Estimation Oriented Co-design of Sensor Scheduling over Stochastic Delayed Channel under Power Constraints

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Abstract: This paper investigates the scheduling problem over a delayed channel. Different from most existing documents, a novel hybrid model is proposed which combines both delay and packet-loss to minimize the error covariance update at the estimator side. With the help of this setup, a co-design problem between power consumption and estimation performance is considered. We first derive out a globally optimal off-line schedule. Moreover, an on-line schedule based on a designed threshold is proposed to further enhance the performance, which is aided by feedback information. Comparisons between on-line and off-line strategies are illustrated by numerical simulations, which has shown the superiority of on-line one to the off-line one.

Keywords: state estimation, delayed sensor networks, co-design problem.

1. INTRODUCTION

The past few decades have witnessed the significant improvement in communication technologies, which leads to a wide utilization for wireless sensor networks in control systems. However, due to the limited wireless resources of sensors, i.e., power or bandwidth Lyu et al. (2018), Chen et al. (2015), Zhu et al. (2018), and etc, the quality of communication can be seriously affected. This may result in time-delay or even packet-loss, which indirectly degrades the performance of the entire system. Consequently, it is a key and urgent task to design a suitable transmission strategy to ensure the performance of the system, especially for resource-limited cases.

Numbers of works have been accomplished on the trade-off between estimation performance and communication resources in time or state domains. For example, in Shi and Zhang (2012), an optimal time-triggered transmission schedule of two Markovian systems is proposed under bandwidth constraint. Scheduling problem of an energy harvesting sensor is illustrated in Li et al. (2017), where an approximately analytical form of optimal solution is presented using dynamic programming algorithm. Qi et al. (2016) have focused on the case over a time-varying channel, where an optimal scheme is presented in a closed-form. Li et al. (2018a) have discussed the scheduling problem over relay-assisted wireless control systems, where different on-line strategies are designed with satisfying performance. He also investigates the scheduling problem over multiple power levels in Li et al. (2018b), where a hierarchical event-triggered on-line scheduling scheme is proposed. The above literatures mainly emphasize the issues of possible packet-loss over data transmissions. Other kinds of trade-off problems over noisy channels are formulated via co-design manners in Gatsis et al. (2014), Dey et al. (2017) and etc.

In the practical scenes, transmission delays often occur in wireless communications, which is a non-negligible factor existing especially in resource-limited scenarios. Some literatures have explored the scheduling problem under delayed channel setup. For example, in Li et al. (2019), a latency-aware virtual network embedding method is proposed for IWNs, which guarantees the deadlines for various industrial networks. In Shi et al. (2011), scheduling problem over a delayed channel with one time-step delay is investigated. In Ren et al. (2018), multi-hop scheduling based on delayed network is investigated with the upper and lower bounds of cost provided. However, how to obtain and analyze the cost with a higher accuracy is an intractable task under both delayed and power limitations. Therefore, in this paper, we accomplish a wide research on delayed networks for the power-constrained cases. Our contributions can be summarized as the following two folds:

- **A power-constrained delayed transmission model:** We build up a more general model that combines both time delay and packet drop-out, which minimizes the update of covariance at the same time.
- **Off-line and on-line strategies design:** Under our proposed delayed model, we design two different kinds of scheduling schemes in infinite-time horizon, i.e., off-line scheduling and on-line scheduling. Especially, for the on-line scheduling scheme, we give the determina-
tion process of proposed selection probabilities. Based on these conclusions, we figure out the optimal solution of... to make decisions or not, respectively. It is noticed that original problem (7) can be converted into (8) as follows:

\[ d_k^i = \arg \min \{ i + d_k^i = k \mid k - d_{k-1} \leq i \leq k \} \]

We always regard the remarkably large delays as packet-loss in the practical scenes. Thus we introduce a parameter to represent the upper-bound of time delay. We consequently denote the packet-loss at the estimator side as \( d_k = \infty \).

At each time of transmission, the sensor will decide on which power level is used to transmit packet. Denote \( \theta = \{ \omega_k \}_{k=0}^{T-1} \) as the transmission power sequence used at each time. We have the state iteration as

\[ \hat{x}_k = \begin{cases} A\hat{x}_{k-1}, & d_k = i, \\ A\hat{x}_{k-1} + K_k (y_k - C\hat{x}_{k-1}), & d_k = \infty. \end{cases} \]

with the covariance update

\[ P_k = \begin{cases} \hat{T}, & d_k = i, \\ \hat{P}_{k-1}, & d_k = \infty. \end{cases} \]

The main goal of our paper is to design a proper transmission policy to optimize the following co-design problem in a infinite-time scale, i.e.,

\[ J(\theta) = \lim_{T \to \infty} \sum_{k=0}^{T-1} \text{Tr}(E[P_k]) + \mu \omega_k, \omega_k \in \{ \delta, \Delta \}. \]

where \( \mu \geq 0 \) is the introduced factor which balances the performance of estimation and the cost of power consumption.

