Optimal Operation of a Green Server with Bursty Traffic

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***Abstract*—To reduce the energy consumption of various information and communication systems, sleeping mechanism design is considered to be a key problem. Prior work has derived optimal single server sleeping policies only for non-bursty, memoryless Poisson arrivals. In this paper, for the first time, we derive the optimal sleep operation for a single server facing bursty traffic arrivals. Specifically, we model job arrivals as a discrete-time interrupted Bernoulli process (IBP) which models bursty traffic arrivals. Key factors including the switching and working energy consumption costs as well as a delay penalty are accounted for in our model. As the arrival process state (busy or quiet) cannot be directly observed by the server, we formulate the problem as a POMDP (partially observable Markov decision process), and show that it can be tractably solved as a belief-MDP by considering the time interval since the last observed arrival t. We prove that the optimal sleeping policy is hysteretic and the numerical results reveal that the optimal policy is a t-based two-threshold policy, where the sleeping thresholds change with t. The simulation results show that our policy outperforms the previously derived Poisson-optimal policy and that the system cost decreases with the burstiness of traffic.**

I. Introduction

Reducing the energy consumption of communications and networks is one of the main challenges and brings benefits in many aspects including economic and environmental concern. For example, in upcoming 5G networks, the energy consumption and cost per bit have to be reduced by at least 100 times [1], which reveals the growing importance of ”greening” the networks.

Considered as one of the most efficient methods to reduce energy consumption, sleeping mechanisms have been studied widely in recent years. The trade-off between energy saving from sleeping and delay are studied in [2]–[4], [10]. In these works, the traffic is modeled as a random Poisson process. In practice, however, traffic and jobs have a bursty nature especially for data and video traffic [5], which might bring in more dynamics and chances for a server to sleep. Therefore, we study the optimal sleeping policy for a single server with bursty traffic.

In [10], the authors discuss multiple hysteresis sleeping mechanism and their delay performance under Poisson traffic arrival. In previous work [13], the authors consider a single server and find the optimal sleeping policy with Poisson arrivals by formulating the problem into a continuous-time MDP, where the system state only changes when there is an arrival or a departure. The optimal policy has been proved to be a two-threshold policy, where the queue length in the server will be compared to an ON threshold and an OFF threshold, to decide whether the action is ON, OFF or to stay at the current operation mode. In this situation, if there is no arrivals or departures for a long time, which would happen with a higher probability under bursty traffic, keeping the server on would potentially consume more power. If the server could make decisions in the middle of the queue length changes, we might gain higher energy efficiency. In this work, for the first time, we show how to optimally operate the sleep mode for a single server under bursty traffic. For tractability we consider a discrete-time Interrupted Bernoulli Process, which can be used to approximate an interrupted Poisson Process arbitrarily well (as the time duration per slot tends to zero), to reflect the burstiness of traffic.

Note that in [6], the authors did study the sleeping performance of a single server under bursty traffic, assuming an N-based policy, where the server goes to sleep when the buffer is empty and wakes up when there are N jobs accumulated in the buffer. They find the optimal transmit power and the waking-up threshold N to minimize the energy consumption, with a certain constraint of delay. However, that work does not consider whether the N-based policy is the optimal policy under bursty traffic. To our knowledge, this work is the first to find the optimal sleeping policy with a POMDP (partially observable Markov decision process) formulation, and our result shows that for the optimal policy under bursty arrivals, the sleep decision should be made not only based on the queue length, but also based on a measure of time.

A POMDP is a generalization of an MDP where we cannot observe the MDP-determined system state directly. Instead, a probability distribution over the state space is recorded and updated. POMDP has been used to analyze the communication systems widely in [7]–[9]. In [8], the authors use POMDP to analyze opportunistic spectrum access. Decisions of channel selection are discussed in [7], [9]. To our knowledge, this work provides the first optimal solution for the IBP arrivals with POMDP formulation.

