RSU does not stop before time $K-a$, it is optimal to ignore those vehicles with transit delay larger than b^* because for such a vehicle, the expected cost of stopping at the next vehicle is less. So stopping rule (17) is optimal for Problem (7). The optimal stopping rule can be rewritten as

$$N^{\mathrm{m}}_{K-a}(\lambda) = \min\{n : T_n \ge K-a, G_n \le b^*\} \qquad (18)$$

which means from moment $K-a$, the source RSU should stop at the first vehicle whose transit delay is not more than b^*. Similar to (14), the expected optimal stopping time is

$$\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda)}\right] = K - a + \frac{\mu}{F_G(b^*)} \qquad (19)$$

since the arrival rate of vehicles whose transit delay is not more than b^* is $F_G(b^*)/\mu$.

Upon an optimal stopping, the expectation of transit delay (which is the average transmit delay of a vehicle conditioned on that its transit delay is not more than b^*) is

$$\mathbb{E}\left[G_{N^{\mathrm{m}}_{K-a}(\lambda)}\right] = \frac{\int_a^{b^*} g f_G(g)\,\mathrm{d}g}{F_G(b^*)}. \qquad (20)$$

Recall that $V_{K-a}(\lambda)$ denotes the optimal cost of Problem (7) when we start observation from moment $K-a$. Thus, we have

$$\begin{aligned}
&V_{K-a}(\lambda)\\
=&\mathbb{E}\left[Z_{N^{\mathrm{m}}_{K-a}(\lambda)}(\lambda)\right]\\
=&WP\kappa + r(B-\lambda)\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda)}\right]\\
&+ r(B-C)\left(\mathbb{E}\left[G_{N^{\mathrm{m}}_{K-a}(\lambda)}\right] - K\right)\\
=&WP\kappa + r(B-\lambda)\left(K - a + \frac{\mu}{F_G(b^*)}\right)\\
&+ r(B-C)\left(\frac{\int_a^{b^*} g f_G(g)\,\mathrm{d}g}{F_G(b^*)} - K\right)\\
=&WP\kappa + r(C-\lambda)K - r(B-\lambda)a\\
&+ r(B-C)\frac{1}{F_G(b^*)}\left(\frac{(B-\lambda)\mu}{B-C} + \int_a^{b^*} x f_G(x)\,\mathrm{d}x\right)\\
=&WP\kappa + r(C-\lambda)K - r(B-\lambda)a + r(B-C)\phi(b^*)\\
=&WP\kappa + r(C-\lambda)K - r(B-\lambda)a + r(B-C)b^* \qquad (21)
\end{aligned}$$

in which the second equality comes from (8), the third equality comes from (19) and (20), and the last two equalities come from the definition of $\phi(\cdot)$ in (11) and $\phi(b^*) = b^*$ (from Theorem 5), respectively.

Remark: To get the optimal stopping rule, the value of b^*, which is the converging point of sequence $\{b_i\}_{i=1,2,...}$, should be obtained. From Theorem 5, the value of b^* can be obtained by any method to find the unique root of $\phi(g) = g$ for $g \in (a, b]$ or by any method to find the minimum of $\phi(g)$ for $g \in (a, b]$.

C. Optimal stopping rule for Problem (7) (with a specific λ) when $0 \le T_n < K - a$

Since we have obtained the optimal stopping rule for $T_n \ge K-a$ in Section III-B, next we only need to consider vehicles arriving between $[0, K-a)$. Denote $V_t(\lambda)$ as the optimal cost of Problem (7) when we start observation from moment t (not including moment t). So the optimal cost of Problem (7) is $V(\lambda) = V_0(\lambda)$. As a boundary condition, when $t = K - a$, $V_t(\lambda)$ is given in (15) when $b_1 \ge b$ or in (21) when $b_1 < b$. Next we will derive $V_t(\lambda)$ for $t \in [0, K - a)$ using this boundary condition.

Suppose a vehicle, say vehicle n, arrives at moment T_n, and if it is selected, the cost is $Z_n(\lambda)$. The source RSU needs to decide whether it is optimal to stop at this vehicle. The optimality equation of dynamic programming [28] states that, if $Z_n(\lambda) < V_{T_n}(\lambda)$ (i.e., the cost of current vehicle is less than the optimal cost of ignoring the current vehicle and continuing to wait for future vehicles), then it is optimal to stop at vehicle n; otherwise, it is optimal to continue observation of future vehicles.

For moment t, consider an interval $(t - \Delta t, t)$ in which $\Delta t > 0$ is sufficiently small. Since the vehicle arrival process is a Poisson process with average arrival rate $1/\mu$, within interval $(t - \Delta t, t)$, the probability that one vehicle arrives is $\Delta t/\mu$, the probability that no vehicle arrives is $(1 - \Delta t/\mu)$, and the probability that two or more vehicles arrive is $o(\Delta t)$ (higher order of Δt). Next we give an expression for $V_{t-\Delta t}(\lambda)$.

- If there is no vehicle arriving during the interval $(t - \Delta t, t)$: Then the source RSU has to wait for vehicles arriving after moment t for chance of transmission. For this case, the optimal costs starting from t and $(t - \Delta t)$ are the same, i.e., $V_{t-\Delta t}(\lambda) = V_t(\lambda)$.
- If there is one vehicle, say vehicle n, arriving at $T_n = t - \Delta t'$ where $0 < \Delta t' < \Delta t$: From (6) and (4), we have $Z_n(\lambda) = WP\kappa + r\,(C - \lambda)\,(t - \Delta t') + r\,(B - C)\,(t - \Delta t' + G_n - K)^+$.
  When

$$\begin{aligned} Z_n(\lambda) &= WP\kappa + r\,(C-\lambda)\,(t-\Delta t') \\ &\quad + r\,(B-C)\,(t-\Delta t' + G_n - K)^+ \le V_{t-\Delta t'}(\lambda), \end{aligned} \tag{22}$$

  then it is optimal to stop at vehicle n and there is no need to continue the observation after t. Define a function[10]

$$\rho(t,\lambda) \triangleq \max\big\{g \in [a,b] : WP\kappa + r\,(C-\lambda)\,t + r\,(B-C)\,(t+g-K)^+ \le V_t(\lambda)\big\}.$$

  Then (22) is equivalent to $G_n \le \rho(t - \Delta t', \lambda)$, which happens with probability $F_G(\rho(t - \Delta t', \lambda))$. When (22) holds, it is optimal to stop at vehicle n, and we have

$$\begin{aligned} &V_{t-\Delta t}(\lambda) \\ &= \mathbb{E}\left[Z_n(\lambda)\right] \\ &= WP\kappa + r\,(C-\lambda)\,(t-\Delta t') \\ &\quad + r(B-C)\frac{\int_a^{\rho(t-\Delta t',\lambda)} (t-\Delta t' + x - K)^+ f_G(x)\,\mathrm{d}x}{F_G(\rho(t-\Delta t',\lambda))}. \end{aligned}$$

  If (22) does not hold (with probability $1 - F_G(\rho(t - \Delta t', \lambda))$), it is optimal to skip vehicle n and continue to wait for other vehicles that come after moment t. Therefore, we have $V_{t-\Delta t}(\lambda) = V_t(\lambda)$.