3. STRATEGIES DESIGN

In this section, we will design our proposed optimal strategies from two different perspectives, i.e., the off-line and on-line schedules, where arriving feedback information is available for sensor to make decisions or not, respectively. It is noticed that original problem (7) can be converted into (8) as follows:
where the parameter $\varpi$ is defined as an average power budget over an infinite-time horizon. Besides, the following definitions are given.

- **State:** We define $i$ as the state $P_k = h_i^t(P)$, $i = 0, 1, 2, \ldots$
- **Steady-state probability:** Denote $\pi_i$ as the steady-state probability of state $h_i^t(P)$; denote $\pi(\cdot)$ as the steady-state probability of a specific state $\cdot$.
- **Transition probability:** Denote $\pi(m, n)$ as the transition probability from the state $n$ to $m$.
- **Equivalent drop-out length:** Define $\tau_k$ as the equivalent drop-out length, i.e.

$$
\tau_k = \begin{cases} 
  d_k, & \text{if } d_k < \infty, \\
  \tau_{k-1} + 1, & \text{if } d_k = \infty.
\end{cases}
$$

### 3.1 Model of Delay in Time Domain

In order to derive out the delayed model. We first provide the following lemma.

**Lemma 1.** For the proposed minimum principle, we have the transition relationship with respect to different values of delay are

- For $i \leq d$ and $j \leq d$, we have

$$
\pi(d_{k+1} = j, d_k = i) = \lambda_j,
$$

$$
\pi(d_{k+1} = i + 1, d_k = i) = 1 - \sum_{j=0}^i \lambda_j.
$$

- For $d_k = \infty$ and $j \leq d$, we have

$$
\pi(d_{k+1} = j, d_k = \infty) = \lambda_j,
$$

$$
\pi(d_{k+1} = \infty, d_k = \infty) = 1 - \sum_{j=0}^d \lambda_j.
$$

where $\lambda_0, \lambda_1, \ldots, \lambda_d$ is defined in (3).

**Proof.** According to the minimum principle, we have

$$
\pi(d_{k+1} = j, d_k = i) = \frac{\Pr(d_{k+1} = j)}{\Pr(d_{k+1} = \infty)} \cdot \frac{\Pr(d_{k+1} = j)}{\Pr(d_{k+1} = \infty)} \cdot \ldots \cdot \frac{\Pr(d_{k+1} = j)}{\Pr(d_{k+1} = \infty)}
$$

where the second equality is due to the independence of distribution $d_k$ for different instants, thus the first case is proved. Similarly, the second case follows as long as we take the upper-bound into account, which completes the proof.

**Lemma 2.** For the sequence $\{H_i^t(P)\}_{i=1}^{\infty}$ for $\forall i \leq j$, it always holds that

$$
\Tr[H_i^t(P)] \leq \Tr[H_j^t(P)].
$$

where $H_i^t(P) \triangleq \mathbb{E}[P_i|\omega_0 = \Delta, \omega_1 = \omega_2 = \cdots = \omega_l = \delta]$.

**Proof.** Rewrite $H_i^t(P)$ as

$$
H_i^t(P) = c_{i,0}P + c_{i,1}h_1(P) + \ldots + c_{i,i}h_i^t(P),
$$

where $c_{i,j}$ denotes the relative coefficient. According to Lemma 1, it holds that $c_{i,0} < c_{i,0}, c_{i,1} > c_{i,1} = 0$, and $c_{i,j} = c_{i-1,j}, c_{i,i-1} < c_{i-1,i-1}, c_{i,i} > c_{i-1,i} = 0$. Therefore, it follows that

$$
\Tr[H_i^t(P) - H_j^t(P)] = c_{i,j}[\Tr(h_i^t(P) - h_j^t(P)) \geq 0],
$$

which completes the proof.