In this paper, we make the following contributions:

- We formulate this decision problem into a Partially Observable Markov decision process and give the numerical results for the optimal sleeping policy and analyze the structure of it.
- According to the numerical results, we find that the optimal policy seems to be a t-based two-threshold policy, where the sleeping thresholds not only depend on the queue length, but also the time interval since the last arrival t. The server would postpone several time slots to switch its operation mode from ON to OFF, and switch earlier from OFF to ON, instead of shutting down immediately when the buffer is empty or keeping sleeping when there are not enough jobs waiting in the buffer.
- By adding the time interval since the last arrival into the system state, the system cost, which is a combination of energy consumption and delay, is always lower than the optimal solution for memoryless arrivals in previous work [13].
- From the simulation results, we find that the system cost decreases with burstiness of the arrival process.

The rest of this paper is organized as follows. The system model and POMDP approach are introduced in Section II. We analyze the structure of the optimal policy in Section III. In Section IV, numerical results and simulations are given. Conclusions and future work are presented in Section V.

II. POMDP Approach

In this section, we first introduce the interrupted Bernoulli process (IBP) traffic model and formulate the decision problem into a POMDP. After that, we try to solve the POMDP with a belief-MDP and give the expressions for the cost function and the transition matrix.

A. Traffic Model

We consider a single server with a finite buffer with a size of B. There are two operation modes for the server, ON and OFF, which represent the working mode and the sleeping mode, respectively. The system is modeled as a discrete-time system where time is divided into time slots and there is at most one arrival or departure in one time slot. Assume that the job arrivals follow an IBP with parameters (λ, α, β), which includes a quiet phase and a busy phase. As shown in Fig. 1, the time spent in the busy and quiet phases are both geometrically distributed, with expected durations α and β time slots, respectively. That is, given that the process is in the busy phase (or the quiet phase) at time slot n, it would change to the quiet phase (or the busy phase) with probability α^{-1} (or β^{-1}), or would remain in the same phase at the next time slot $n+1$ with probability $(1-\alpha^{-1})$ (or $(1-\beta^{-1})$).

In the busy phase, the time interval between two job arrivals during the phase also follows a geometric distribution with success probability λ at each time slot, which is also known as the arrival rate. That is, the mean interarrival time in the busy phase is λ^{-1} time slots. There is no job arrival in the quiet phase. Therefore, with varying λ, α and β, traffic with

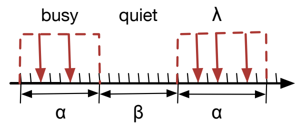

Fig. 1. An example of IBP arrivals with parameters (λ, α, β).

different bursty levels is able to be generated. Based on [11], the global average interarrival time, ρ, is given by

$$\rho = \frac{1}{\lambda}\frac{\alpha+\beta}{\alpha}. \tag{1}$$

The squared coefficient of variation (SCV) of the interarrival time, C^2, is given by

$$C^2 = 1 + \lambda\left[\frac{\frac{1}{\alpha}(2-\frac{1}{\alpha}-\frac{1}{\beta})}{(\frac{1}{\alpha}+\frac{1}{\beta})^2} - 1\right]. \tag{2}$$

The larger C^2 is, the higher bursty level the arrival process has. We also assume that the jobs need a geometrically distributed period of work from the server with success probability μ, of which the mean service time needed is μ^{-1} time slots for each job. Note that with arbitrarily small period of one time slot, the IBP can approximate arbitrarily well the continuous time interrupted Poisson process (IPP), which is one of the most typical models to reflect traffic burstiness.

B. POMDP Formulation

If the state of the arrival process (busy or quiet) can be observed directly, the optimal operation decision problem for the server can be formulated into an MDP, by adding the state of the arrival process S into the state of the Poisson arrival MDP problem. Note that $S \in \{\text{Busy, Quiet}\}$. However, we assume that the actual state of the arrival IBP process cannot be observed directly. As a result, we formulate this problem as a discrete-time partially observable Markov decision process and the state updates at each time slot.

At each time slot, the server takes a certain action based on the current state and the system transits to another state with known transition probabilities. After that, the system would receive an observation based on the new state and the action, which helps us determine the underlying state and make the decision for the next time slot. Finally, the action and the former state incur a cost for the system. Our objective is to decide which action to choose at each time slot to minimize the total expected discounted costs over time. The POMDP formulation of this optimal operation problem is defined as follows.