As a summary, we have

$$\begin{aligned} &V_{t-\Delta t}(\lambda) \\ =&(1-\Delta t/\mu)V_t(\lambda) + (\Delta t/\mu)\big(1 - F_G(\rho(t-\Delta t',\lambda))\big)V_t(\lambda) \\ &+ (\Delta t/\mu)F_G(\rho(t-\Delta t',\lambda))\Bigg(WP\kappa + r\,(C-\lambda)\,(t-\Delta t') \\ &+ r\,(B-C)\,\frac{\int_a^{\rho(t-\Delta t',\lambda)}(t-\Delta t' + x - K)^+ f_G(x)\,\mathrm{d}x}{F_G(\rho(t-\Delta t',\lambda))}\Bigg) \\ &+ o(\Delta t) \\ =&V_t(\lambda) + (\Delta t/\mu)F_G(\rho(t-\Delta t',\lambda)) \\ &\times\Bigg(-V_t(\lambda) + WP\kappa + r\,(C-\lambda)\,(t-\Delta t') \\ &+ r\,(B-C)\,\frac{\int_a^{\rho(t-\Delta t',\lambda)}(t-\Delta t' + x - K)^+ f_G(x)\,\mathrm{d}x}{F_G(\rho(t-\Delta t',\lambda))}\Bigg) \\ &+ o(\Delta t). \end{aligned}$$

After some algebraic operations, we have

$$\begin{aligned} &\mu\frac{V_t(\lambda) - V_{t-\Delta t}(\lambda)}{\Delta t} \\ =&F_G(\rho(t-\Delta t',\lambda))\Bigg(V_t(\lambda) - WP\kappa - r\,(C-\lambda)\,(t-\Delta t') \\ &- r\,(B-C)\,\frac{\int_a^{\rho(t-\Delta t',\lambda)}(t-\Delta t' + x - K)^+ f_G(x)\,\mathrm{d}x}{F_G(\rho(t-\Delta t',\lambda))}\Bigg) \\ &+ o(\Delta t)/\Delta t. \end{aligned}$$

Letting Δt approach zero, it follows

$$\begin{aligned} \mu\frac{\partial V_t(\lambda)}{\partial t} =& F_G(\rho(t,\lambda))\Bigg(V_t(\lambda) - WP\kappa - r\,(C-\lambda)\,t \\ &- r\,(B-C)\,\frac{\int_a^{\rho(t,\lambda)}(t + x - K)^+ f_G(x)\,\mathrm{d}x}{F_G(\rho(t,\lambda))}\Bigg). \end{aligned} \tag{23}$$

With the aforementioned boundary condition, equation (23) can be solved numerically to get $V_t(\lambda)$ for $t \in [0, K - a)$.

Therefore, for Problem (7), upon arrival of vehicle n at moment T_n, if $T_n < K - a$, an optimal stopping rule works as follows. The source RSU first calculates (from (6)) the cost of vehicle n given as $Z_n(\lambda) = WP\kappa + r(C - \lambda)T_n + r(B - C)(T_n + G_n - K)^+$. If $Z_n(\lambda)$ is less than $V_{T_n}(\lambda)$,

[10]Note that if $WP\kappa + r\,(C-\lambda)\,t + r\,(B-C)\,(t+g-K)^+ \le V_t(\lambda)$ never holds for $g \in [a, b]$, then $\rho(t, \lambda) = a$.

then the source RSU stops at vehicle n; otherwise, the source RSU continues to observe future vehicles. The optimal cost of Problem (7) is $V(\lambda) = V_0(\lambda)$.

D. Overall Optimal Stopping Rule for Problem (7) (with a specific λ)

As a summary of Sections III-B and III-C, for Problem (7), the optimal cost is $V(\lambda) = V_0(\lambda)$, and an optimal stopping rule works as shown in (24) on top of the next page. In other words, when the waiting time is less than $K - a$, then the source RSU stops at the first vehicle such that $Z_n(\lambda) = WP\kappa + r(C-\lambda)T_n + r(B-C)(T_n + G_n - K)^+ < V_{T_n}(\lambda)$; when the waiting time is more than $K - a$, then the source RSU stops at the next vehicle if $b_1 \geq b$ or stops at the next vehicle with transmit delay less than b^* if $b_1 < b$.

E. Optimal Stopping Rule for Problem (3)

From Theorem 3, there exists $\lambda^* \in (C, B]$ such that $V(\lambda^*) = 0$. From proof of Theorem 3, $V(\lambda)$ is continuous and decreasing for $\lambda \in [C, B]$. So λ^* can be found by a bisection search. Then from Theorem 2, an optimal stopping rule of Problem (3) is $N^\dagger(\lambda^*)$ in the form of (24), and the optimal rate of cost (i.e., the optimal objective function of Problem (3)) is λ^*.

To implement the optimal stopping rule $N^\dagger(\lambda^*)$, the value of λ^*, the values of $V_t(\lambda^*)$ for $t \in [0, K-a)$, and values of b, b_1 and b^* can be calculated off-line in advance and stored at the source RSU when the source RSU is setup. Then it can be seen that the computational complexity of the optimal stopping rule $N^\dagger(\lambda^*)$ in the form of (24) is fairly low. Thus, upon a vehicle arrival, the source RSU is able to quickly make a decision, and the energy consumption in the computation is negligible.

Next we continue to calculate the expected optimal stopping time of Problem (3) given as $\mathbb{E}\left[T_{N^\dagger(\lambda^*)}\right]$, the expected energy consumption per unit time, and the expected traffic loss rate.

Define function $\alpha(t) = \mathbb{E}\left[T_{N^\dagger(\lambda^*)} \,\middle|\, T_{N^\dagger(\lambda^*)} \geq t\right]$, which is the expected optimal stopping time if we know that the stopping time is not before time t. Recall that when we start observation from moment $K-a$, the expected optimal stopping time is $\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda^*)}\right] = K - a + \mu$ given in (14) when $b_1 \geq b$ or $\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda^*)}\right] = K - a + \mu/F_G(b^*)$ given in (19) when $b_1 < b$. If we extend the definition of b^* to the scenario with $b_1 \geq b$ such that $b^* = b$ when $b_1 \geq b$ holds, then we have a uniform expression of expected optimal stopping time after moment $K-a$ for both $b_1 \geq b$ and $b_1 < b$ as: $\mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda^*)}\right] = K - a + \mu/F_G(b^*)$. In other words, a boundary condition of $\alpha(t)$ is

$$\alpha(K-a) = \mathbb{E}\left[T_{N^{\mathrm{m}}_{K-a}(\lambda^*)}\right] = K - a + \frac{\mu}{F_G(b^*)}. \tag{25}$$

Following the same method of deriving (23), we can derive the following equation

$$\mu \frac{\mathrm{d}\alpha(t)}{\mathrm{d}t} = \alpha(t) - F_G(\rho(t, \lambda^*))t. \tag{26}$$

Based on (25) and (26), $\alpha(t)$ can be numerically calculated for $t \in [0, K-a)$. And the expected optimal stopping time of Problem (3) is $\mathbb{E}\left[T_{N^\dagger(\lambda^*)}\right] = \alpha(0)$.