### 3.2 Optimal Off-line Strategy

**Lemma 3.** An optimal off-line schedule $\theta_{off}^*$ under power constraint $\varpi$ over infinite-time horizon can be periodically presented as follows:

$$
\theta_{off}^* = \left\{ \begin{array}{ll}
  \theta_{off}^{l+1}, & \text{w.p. } p^*, \\
  \theta_{off}^l, & \text{w.p. } 1 - p^*,
\end{array} \right.
$$

where $\theta_{off}^{l+1} \text{ and } \theta_{off}^l$ are defined as $\theta_{off}^l : \theta_{off}^{l+1} \triangleq (\Delta, \delta_l)$, and $\theta_{off}^{l+2} \triangleq (\Delta, \delta_{l+1})$, $\delta_x \triangleq (\delta, \ldots, \delta) (x \text{ times}), l = \left[ \frac{\Delta - \varpi}{\delta} \right]$.

**Proof.** Rewrite $\theta_{off}^* = \oplus_{i=0}^{\infty} (\Delta, \delta_i)$. For $\forall l_i, l_j \geq 0 (i \neq j)$ and $l_i \geq l_i + 2$, it follows that

$$
J(\Delta, \delta_l) + J(\Delta, \delta_l) - J(\Delta, \delta_{l+1}) - J(\Delta, \delta_{l-1}) = H_l^t(P) - H_{l+1}^t(P) \geq 0,
$$

which implies the property $\max_{i \neq j} |l_i - l_j| \leq 1$, and the form of $\theta_{off}^*$ must satisfy (13). The proof is now completed.

**Theorem 4.** (Optimal off-line schedule). For different values of $\mu$, the optimal $\theta_{off}^*$ over infinite-time horizon can be explicitly given as

- For $\mu \leq \frac{\Tr(h(P)) - \Tr(P)}{\Delta - \delta}$,

$$
\theta_{off}^* = (\Delta, \Delta, \Delta, \Delta, \ldots),
$$

with $\varpi^* = \Delta$.

- For $\mu \in (\mu_i, \mu_{i+1})$, $\theta_{off}^* = (\Delta, \delta_i, \Delta, \delta_i, \ldots)$, with $\varpi^* = \frac{1}{i+1}(\Delta + \delta)$, where $l$ is the same as that denoted in Lemma 3 and the sequence $\{\mu_i\}_{i=0}^{\infty}$ is defined as

$$
\mu_{i+1} = \frac{(i+1)\Tr[H_{i+1}^t(P)] - \Tr[H_{i+1}^t(P)]}{\Delta - \delta}.
$$

**Proof.** The proof is omitted because of the limited space.

### 3.3 On-line Strategy Design

In this subsection, we will discuss a different scheduling framework, i.e., the on-line policy. For the on-line case, at each instant, the feedback information can be used to make decisions, which is shown in Fig. 2.

Aided by this feedback framework, how to design a proper schedule to switch between different power levels is a challenging task because of the intractability brought by the stochastic delay characteristics. Inspired by the idea of event-triggered scheme illustrated in Demirel et al. (2019) and Demirel et al. (2018), considering the power consumption for feedback is regarded to be relative small Ren et al. (2018), we propose an on-line scheduling scheme based on a designed threshold, which additionally cut the communication cost.
Fig. 2. The framework of on-line scheduling.

**Algorithm 1 On-line Scheduling Scheme**

Parameters: $\lambda_1, \lambda_2, \cdots, \lambda_d, \tau_k, d, \alpha, \beta$.

Initiation: $\omega_0 = 0$.

1: $\tau_{th} = \tau_{th}$, \hspace{0.5cm} $\Pr(\tau_{th} = \tau_{th}) = \alpha$,
2: $\tau_{th} + 1$, \hspace{0.5cm} $\Pr(\tau_{th} = \tau_{th} + 1) = \beta$.

3: while $\tau_k \neq \tau_{th}$ do
4: if $\omega_k = \infty$ then
5: $\tau_k + 1 \gets \tau_k + 1$, $\omega_k + 1 = \delta$;
6: else
7: $\tau_k + 1 \gets \omega_k$, $\omega_k + 1 = \delta$;
8: end if
9: $k \leftarrow k + 1$, jump to Line 2;
10: $\omega_k + 1 = \Delta$, $k \leftarrow k + 1$, jump to Line 1;

Proposition 5 reveals the fact that $\pi_0$ is an constant independent of the specific schedules under an given power budget, which provides an accessible way to compare performance between different proposed schedules.

Based on the above proposition, we accomplish our derivations of $J(\theta_{on})$ by the following two different cases. For the explicit presentation, we introduce the notation $\lambda_{\infty, i} \triangleq 1 - \sum_{j=0}^{\infty} \lambda_j$, and $\pi_T$ as the probability of triggering.