The actual system state is (S, R, Q, W), if the arrival process is in state S, the queue length in the server is Q and the operation state of the server is $W \in \{\text{ON, OFF}\}$ in the current time slot. R is a Boolean variable that $R=1$ indicates there is a job arrival in the passing time slot. The state space is $\Omega = \{\text{Busy}, \text{Quiet}\} \times \{0,1\} \times \{0,1,2,...,B\} \times \{\text{ON, OFF}\}$. Note that departures are assumed to happen earlier than arrivals at each time slot. Thus, $R=1$ indicates there has to be at least one job in the buffer, that is, $Q>0$. We use S_n, R_n, Q_n and W_n to denote the state at time slot n, where n is a non-negative integer.

At each time slot, the server takes an action $a \in \Phi$. The action space only contains two actions, that is, $\Phi = \{$ON, OFF$\}$. The server processes the jobs at rate 1 only when it is ON; otherwise, the server is in OFF mode and no job could be processed. The server consumes a constant E_{on} energy each time slot when it is ON. Every action that switches the mode of the server (ON to OFF, or OFF to ON) would consume E_{sw} energy.

After transiting to a new state, an observation (R, Q, W) is taken by the server. All the state elements except the IBP state S can be observed directly.

The cost function is determined by the current state and the action. We consider the energy consumption including both the switching consumption and the operation consumption when the server is ON. The delay of the jobs are counted in the cost function as a penalty that is proportional to the sojourn time of each job. By changing the weighting between energy consumption and the delay penalty, we are able to model systems with different emphasis on delay tolerance and energy saving.

The solution to this POMDP is a policy that indicates how to choose an optimal action in each state, or correspondingly, at each time slot.

C. Belief-MDP Formulation

In the POMDP formulation, the server would keep a belief of the probability distribution over the state space at the current time slot, upon the action taken and the observation. It is not hard to find that the only uncertainty of the state is the IBP phase S, with (R, Q, W) known. Therefore, we define p to indicate the probability of being in busy phase knowing all the past observations and actions, and p_n denotes the belief at time slot n. Because the state is Markovian and the IBP busy phase probability can be only extracted from R, but not Q and W, the belief p_n can be updated only based on the previous belief p_{n-1} and R_n. That is,

$$p_n = \text{Pr}[S_n = \text{Busy}|R_n, p_{n-1}]. \tag{3}$$

To solve this POMDP, we formulate this problem into an MDP where each belief is a state. As a result, the state of this belief-MDP is $i = (p, R, Q, W)$. If $R_n = 1$, which means there is a job arrival at time slot n, the arrival process has to be in the Busy phase, therefore, $p_n = 1$; otherwise, if $R_n = 0$ and there is no job arrival at time slot n, p_n can be calculated conditionally based on p_{n-1}, α and β. Note that the state at time slot n can be expressed by i_n.

The action space remains the same with the POMDP formulation. The action taken at time slot n decides the server's operation mode at time slot $n+1$, which can be expressed by:

$$A_\pi(i_n) = W_{n+1}, \tag{4}$$

where π is a certain policy that determines the rules for the server to take an action. $A_\pi(i_n)$ denotes the action taken under state i_n based on policy π.

We define $C(i, A_\pi(i))$ as the cost function received at state i under policy π, which is a combination of energy consumption and delay, given by:

$$C(i, A_\pi(i)) = |W - A_\pi(i)|E_{sw} + \omega Q + A_\pi(i)E_{on}, \tag{5}$$

where the first term is the energy consumption caused by the operation mode switching. ω is the weighting parameter corresponding to the delay penalty caused by congestion, which is proportional to the queue length Q, and $A_\pi(i)E_{on}$ is the energy consumption of the server. Note that the cost function above does not depend on p, but only depends on W, $A_\pi(i)$ and Q.