When the optimal stopping rule $N^\dagger(\lambda^*)$ is used, the objective function of Problem (3) is given as

$$\begin{aligned} &\frac{WP\kappa + C\mathbb{E}\left[rT_{N^\dagger(\lambda^*)}\right] + (B-C)\mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]}{\mathbb{E}\left[rT_{N^\dagger(\lambda^*)}\right]} \\ &= \frac{WP\kappa + Cr\alpha(0) + (B-C)\mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]}{r\alpha(0)}. \end{aligned}$$

Since an optimal stopping rule of Problem (3) should attain the optimal rate of cost (also the optimal objective function of Problem (3)) given as λ^* (from Theorem 2), we have

$$\frac{WP\kappa + Cr\alpha(0) + (B-C)\mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]}{r\alpha(0)} = \lambda^*$$

which leads to

$$\mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right] = \frac{r\alpha(0)(\lambda^* - C) - WP\kappa}{B - C}. \tag{27}$$

Therefore, the traffic loss rate of the optimal stopping rule $N^\dagger(\lambda^*)$ is the ratio of the expected discarded traffic amount upon a stop to the expected total traffic amount accumulated before a stop, given as

$$\frac{\mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]}{r\mathbb{E}\left[T_{N^\dagger(\lambda^*)}\right]} = \frac{r\alpha(0)(\lambda^* - C) - WP\kappa}{r\alpha(0)(B-C)}.$$

And the energy consumption per time unit is

$$\frac{P\kappa + P\frac{r\mathbb{E}\left[T_{N^\dagger(\lambda^*)}\right] - \mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]}{R}}{\mathbb{E}\left[T_{N^\dagger(\lambda^*)}\right]} = \frac{P\kappa + P\frac{r\alpha(0) - \mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]}{R}}{\alpha(0)}$$

in which the numerator is the expected energy consumption when the source RSU stops, the denominator is the expected stopping time, and $\mathbb{E}\left[A_{N^\dagger(\lambda^*)}\right]$ is given in (27).

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the derived stopping strategy, and compare with Matlab simulations. If a vehicle is selected to help, four-way handshake of RTS-CTS-DATA-ACK is used. The data transmission rate is R = 11 Mbps, and transmission power is $P = 15.5$ dBm $= 35.5$ mW. The overhead duration $\kappa = 938.91$ μs consists of the following components: RTS duration (ratio of RTS size to basic rate, plus preamble time), CTS duration (ratio of CTS size to basic rate, plus preamble time), ACK duration (ratio of ACK size to R, plus preamble time), as well as overhead for data transmission (MAC header time, given as ratio of MAC header size to R, and preamble time), in which basic rate is 2 Mbps, preamble time is 192 μs, and RTS, CTS, ACK, and MAC header have sizes of 20 bytes, 14 bytes, 14 bytes, and 34 bytes, respectively. The traffic coming rate is $r = 5$ bps at the source RSU. The energy cost is $W = 1$ unit of cost per μJoule. The delay bound K is usually application dependent (e.g., a delay bound

$$N^\dagger(\lambda) = \begin{cases} \min\{n : WP\kappa + r\,(C-\lambda)\,T_n + r\,(B-C)\,(T_n+G_n-K)^+ \le V_{T_n}(\lambda)\} & \text{if } T_n < K-a \\ \min n \text{ if } b_1 \ge b \text{ or } \min\{n : G_n \le b^*\} \text{ if } b_1 < b & \text{if } T_n \ge K-a. \end{cases} \quad (24)$$

of 120 minutes is adopted in [4]; the delay bound in [31] is 5–20 minutes). In our simulation, each traffic unit is expected to be delivered to the destination RSU within delay bound $K = 1800$ seconds. If a traffic unit is discarded at the source RSU, a cost of $B = 0.5$ per bit is charged. The distance of the source RSU to the destination RSU is $D = 10,000$ meters. At the source RSU, vehicle inter-arrival time follows an exponential distribution with parameter $\mu = 400$ seconds. The speeds of those vehicles are truncated Gaussian random variables [11] which have mean $\bar{v} = 25$ m/s and variance $\sigma^2 = 9$ [29]. The minimum and maximum speeds are $v_{\min} = 18$ m/s and $v_{\max} = 32$ m/s, respectively. Thus, speeds of vehicles are i.i.d. random variables with CDF:

$$F_V(v) = \begin{cases} 0 & \text{if} \quad v < v_{\min} \\ \frac{\int_{v_{\min}}^{v} e^{-(x-\bar{v})^2/2\sigma^2}\,\mathrm{d}x}{\int_{v_{\min}}^{v_{\max}} e^{-(x-\bar{v})^2/2\sigma^2}\,\mathrm{d}x} & \text{if} \quad v_{\min} \le v \le v_{\max} \\ 1 & \text{otherwise.} \end{cases}$$

The transit delay of vehicle n is $G_n = D/V_n$, where V_n is the speed of vehicle n. And G_n's are i.i.d. random variables with CDF:

$$\begin{aligned} F_G(g) &= 1 - F_V\left(\frac{D}{g}\right) \\ &= \begin{cases} 0 & \text{if} \quad g < a \\ \frac{\int_{D/g}^{v_{\max}} e^{-(x-\bar{v})^2/2\sigma^2}\,\mathrm{d}x}{\int_{v_{\min}}^{v_{\max}} e^{-(x-\bar{v})^2/2\sigma^2}\,\mathrm{d}x} & \text{if} \quad a \le g \le b \\ 1 & \text{if } g > b \end{cases} \end{aligned}$$

where $a = D/v_{\max} = 312.5$ seconds and $b = D/v_{\min} = 555.6$ seconds are the smallest and the largest transit delay, respectively.

A. Optimal stopping rule (24) for Problem (7)

We first evaluate our optimal stopping rule (24) for Problem (7). For $\lambda \in [0.0032, 0.05]$,[12] Fig. 1 shows the numerically calculated values of $V(\lambda) = V_0(\lambda)$ (optimal cost of Problem (7)) based on our derivation in Section III-C. Matlab simulations[13] are also carried out to get the cost of Problem (7) by using the stopping rule $N^\dagger(\lambda)$ given in (24), and the simulation results are also shown in Fig. 1. It can be seen that numerical and simulation results match well. As indicated in proof of Theorem 3, $V(\lambda)$ is a continuous and decreasing function of $\lambda \in [C, B]$.

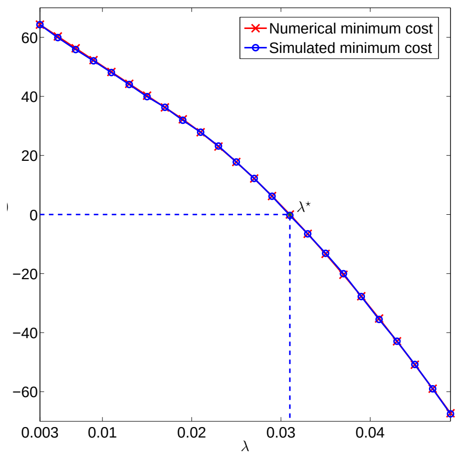

Fig. 1. $V(\lambda)$ for $C \le \lambda \le B$ for Problem (7).

B. Optimal stopping rule of Problem (3)

Now we focus on Problem (3). From Fig. 1, we have $\lambda^* = 0.031$ since $V(\lambda^*) = 0$. And from our analysis in Section III-E, an optimal stopping rule of Problem (3) is as follows, with optimal rate of cost being $\lambda^* = 0.031$.

- When $T_n < K - a = 1487.5$ seconds, by (24) with $\lambda = \lambda^* = 0.031$, an optimal stopping rule of Problem (3) is

$$\begin{aligned} &N^\dagger(0.031) \\ &= \min\{n : WP\kappa + r(C - 0.031)T_n \\ &\qquad + r(B-C)A_n \le V_{T_n}(0.031)\} \\ &= \min\{n : 33.33 - 0.1389T_n + 2.48(T_n + G_n - 1800)^+ \\ &\qquad \le V_{T_n}(0.031)\}. \end{aligned}$$

- When $T_n \ge K - a = 1487.5$ seconds and $\lambda = \lambda^*$, since $b_1 = \phi(b) = \phi(555.6) = 805.39 > b = 555.6$, by (24) with $\lambda = \lambda^* = 0.031$, an optimal stopping rule of Problem (3) is

$$\min\{n : T_n \ge K - a = 1487.5\}.$$

Next we vary the value of B from 0.2 to 1. For Problem (3) with each value of B, we numerically calculate λ^* (which is the numerically obtained optimal rate of cost for Problem (3), and can be found, as aforementioned in Section III-E, by a bisection search such that $V(\lambda^*) = 0$) and obtain the optimal stopping rule $N^\dagger(\lambda^*)$ in the form of (24) with $\lambda = \lambda^*$. We also run computer simulations for the objective function of Problem (3) with stopping rule being $N^\dagger(\lambda^*)$ and get the simulated

[11] Here "truncated Gaussian random variable" means the probability density function of a Gaussian random variable is truncated with a minimum value and a maximal value.

[12] In this example, $C = WP/R = 0.0032$. Since $\lambda^* \in (C, B]$ (from Theorem 3), the minimum value of λ in Fig.1 is 0.0032.

[13] When simulations are carried out to evaluate the proposed stopping rule or the subsequently presented heuristic stopping rule, the stopping rule is applied for each vehicle arrival to decide whether or not to stop. And once the source RSU stops and forwards its traffic to the selected vehicle, it keeps observing subsequent vehicles for its next stopping decisions. In other words, in the simulations, repeated stopping problems are dealt with. And simulation statistics are averaged over 10^6 stops.

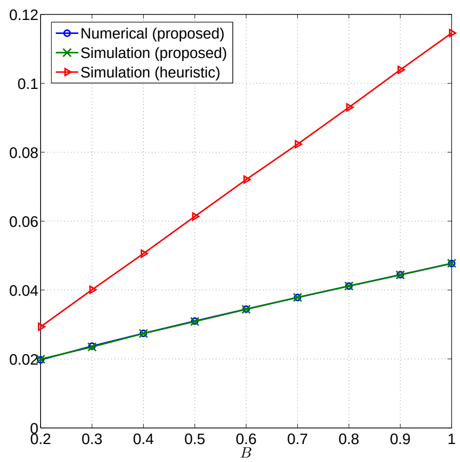

Fig. 2. The rate of cost of the heuristic rule (simulation results) and the proposed optimal stopping rule (numerical and simulation results) for Problem (3).

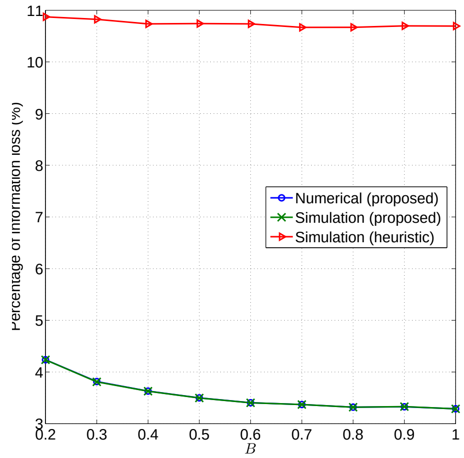

Fig. 4. The percentage of traffic loss of the heuristic rule (simulation results) and the proposed optimal stopping rule (numerical and simulation results) for Problem (3).

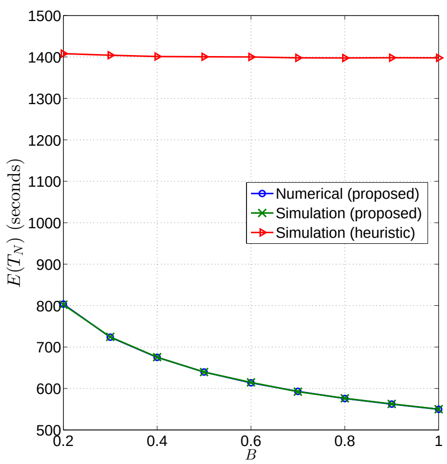

Fig. 3. Average stopping time of the heuristic rule (simulation results) and the proposed optimal stopping rule (numerical and simulation results) for Problem (3).

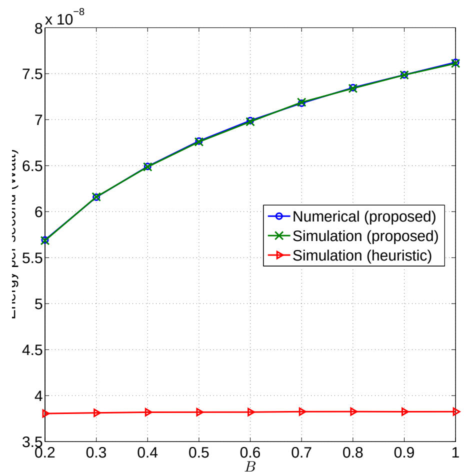

Fig. 5. The energy consumption per second of the heuristic rule (simulation results) and the proposed optimal stopping rule (numerical and simulation results) for Problem (3).

rate of cost. Both the numerically calculated optimal rate of cost (i.e., λ^*) and the simulated rate of cost for different B values are shown in Fig. 2. We can see that the numerical and simulation results match well.

Fig. 2 also shows the simulated rate of cost using a heuristic stopping rule for different values of B. The heuristic stopping rule is the simple myopic stopping rule: Upon a vehicle arrival (say vehicle n), if its rate of cost is less than the rate of cost of the next vehicle, vehicle $n+1$, by assuming that vehicle $n+1$ has an average inter-arrival time (i.e., $X_{n+1} = \mu$) and has an average transit delay (i.e.,$G_{n+1} = \int_a^b g f_G(g)\, \mathrm{d}g$), then the source RSU stops at vehicle n; Otherwise, the source RSU skips vehicle n and waits for other vehicles. In other words, the heuristic stopping rule is shown in (28) on top of next page. From Fig. 2, it can be seen that the proposed stopping rule has a much lower rate of cost than the heuristic rule.