D. State Simplification

From the definition of p_n in Eq.3, we find that if $R_n = 1$, then $p_n = 1$ and if $R_n = 0$, p_n can be calculated by iterations, which is given as follows:

$$\begin{aligned} p_n &= \text{Pr}[S_n = \text{Busy}|R_n = 0, p_{n-1}] \\ &= \frac{\text{Pr}[S_n = \text{Busy}, R_n = 0|p_{n-1}]}{\text{Pr}[R_n = 0|p_{n-1}]} \\ &= \frac{(1-\lambda)\text{Pr}[S_n = \text{Busy}|p_{n-1}]}{1 - \lambda\text{Pr}[S_n = \text{Busy}|p_{n-1}]} \\ &= \frac{(1-\lambda)[(1-\frac{1}{\alpha}-\frac{1}{\beta})p_{n-1} + \frac{1}{\beta}]}{1-\lambda[(1-\frac{1}{\alpha}-\frac{1}{\beta})p_{n-1} + \frac{1}{\beta}]}. \end{aligned} \tag{6}$$

Note that $\text{Pr}[S_n = \text{Busy}|p_{n-1}] = p_{n-1}\text{Pr}[S_n = \text{Busy}|S_{n-1} = \text{Busy}] + (1-p_{n-1})\text{Pr}[S_n = \text{Busy}|S_{n-1} = \text{Quiet}] = (1-\frac{1}{\alpha}-\frac{1}{\beta})p_{n-1} + \frac{1}{\beta}]$. Assume there is a sequence $\{m_k\}$, $m_0 = 1$, the iteration between m_k and m_{k-1} is the same as Eq.6. All the possible values of p_n are included in $\{m_k\}$. Moreover, we find the subscript of the sequence is exactly the time interval since the last arrival, denoted by t, which covers exactly the same information of (p, R). Therefore, we are able to simply the $i = (p = m_k, R, Q, W)$ state into $i = (t = k, Q, W)$ state, which is clear enough to show that the belief state space of our formulation is countable, as the values of t are non-negative integers. In the rest of the paper, we use (t, Q, W) formulation instead.

E. Transition Probability

One of the most important part in the transition probability calculation is to calculate the probability of being in Busy phase at time slot $n+1$, given t_n. The calculation is given below.

$$\begin{aligned} &\text{Pr}[S_{n+1} = \text{Busy}|t_n = k] \\ &= \text{Pr}[S_{n+1} = \text{Busy}|S_n = \text{Busy}, t_n = k]\text{Pr}[S_n = \text{Busy}|t_n = k] \\ &+ \text{Pr}[S_{n+1} = \text{Busy}|S_n = \text{Quiet}, t_n = k]\text{Pr}[S_n = \text{Quiet}|t_n = k] \\ &= (1-\frac{1}{\alpha})m_k + \frac{1}{\beta}(1-m_k). \end{aligned} \tag{7}$$

For simplicity, we also define a sequence $\{q_k\}$, where for each k, $q_k = (1-\frac{1}{\alpha})m_k + \frac{1}{\beta}(1-m_k)$ to indicate the probability given above.

Since the system state updates at each time slot, the queue length in the buffer might remain the same in our formulation. The transition probability at state (t, Q, W), are discussed in three cases based on the value of Q and given as follows.
For $Q = 0$,

$$\text{Pr}[(k, 0, W) \to (0, 1, A_\pi(k, 0, W))] = q_k\lambda, \tag{8}$$

$$\text{Pr}[(k, 0, W) \to (k+1, 0, A_\pi(k, 0, W))] = 1 - q_k\lambda. \tag{9}$$

Note that departures take place earlier than arrivals at each time slot. Therefore, when $Q = 0$, t cannot be 0.
For $Q = B$,

$$\Pr[(k, B, W) \to (k + 1, B, \text{ON})] = (1 - q_k\lambda)(1 - \mu), \quad (10)$$
$$\Pr[(k, B, W) \to (0, B, \text{ON})] = q_k\lambda, \quad (11)$$
$$\Pr[(k, B, W) \to (k + 1, B - 1, \text{ON})] = (1 - q_k\lambda)\mu. \quad (12)$$

We assume that if there are B jobs in the buffer at the current time slot, the server will always take the ON action to process the jobs.
For $0 < Q < B$,

$$\Pr[(k, Q, W) \to (0, Q + 1, \text{OFF})] = q_k\lambda, \quad (13)$$
$$\Pr[(k, Q, W) \to (k + 1, Q, \text{OFF})] = 1 - q_k\lambda, \quad (14)$$
$$\Pr[(k, Q, W) \to (0, Q + 1, \text{ON})] = q_k\lambda(1 - \mu), \quad (15)$$
$$\Pr[(k, Q, W) \to (0, Q, \text{ON})] = q_k\lambda\mu, \quad (16)$$
$$\Pr[(k, Q, W) \to (k + 1, Q, \text{ON})] = (1 - q_k\lambda)(1 - \mu), \quad (17)$$
$$\Pr[(k, Q, W) \to (k + 1, Q - 1, \text{ON})] = (1 - q_k\lambda)\mu. \quad (18)$$