Figs. 3-5 shows the average stopping time, average percentage of traffic loss, and average energy consumption per time unit, respectively, for both the proposed stopping rule (analytical results from Section III-E and simulation results) and the heuristic rule (simulation results). When penalty B increases, the proposed stopping rule is more conservative to decide on continuation, and therefore, the average stopping time decreases in Fig. 3 and the percentage of traffic loss decreases in Fig. 4. Since more percentage of traffic is delivered when B increases, more energy is consumed, as shown in Fig. 5. On the other hand, for the heuristic stopping rule, increase of B only slightly decreases the average stopping time. This can be roughly explained as follows.

- When $T_n \leq K - \mu - \int_a^b g f_G(g)\, \mathrm{d}g = 994.8$ second, we have $(T_n + G_n - K)^+ \leq (T_n + b - K)^+ \leq (994.8 + b - K)^+ = 0$. Since $(T_n + G_n - K)^+ = \max(T_n + G_n - K, 0) \geq 0$, we have $(T_n + G_n - K)^+ = 0$. Further, we

$$\min\left\{n : \frac{WP\kappa + rCT_n + r(B-C)(T_n+G_n-K)^+}{rT_n} \leq \frac{WP\kappa + rC(T_n+\mu) + r(B-C)(T_n+\mu+\int_a^b g f_G(g)\,\mathrm{d}g - K)^+}{r(T_n+\mu)}\right\}. \tag{28}$$

have $(T_n+\mu+\int_a^b g f_G(g)\,\mathrm{d}g-K)^+=0$. Therefore, the inequality in (28) becomes

$$\frac{WP\kappa+rCT_n}{rT_n} \leq \frac{WP\kappa+rC(T_n+\mu)}{r(T_n+\mu)}$$

which apparently never holds. Therefore, when $T_n \leq 994.8$ second, the heuristic stopping rule never decides on stopping.

- When $T_n \geq K-a = 1487.5$ second, we have $(T_n+G_n-K)^+ = T_n+G_n-K$, and $(T_n+\mu+\int_a^b g f_G(g)\,\mathrm{d}g - K)^+ = T_n+\mu+\int_a^b g f_G(g)\,\mathrm{d}g-K$, and therefore, the inequality in (28) becomes (29) on top of next page. Recall that B varies from 0.2 to 1 in Figs. 3-5. If B takes the minimum value 0.2, we have $C=0.0032 \ll B-C$, $WP\kappa = 33.33 \ll r(B-C)(K-a) \leq r(B-C)T_n$. So in (29), we can approximately omit $WP\kappa+rCT_n$ and $WP\kappa+rC(T_n+\mu)$ from the numerator on both sides, respectively, and get

$$\frac{T_n+G_n-K}{T_n} \leq \frac{T_n+\mu+\int_a^b g f_G(g)\,\mathrm{d}g-K}{T_n+\mu}$$

in which B does not exist. Therefore, when $T_n \geq K-a = 1487.5$ second, the value of B almost does not affect the stopping time.
- When $T_n \in (994.8 \text{ second}, 1487.5 \text{ second})$, the heuristic stopping rule is more conservative when the penalty B increases.

Overall, for the heuristic stopping rule, the value of B only affects the stopping decision for vehicle n when $T_n \in$ (994.8 second, 1487.5 second). Therefore, when B increases, the average stopping time of the heuristic rule only slightly decreases in Fig. 3. This also explains that the percentage of traffic loss slightly decreases in Fig. 4, and that the average energy consumption per second slightly increases in Fig. 5.

V. Effect of Wireless Transmission Errors

Now we briefly investigate the case when there are wireless transmission errors (e.g., due to wireless link outage or collisions). In specific, if a transmission error happens with the RTS, CTS, DATA, or ACK exchange between the source RSU and a vehicle, retransmission(s) will be needed, which consume more energy. And if the RTS-CTS-DATA-ACK handshake cannot be completed before the vehicle leaves the communication coverage area of the source RSU, the DATA will remain in the source RSU's buffer, and wait for future vehicles.

First we analyze the effect of wireless transmission errors on our optimal stopping rule. When the source RSU makes a decision on whether or not to stop, it does not know how much energy will be consumed if it decides to stop, since possible retransmissions may enlarge the energy consumption. Therefore, the source RSU needs to assess the *expected* energy consumption when it decides whether or not to stop. Denote the probabilities that an RTS, CTS, DATA, and ACK message is successfully received as p_1, p_2, p_3, and p_4, respectively. Then the information exchange between the source RSU and the vehicle follows a Markov chain with five states: RTS, CTS, DATA, ACK and SUCCESS, as shown in Fig. 6, in which SUCCESS means that the handshake is successfully completed. In the figure, $\mathrm{e_{RTS}}$, $\mathrm{e_{CTS}}$, $\mathrm{e_{DATA}}$, and $\mathrm{e_{ACK}}$ are the energy consumption for transmission of an RTS, CTS, DATA, and ACK message, respectively.

Denote $\overline{\mathrm{E}}_{\mathrm{RTS}}$, $\overline{\mathrm{E}}_{\mathrm{CTS}}$, $\overline{\mathrm{E}}_{\mathrm{DATA}}$, and $\overline{\mathrm{E}}_{\mathrm{ACK}}$ as the expected energy consumption to reach SUCCESS state if we begin with RTS, CTS, DATA and ACK state, respectively. We have the following equations:

$$\begin{aligned}
\overline{\mathrm{E}}_{\mathrm{ACK}} &= p_4\mathrm{e_{ACK}} + (1-p_4)\left(\mathrm{e_{ACK}}+\overline{\mathrm{E}}_{\mathrm{RTS}}\right)\\
\overline{\mathrm{E}}_{\mathrm{DATA}} &= p_3\left(\mathrm{e_{DATA}}+\overline{\mathrm{E}}_{\mathrm{ACK}}\right) + (1-p_3)\left(\mathrm{e_{DATA}}+\overline{\mathrm{E}}_{\mathrm{RTS}}\right)\\
\overline{\mathrm{E}}_{\mathrm{CTS}} &= p_2\left(\mathrm{e_{CTS}}+\overline{\mathrm{E}}_{\mathrm{DATA}}\right) + (1-p_2)\left(\mathrm{e_{CTS}}+\overline{\mathrm{E}}_{\mathrm{RTS}}\right)\\
\overline{\mathrm{E}}_{\mathrm{RTS}} &= p_1\left(\mathrm{e_{RTS}}+\overline{\mathrm{E}}_{\mathrm{CTS}}\right) + (1-p_1)\left(\mathrm{e_{RTS}}+\overline{\mathrm{E}}_{\mathrm{RTS}}\right).
\end{aligned}$$

By solving the above equations, we have the expected energy consumption if the source RSU stops, as follows:

$$\overline{\mathrm{E}}_{\mathrm{RTS}} = \frac{\mathrm{e_{RTS}}+p_1\mathrm{e_{CTS}}+p_1p_2\mathrm{e_{DATA}}+p_1p_2p_3\mathrm{e_{ACK}}}{p_1p_2p_3p_4}.$$