F. The Optimal Operation Policy

We apply dynamic programming to solve this MDP problem. The objective of choosing the server operation policy is to minimize the expected discounted sum of the costs over time, and the value function is shown below.

$$V(i_0) = \min_{\pi} \mathrm{E}[\sum_{n=0}^{\infty} \gamma^n C(i_n, A_\pi(i_n))], \quad (19)$$

where γ is the discount factor that indicates how important the future costs are to the value function, and i_n is the system state at time slot n. The value function given by the Bellman equation is given below:

$$V(i) = \min_a \{C(i, a) + \gamma \sum_j P^a_{i \to j} V(j)\}, \quad (20)$$

where a is the action taken by the server and $P^a_{i \to j}$ is the transition probability from state i to state j that has been defined in Section II-C. As a result, the optimal operation policy for each state is

$$A_{\pi^*}(i) = \arg\min_{a \in \Phi} \{C(i, a) + \gamma \sum_j P^a_{i \to j} V(j)\}. \quad (21)$$

III. Analysis of Structural Properties

Intuitively, the optimal policy under IBP traffic model might have the similar properties with the optimal policy under memoryless traffic model. Concretely, due to the switching cost from OFF to ON mode, the server may not choose to turn ON immediately when $Q > 0$. This leads to *hysteretic*, which is defined as follows.

***Definition** 1:* A policy π is called hysteretic if for some $d \in \Phi$, $A_\pi(t, Q, d) = a$ implies $A_\pi(t, Q, a) = a$, $a \in \Phi$.

We are able to prove this conjecture and give the following theorem.

***Theorem** 1:* The optimal operation policy (21) is hysteretic.

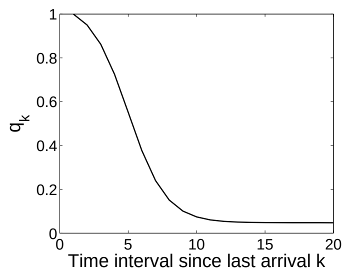

Fig. 2. The busy phase probability evolution in sequence $\{q_k\}$.

Proof: Theorem 1 in [12] points out that the optimal policy is hysteretic if the policy can be written as

$$A_{\pi^*}(i) = \arg \min_{a \ in\Phi} \{s(W, a) + w(t, Q, a)\}, \quad (22)$$

and the function s satisfies

$$s(a, b) \le s(a, c) + s(c, b), \quad \forall a, b, c \in \Phi, \quad (23)$$
$$s(a, a) = 0, \quad \forall a \in \Phi. \quad (24)$$

Therefore, if we give definitions:

$$s(W, a) \triangleq |W - a|E_{sw}, \quad (25)$$
$$w(t, Q, a) \triangleq \omega Q + aE_{on} + \gamma \sum_j P^a_{i \to j} V(j), \quad (26)$$

Eq.(22) becomes the same as Eq.(21). $s(W, a)$ is the switching cost when the current state is W and the action taken is a. $w(Q, a)$ is the serving cost including the future part.

It is straightforward that $s(W, a)$ defined in Eq.(25) satisfies the two conditions needed in Eqs.(23)(24). As a result, the optimal operation policy is hysteretic. ■

To explain this property clearer, if the decision with certain t and Q is to turn ON from OFF, then the decision for the corresponding ON state with the same t and Q is to stay ON as well.

IV. Numerical and Simulation Results

We give numerical results and performance analysis for the optimal policy under our formulation in this section. Moreover, we compare the performance of the optimal policy with the queue-based policy in the prior work [13].