The energy consumed to send data (i.e., $\mathrm{e_{DATA}}$) contains two parts: energy used to send MAC header and preamble: $\mathrm{e_{MAC+preamble}}$, and energy used to send actual data: $\mathrm{e_{PAYLOAD}}$ (which is equal to $P(rT_n-A_n)/R$). Since W is cost weight for energy consumption, to successfully transmit traffic from the source RSU to a vehicle, the expected cost of energy consumption is

$$\frac{WP\frac{rT_n-A_n}{R}}{p_3p_4} + W\frac{\mathrm{e_{RTS}}+p_1\mathrm{e_{CTS}}+p_1p_2\mathrm{e_{MAC+preamble}}+p_1p_2p_3\mathrm{e_{ACK}}}{p_1p_2p_3p_4}.$$

After a comparison with the cost expression of energy consumption given in Section II, it can be seen that: our analysis and solution in Section II and III are still valid, if we replace parameter C with $C/(p_3p_4)$ and replace parameter κ with

$$\frac{\mathrm{e_{RTS}}+p_1\mathrm{e_{CTS}}+p_1p_2\mathrm{e_{MAC+preamble}}+p_1p_2p_3\mathrm{e_{ACK}}}{Pp_1p_2p_3p_4}.$$

With these replacements, similar to Fig. 2, we get the numerical result and simulation result of our derived optimal stopping rule, as well as the simulation result of the heuristic rule, as shown in Fig. 7. In the numerical and simulation results, each

$$\frac{WP\kappa + rCT_n + r(B-C)(T_n + G_n - K)}{rT_n} \le \frac{WP\kappa + rC(T_n+\mu) + r(B-C)(T_n + \mu + \int_a^b g f_G(g)\,\mathrm{d}g - K)}{r(T_n+\mu)}. \quad (29)$$

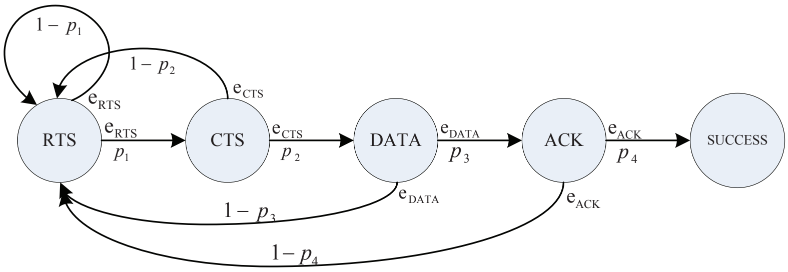

Fig. 6. Information exchange between the source RSU and a vehicle.

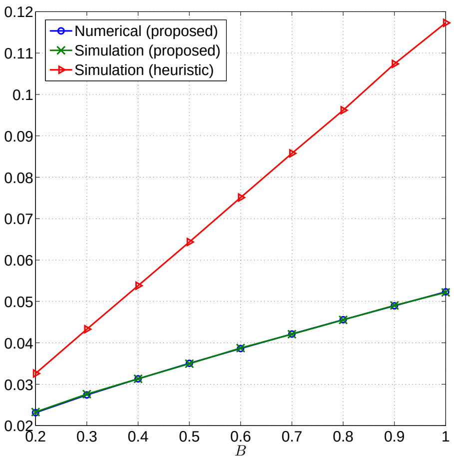

Fig. 7. The rate of cost of the heuristic rule (simulation results) and the proposed optimal stopping rule (numerical and simulation results) for Problem (3) when there are transmission errors ($p_1 = p_2 = p_3 = p_4 = 0.9$).

message (RTS, CTS, DATA, or ACK) is successfully received with a probability 0.9, which means $p_1 = p_2 = p_3 = p_4 = 0.9$. In the simulation for our derived optimal stopping rule and the heuristic rule, if the RTS-CTS-DATA-ACK handshake cannot be completed before the vehicle is outside the communication coverage of the source RSU[14] (the coverage radius is set to be 300 meters in the simulation), the RSU keeps the traffic in its buffer and waits for future vehicle. It can be seen that the numerical and simulation results for our derived stopping rule match with each other. Compared to Fig. 2, wireless transmission errors lead to larger rate of cost in our derived stopping rule and the heuristic rule.

VI. Conclusion and Further Discussion

In this work, we have studied the traffic scheduling in vehicular delay tolerant networks by taking into account the queueing delay, the transmit delay, and the energy consumption. By setting the objective to minimize the rate of cost, we theoretically derive an optimal stopping rule of the source RSU.

In this paper, all vehicles passing by the source RSU will also pass by the destination RSU. Actually our research can be extended to the case when some arrival vehicles do not pass by the destination RSU. Recall that vehicle arrivals at the source RSU follow a Poisson process with rate $1/\mu$ (μ is the average inter-arrival time). Let β denote the percentage of the passing-by vehicles at the source RSU that will also pass by the destination RSU. Then the problem is equivalent to the case that vehicles arrive with rate $\beta(1/\mu)$ (i.e., average inter-arrival time is μ/β) and all vehicles will pass by the destination RSU.

We also assume there is only one destination RSU. However, our research can be extended to the case when the source RSU can send its traffic to any one of several destination RSUs (that have backbone connection). As an example, consider a source RSU that has two paths, with destination RSU #1 and destination RSU #2, respectively. The transit delay of the two paths have CDF $F_{G_1}(g)$ and $F_{G_2}(g)$, respectively. For the vehicles arriving at the source RSU, denote α and $1-\alpha$ as the percentage of vehicles passing by destination RSU #1 and #2, respectively. Then, the problem is equivalent to the case that only a single destination RSU exists and the transit delay of vehicles has the following effective CDF: $F_G(g) = \alpha F_{G_1}(g) + (1-\alpha)F_{G_2}(g)$.

From the above discussion it can be seen that if a vehicle does not pass by any destination RSU, then the source RSU (called source RSU #1) cannot ask the vehicle to help. However, if the vehicle will pass by another source RSU (called source RSU #2 that does not have backbone connection either) closer to a destination RSU, then it may be beneficial for source RSU #1 to forward its traffic to the vehicle, expecting that the vehicle will deliver the traffic to source RSU #2, which will ask its passing-by vehicles to help deliver the traffic to a destination RSU. Further, a vehicle, who carries the traffic of a source RSU, may pass the traffic to another vehicle later, if it takes the latter vehicle less time to arrive at an RSU with backbone network connection. The cooperative traffic delivery will be considered as a future research topic.

[14]Note that this rarely happens, since the available communication time of the source RSU and the vehicle is large enough if the transmission successful probability is not extremely low.

Appendix

A. Proof of Theorem 1

According to [28], if the following two conditions are met:

$$1.\ \mathbb{E}\left[\inf_{n} Z_n(\lambda)\right] > -\infty \tag{30}$$

$$2.\ \lim_{n\to\infty} Z_n(\lambda) \geq Z_\infty(\lambda) \quad \text{almost surely (a.s.),} \tag{31}$$

then there exits an optimal stopping rule $N^\dagger(\lambda)$ such that $\mathbb{E}\left[Z_{N^\dagger(\lambda)}(\lambda)\right] = V(\lambda)$, where $V(\lambda) = \inf_{N\geq 1}\mathbb{E}\left[Z_N(\lambda)\right]$.

From (4), we have

$$A_n \geq \begin{cases} 0 & \text{if} \quad T_n < K - a \\ r(T_n + G_n - K) & \text{if} \quad T_n \geq K - a. \end{cases} \tag{32}$$

For $\lambda \leq B$, we have

$$\begin{aligned} & Z_n(\lambda) \\ & = WP\kappa + r\,(C-\lambda)\,T_n + (B-C)A_n \\ & \geq WP\kappa + r\,(C-B)\,T_n + (B-C)A_n \\ & \overset{\text{(e1)}}{\geq} \begin{cases} WP\kappa + r\,(C-B)\,T_n & \text{if} \quad T_n < K-a \\ WP\kappa + r(B-C)(G_n - K) & \text{if} \quad T_n \geq K-a \end{cases} \\ & \overset{\text{(e2)}}{\geq} \begin{cases} WP\kappa + r\,(C-B)\,(K-a) & \text{if} \quad T_n < K-a \\ WP\kappa + r(B-C)(a-K) & \text{if} \quad T_n \geq K-a \end{cases} \\ & = WP\kappa + r(B-C)(a-K) > -\infty \end{aligned}$$

where inequality (e1) follows from (32), and inequality (e2) follows from $B > C$ and $G_n \geq a$. Thus, the first condition in (30) is established.

When $n \to \infty$, we have $T_n \to \infty$ a.s., and thus from (4), we have $A_n = r(T_n + G_n - K)$, and

$$\begin{aligned} & \lim_{n\to\infty} Z_n(\lambda) \\ = & \lim_{n\to\infty} \left\{WP\kappa + r\,(C-\lambda)\,T_n + (B-C)r(T_n + G_n - K)\right\} \\ = & \lim_{n\to\infty} \left\{WP\kappa + r\,(B-\lambda)\,T_n + (B-C)r(G_n - K)\right\}. \end{aligned}$$

Define $Z_\infty(\lambda) = \infty$. Then we have $\lim_{n\to\infty} Z_n(\lambda) = Z_\infty(\lambda)$ a.s., and the second condition in (31) is satisfied.

B. Proof of Theorem 2

According to the condition i), we have $\mathbb{E}\left[Y_N - \lambda^* r T_N\right] \geq 0$ for any stopping rule N, which leads to

$$\frac{\mathbb{E}\left[Y_N\right]}{\mathbb{E}\left[rT_N\right]} \geq \lambda^*. \tag{33}$$

From condition ii), we have $\mathbb{E}\left[Z_{N^\dagger(\lambda^*)}(\lambda^*)\right] = V(\lambda^*) = 0$, which means $\mathbb{E}\left[Y_{N^\dagger(\lambda^*)} - \lambda^* r T_{N^\dagger(\lambda^*)}\right] = 0$. This leads to

$$\frac{\mathbb{E}\left[Y_{N^\dagger(\lambda^*)}\right]}{\mathbb{E}\left[rT_{N^\dagger(\lambda^*)}\right]} = \lambda^*. \tag{34}$$

From (33) and (34), $N^\dagger(\lambda^*)$ is an optimal stopping rule for

$$\inf_{N\geq 1} \frac{\mathbb{E}\left[Y_N\right]}{\mathbb{E}\left[rT_N\right]}$$

which is Problem (3), and the optimal rate of cost is

$$\frac{\mathbb{E}\left[Y_{N^\dagger(\lambda^*)}\right]}{\mathbb{E}\left[rT_{N^\dagger(\lambda^*)}\right]} = \lambda^*.$$

C. Proof of Theorem 3

Based on the definition of $Z_n(\lambda)$ in (6), when $\lambda = C$, for any n we have $Z_n(\lambda)\Big|_{\lambda=C} \geq WP\kappa > 0$. Hence, based on the definition of $V(\lambda)$ in (7), we have $V(C) > 0$.

From (5), we have

$$K - a > \frac{WP\kappa}{r(B-C)}.$$

Define

$$\delta \triangleq K - a - \frac{WP\kappa}{r(B-C)} > 0.$$

When $\lambda = B$, from (6) we have $Z_n(B) = WP\kappa - (B-C)(rT_n - A_n)$. From (7), we have

$$V(B) = \inf_{N\geq 1}\mathbb{E}\left[Z_N(B)\right] \leq \inf_{N\geq 1, T_N > K, G_N < a+\delta}\mathbb{E}\left[Z_N(B)\right] \tag{35}$$

because $\{N : N \geq 1, T_N > K, G_N < a+\delta\} \subset \{N : N \geq 1\}$.

When $T_N > K, G_N < a+\delta$, from (4) we have $A_N = r(T_N + G_N - K)$, and further, we have

$$\begin{aligned} Z_N(B) & = WP\kappa - (B-C)(rT_N - A_N) \\ & = WP\kappa - (B-C)r(K - G_N) \\ & < WP\kappa - (B-C)r(K - (a+\delta)) \\ & = 0 \end{aligned} \tag{36}$$

where the last equality comes from the definition of δ.

From (35) and (36), we have $V(B) \leq 0$.

Next we show that $V(\lambda)$ is continuous in $[C, B]$. From Theorem 1, it is shown that for $\lambda \leq B$, there exists an optimal stopping rule denoted $N^\dagger(\lambda)$ for Problem (7). As to be shown in (14) and (19) in Section III-B (which show that the average optimal stopping time of Problem (7) is finite), we have $\mathbb{E}\left[T_{N^\dagger(\lambda)}\right] < \infty$.

Let $C \leq \lambda_1 < \lambda_2 \leq B$. Then

$$\begin{aligned} V(\lambda_1) & = \mathbb{E}\left[Y_{N^\dagger(\lambda_1)}\right] - \lambda_1 \mathbb{E}\left[rT_{N^\dagger(\lambda_1)}\right] \\ & > \mathbb{E}\left[Y_{N^\dagger(\lambda_1)}\right] - \lambda_2 \mathbb{E}\left[rT_{N^\dagger(\lambda_1)}\right] \\ & \geq V(\lambda_2) \end{aligned} \tag{37}$$

where the first equality comes from the optimality of stopping rule $N^\dagger(\lambda_1)$ for Problem (7) with $\lambda = \lambda_1$, the first inequality comes from $\lambda_1 < \lambda_2$, and the second inequality comes from the fact that $V(\lambda_2)$ is the minimum cost of Problem (7) with $\lambda = \lambda_2$.

From (37), it can be seen that $V(\lambda)$ is decreasing in $\lambda \in [C, B]$.

If $\lambda_2 - \lambda_1 < \epsilon / (r\mathbb{E}\left[T_{N^\dagger(\lambda_2)}\right])$ where ϵ is a very small positive value (recalling that $\mathbb{E}\left[T_{N^\dagger(\lambda)}\right]$ is finite for any $\lambda \in$

$(0, B]$), we have

$$\begin{aligned}
&|V(\lambda_2) - V(\lambda_1)| \\
&= V(\lambda_1) - V(\lambda_2) \\
&= V(\lambda_1) - \left(\mathbb{E}\left[Y_{N^\dagger(\lambda_2)}\right] - (\lambda_1 + (\lambda_2 - \lambda_1))\mathbb{E}\left[rT_{N^\dagger(\lambda_2)}\right]\right) \\
&= V(\lambda_1) - \left(\mathbb{E}\left[Y_{N^\dagger(\lambda_2)}\right] - \lambda_1\mathbb{E}\left[rT_{N^\dagger(\lambda_2)}\right]\right) \\
&\qquad + (\lambda_2 - \lambda_1)\mathbb{E}\left[rT_{N^\dagger(\lambda_2)}\right] \\
&\le (\lambda_2 - \lambda_1)\mathbb{E}\left[rT_{N^\dagger(\lambda_2)}\right] < \epsilon
\end{aligned} \tag{38}$$

where the second equality comes from the optimality of $N^\dagger(\lambda_2)$ for Problem (7) with $\lambda = \lambda_2$, and the first inequality comes from the fact that $V(\lambda_1)$ is the minimum cost of Problem (7) with $\lambda = \lambda_1$.