Value iteration algorithm for MDP is applied to get our numerical results. The optimal policy and the value function are updated every iteration, until the value function converges. The details of the algorithm has been given in [13]. To apply the algorithm, we have to restrict the maximum recorded interarrival time as M and set a finite buffer size to get a finite state space. The buffer size B is set to be 80 so that the queue length would not reach the buffer size. The mean durations of the busy phase and the quiet phase, α and β, are set to be 20 time slots and 40 time slots, respectively. The average interval of job arrivals λ^{-1} is 2 time slots and the mean service time μ^{-1} is 1.2 time slots. Therefore, the traffic load of the system is assumed to be $\rho\mu = 0.2$. The length of one time slot is assumed to be 0.1s. Thus, based on [13], the energy consumption for an ON server in a time slot E_{on} is 25J. The switching energy cost is set to be 41.6J. The weighting

(a) The zoomed-in optimal policy for the states with $W =$ ON.

(b) The zoomed-in optimal policy for the states with $W =$ OFF.

Fig. 3. The zoomed-in structure of optimal policy

parameter between energy and delay penalty ω is 10 and the discount factor γ is 0.99, which is chosen to be close to zero.

As for the maximum recorded interarrival time M, the evolution of the sequence $\{q_k\}$ calculated from the parameters above is given in Fig.2. The curve decreases sharply at first and converges to 0.05 when k is larger than 10. Therefore, M is set as 20 to guarantee the convergence of $\{q_k\}$.

Due to limited space, and to get a clearer vision of the structure, we only give the zoomed-in version of the optimal policy in Fig.3, which shows how the decision changes with t and Q in details. Note that the decisions for larger t and Q follow the decisions for the smaller ones with the same Q and t, respectively. It is shown that when the current server state is ON, the server would choose to sleep only if $Q = 0$ and $t \leq 3$, and if the server is OFF in the current time slot, the server would wake up only if $Q = 1$ and $t \geq 4$, or $Q \geq 2$. Note that these decision thresholds depend on the parameters of the arrival process.

We would like to compare our optimal policy in this paper, which is based on a (t, Q, W) state formulation and the policy proposed in [13], which gives the best mapping from tuples of the form (Q, W) to actions. With memoryless arrivals, t will not bring any additional information to the system. Therefore, (Q, W) formulation is sufficient for system with Poisson arrivals. First, note that we are applying the Poisson-optimal policy for the continuous-time system in [13] to the discrete time system we are considering here; we conjecture it would still be optimal for a Bernoulli process.

In the discrete time (Q, W) formulation, we consider the arrival process as memoryless Bernoulli arrivals with the global average interarrival time ρ. Due to the space limitation, we are not able to present the optimal policy in figures. The results show that in (Q, W) formulation, the server would turn OFF form ON only if $Q = 0$ and turn ON from OFF only if $Q \geq 2$, under the same parameters, which is a two-threshold policy. Comparing these two policies, it is found that in our formulation, even if the server is current ON and the queue is empty, it will not sleep immediately but keep ON for two time slots, because the arrival process is much likely in the busy phase and arrivals might happen. Therefore, it would be better for the server to stay ON longer and save the switching cost. In the contrast, the server would turn ON earlier than the (Q, W) formulation when t is large and $Q = 1$. This is because when $t \geq 4$, if the server still stays OFF, the delay penalty will be quite large and have a bad impact on the total cost. Therefore, in this case, the server turns ON earlier than the (Q, W) formulation.

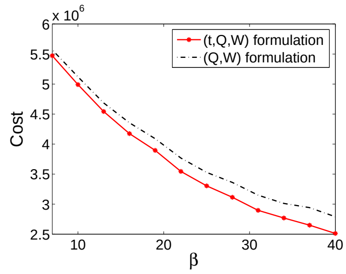

Fig. 4. The comparison of total cost between our optimal policy, which is based on a (t, Q, W) state formulation, and the policy based on a (Q, W) state formulation (from [13]).

The optimal policy in [13] has been proved to be a two-threshold policy. From the comparison given above, we find that by adding t into the state under IBP arrivals, the ON and OFF thresholds become varying with t. The sleeping thresholds of queue length is no longer a constant, but will change with the time interval since last arrival t. It is so called a t-based two-threshold policy. By simulations, we also find that when E_{sw} is sufficiently large, once the server is ON, it will never go to sleep.