From (38), it can be concluded that $V(\lambda)$ is continuous for $\lambda \in [C, B]$. Since $V(C) > 0$ and $V(B) \le 0$ and $V(\lambda)$ is decreasing in $\lambda \in [C, B]$, according to Intermediate Value Theorem [30], there exists a unique $\lambda^* \in (C, B]$ such that $V(\lambda^*) = 0$.

D. Proof of Theorem 4

According to Theorem 2 and Corollary 2 in Chapter 5 of [28], if Problem (7) when $T_n \ge K - a$ is monotone, then its myopic rule (13) is optimal if the following conditions are satisfied:

- i) Z_n can be written as $Z_n = u_n + w_n$, where $\mathbb{E}\left[\sup_n |u_n|\right] < \infty$ and w_n is nonnegative and nondecreasing a.s.;
- ii) $\lim_{n\to\infty} Z_n = Z_\infty$ a.s..

We copy (8) here:

$$Z_n(\lambda) = WP\kappa + r(B - \lambda)T_n + r(B - C)(G_n - K).$$

Define $u_n = WP\kappa + r(B - C)(G_n - K)$ and $w_n = r(B - \lambda)T_n$. Since $\lambda \in (0, B]$, Condition i) is satisfied.

Define $Z_\infty(\lambda) = \infty$. Then

$$\begin{aligned}
&\lim_{n\to\infty} Z_n(\lambda) \\
&= \lim_{n\to\infty} \big(WP\kappa + r(B - \lambda)T_n + r(B - C)(G_n - K)\big) \\
&= Z_\infty(\lambda) \text{ a.s.}
\end{aligned} \tag{39}$$

which means Condition ii) is satisfied.

E. Proof of Theorem 5

Take the first-order derivative of $\phi(g)$ given in (11), we have

$$\begin{aligned}
\frac{\mathrm{d}\phi(g)}{\mathrm{d}g} &= \frac{f_G(g)}{F_G(g)}\left(g - \frac{(B-\lambda)\mu}{(B-C)F_G(g)} - \frac{\int_a^g x f_G(x)\,\mathrm{d}x}{F_G(g)}\right) \\
&= \frac{f_G(g)}{F_G(g)}\left(g - \phi(g)\right) \\
&= \frac{f_G(g)}{(F_G(g))^2}\left(g - \phi(g)\right)F_G(g) \\
&= \frac{f_G(g)}{(F_G(g))^2}\Psi(g)
\end{aligned} \tag{40}$$

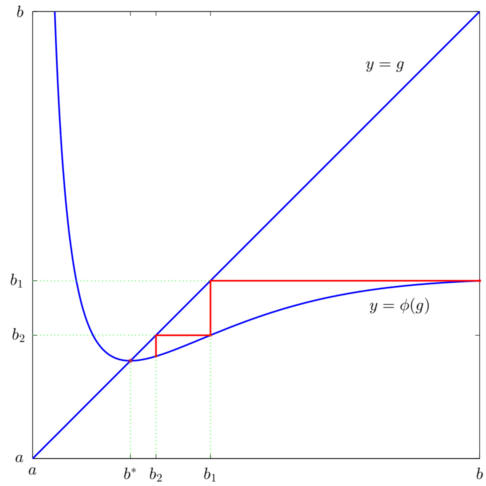

Fig. 8. Curves $y = \phi(g)$ and $y = g$, and the procedure of obtaining $b \to b_1 \to b_2 \to \dots$.

in which $\Psi(g) \triangleq \big(g - \phi(g)\big)F_G(g)$. Then $\Psi(b) = (b - \phi(b))F_G(b) = b - \phi(b) = b - b_1 > 0$. Replacing $\phi(g)$ with (11), $\Psi(g)$ can be rewritten as

$$\begin{aligned}
\Psi(g) &= gF_G(g) - \frac{(B-\lambda)\mu}{B-C} - \int_a^g x f_G(x)\,\mathrm{d}x \\
&= \int_a^g (g - x) f_G(x)\,\mathrm{d}x - \frac{(B-\lambda)\mu}{B-C}
\end{aligned}$$

from which it can be seen that $\Psi(g)$ is an increasing function of $g \in (a, b]$, and

$$\lim_{g>a,\ g\to a} \Psi(g) = -\frac{(B-\lambda)\mu}{B-C} < 0.$$

Recalling that $\Psi(b) > 0$, for $g \in (a, b]$ there is a unique root of $\Psi(g) = 0$. Denote the root as b^*. In other words, $\Psi(b^*) = (b^* - \phi(b^*))F_G(b^*) = 0$, which leads to $\phi(b^*) = b^*$. This means, for $g \in (a, b]$, curve $y = \phi(g)$ and curve $y = g$ have a unique common point at $g = b^*$, which proves Part 3) of Theorem 5. Since $\Psi(g)$ is an increasing function of $g \in (a, b]$ and $\lim_{g>a,\ g\to a} \Psi(g) < 0 < \Psi(b)$, we have

- When $g \in (a, b^*)$, $\Psi(g) < 0$. Then from (40) we have $\frac{\mathrm{d}\phi(g)}{\mathrm{d}g} < 0$, which means $\phi(g)$ is a decreasing function of $g \in (a, b^*)$;
- When $g \in (b^*, b]$, $\Psi(g) > 0$. Then from (40) we have $\frac{\mathrm{d}\phi(g)}{\mathrm{d}g} > 0$, which means $\phi(g)$ is an increasing function of $g \in (b^*, b]$.

These also mean that for $g \in (a, b]$, $g = b^*$ minimizes $\phi(g)$, which proves Part 4) of Theorem 5.

Fig. 8 shows the curve $y = \phi(g)$ and curve $y = g$. The red curve in Fig. 8 shows how to get $b_1 = \phi(b)$ from b, get $b_2 = \phi(b_1)$ from b_1, ..., etc. It can be seen that the procedure of obtaining $b \to b_1 \to b_2 \to \dots$ is actually the procedure of finding the unique common point of the curve $y = \phi(g)$ and curve $y = g$. Therefore, it can be concluded that sequence $\{b_i\}_{i=1,2,\dots}$ converges to b^*, and $b > b_1 > b_2 > \dots$, which proves Parts 1) and 2) of Theorem 5.

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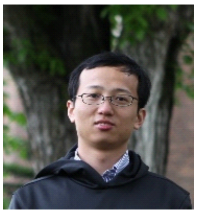

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