Except for the optimal policy, we also compare the cost and energy saving performance of the optimal policies under (t, Q, W) and (Q, W) formulations. By value iterations, the optimal policies are applied at each time slot to decide whether the server would be ON or OFF in the next time slot. The simulation runs for 200000 time slots. Fig.4 shows how the total system cost changes with β, the mean interval for the quiet phase. It is obvious that the total cost under (t, Q, W) formulation is always lower and better than the results under (Q, W) formulation. This improvement in the system cost is caused by the different structure in the optimal policies. That is, comparing with the (Q, W) formulation, in our formulation, the switching cost is lower when the queue length jumps between 0 and 1, and the delay penalty is lower when the queue length is 1. We can also find that the gap between the cost increases with β increasing. The cost also decreases with increasing β under both (t, Q, W) and (Q, W) formulations. The trend is caused by the load decrease and burstiness increase with β increasing.

In Figs. 5 and 6, the total cost and total energy consumption under different weighting parameters between energy and delay, ω, through 200000 time slots are given respectively. On each curve, the cost (or energy consumption) varies with the SCV of the interarrival time, while the global average interarrival time ρ remains 6 time slots. When $\omega = 0$, this POMDP will only minimize the energy consumption without considering the delay. In this case, the cost and energy con-

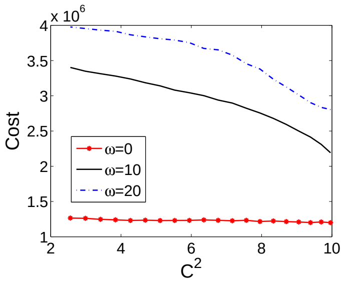

Fig. 5. The total cost changing with burstiness under different weighting between energy and delay.

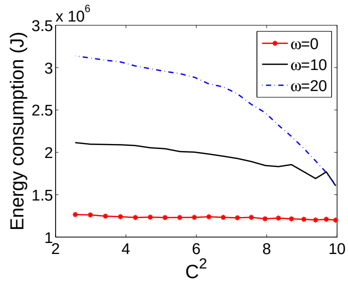

Fig. 6. Energy consumption changing with burstiness under different weighting between energy and delay.

sumption change slightly with the burstiness. However, when ω is non-zero, it is found that the larger burstiness the arrival process is, the lower the cost is, because larger burtiness incurs lower server switching times. While obversing the energy consumption in Fig.6, several hops occur in the curve. These are caused by the shift in the optimal policy. For example, considering the second and third point from the right side when $\omega = 10$, the difference of the optimal policies between these two cases is when C^2 is larger, the server will be ON whenever the queue is not empty. While in the opposite, the third point for the right side represents the case when the server will remain OFF when $Q = 1$ and $t \leq 2$. Therefore, in the latter case, the operation energy is saved, yet with higher delay, which causes the non-monotonicity in burstiness. Under these parameters, the system can save up to 68% energy compared to the non-sleeping server for the case $\omega = 10$ and $C^2 = 10$. When C^2 is large enough, we also find that the optimal policy becomes the same when $\omega = 10$ and $\omega = 20$, as the values of total energy consumption is equal. In this case, the weighting of delay penalty ω cannot influence the optimal policy further, because of the large burstiness.

V. CONCLUSIONS

In this paper, we consider a single server with bursty traffic, which is modeled as IBP arrivals, and formulate the sleeping decision problem into a Partially Observable Markov decision process (POMDP) where we consider the time interval from the last arrival t additionally. The numerical results show the optimal policy is a t-based two-threshold policy and the sleeping thresholds of queue length would change with t. We find that comparing with the formulation with Bernoulli arrivals, the server would postpone several time slots to switch OFF from ON, instead of shutting down immediately when the buffer is empty, and turn ON from OFF earlier when the buffer is not empty. The system cost in our formulation, which considers energy and delay penalty, is always lower than the cost in the formulation with memoryless arrivals [13]. The system cost is also found to decrease with burstiness of the arrival process.

As for the next step of this work, we would like to look into the relationship between the discrete time and continuous time formulations rigorously and how the optimal policy changes with other parameters. Moreover, the problem structure with finite state description leads us to consider Q-learning in the future work. We also want to consider the optimal policy for other bursty arrival models, such as MMBP (Markov Modulated Bernoulli Process).

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