**Case 1 ($\tau_{th} < d$):** Because of the transition relations, we have the equations

$$
\pi(\epsilon_k) = \left\{ \begin{array}{ll}
\alpha \pi_0, & k = 0, \\
\lambda_k \sum_{i=k}^{\tau_{th}-1} \pi(\epsilon_i) + \lambda_{\infty, k-1} \pi(\epsilon_{k-1}), & k = 1, 2, \cdots, \tau_{th} - 1, \\
\lambda_k \pi(\epsilon_{\tau_{th}-1}), & k = \tau_{th},
\end{array} \right.
$$

and

$$
\pi(\psi_k) = \left\{ \begin{array}{ll}
\beta \pi_0, & k = 0, \\
\lambda_k \sum_{i=k}^{\tau_{th}-1} \pi(\psi_i) + \lambda_{\infty, k-1} \pi(\psi_{k-1}), & k = 1, 2, \cdots, \tau_{th}, \\
\lambda_k \pi(\psi_{\tau_{th}-1}), & k = \tau_{th} + 1.
\end{array} \right.
$$

with the solutions provided in the following cases.

- For $\tau_{th} = 0$, $\pi_1 = 1 - \pi_0$.
- For $\tau_{th} \geq 1$, we can obtain the solutions of $\pi_1$ to $\pi_{\tau_{th}+1}$ recursively, i.e.,

$$
\pi_1 = \lambda_{\infty, 0} \pi_0 + (1 - \pi_0 - \pi_T) \lambda_1, \\
\pi_2 = \lambda_{\infty, 1} \pi_1 + (1 - \pi_0 - \pi_T) \lambda_2, \\
\vdots \\
\pi_{\tau_{th}} = \lambda_{\infty, \tau_{th}-1} \pi_{\tau_{th}-1} + (1 - \pi_0 - \pi_T) \lambda_{\tau_{th}}, \\
\pi_{\tau_{th}+1} = 1 - \sum_{i=0}^{\tau_{th}} \pi_i.
$$

**Case 2 ($\tau_{th} \geq d$):** Similarly,

$$
\pi(\epsilon_k) = \left\{ \begin{array}{ll}
\alpha \pi_0, & k = 0, \\
\lambda_k \sum_{i=k}^{\tau_{th}-1} \pi(\epsilon_i) + \lambda_{\infty, k-1} \pi(\epsilon_{k-1}), & k = 1, 2, \cdots, d, \\
\lambda_{\infty, d} \pi(\epsilon_{k-1}), & k = d + 1, \cdots, \tau_{th},
\end{array} \right.
$$

and

$$
\pi(\psi_k) = \left\{ \begin{array}{ll}
\beta \pi_0, & k = 0, \\
\lambda_k \sum_{i=k}^{\tau_{th}-1} \pi(\psi_i) + \lambda_{\infty, k-1} \pi(\psi_{k-1}), & k = 1, 2, \cdots, d, \\
\lambda_{\infty, d} \pi(\psi_{k-1}), & k = d + 1, \cdots, \tau_{th} + 1.
\end{array} \right.
$$

The solution is similar to that of case 1 and thus omitted. Combining the above two cases, the overall cost is calculated as

$$
J(\theta_{on}) = \sum_{i=0}^{\tau_{th}+1} \pi_i T h_i(\mathcal{P}) + \mu \sigma.
$$

### 3.4 Parameters Determination

In this subsection, we make discussions of the parameters determination of $\tau_{th}$ defined in the last subsection. We have
\[ \pi_T = \frac{\varpi - \delta}{\Lambda - \delta}. \]

Based on the definitions, we first calculate the value of \( \tau_{th} \) by the following statement
\[
\tau_{th} \triangleq \arg \max_i \left\{ \sum_{k=0}^i \pi_k \leq 1 - \pi_T \right\} + 1
\]
\[
= \arg \max_i \left\{ \sum_{k=0}^i \pi_k \leq \frac{\Lambda - \varpi}{\Lambda - \delta} \right\} + 1.
\]

Then we can determine the values of \( \alpha \) and \( \beta \) by the following cases.

**Case 1** (\( \tau_{th} = 0 \)): It is obvious that \( \pi_1 \) is only related with \( \pi_0 \), we have
\[
\beta = \frac{\pi_1}{\pi_0}, \quad \alpha = 1 - \beta.
\]

**Case 2** (\( \tau_{th} = 1 \)):
- For \( \tau_{th} < d \), solve the equation of \( \pi (\epsilon_1) + \pi (\psi_2) = \pi_T \), i.e.,
\[
\alpha \lambda_{\infty,0} \pi_0 + (1 - \pi_0 - \pi_T) \lambda_{\infty,1} \pi_T = \pi_T,
\]
and obtain the solutions
\[
\alpha = \frac{1 + \lambda_1}{\lambda_{\infty,0} \pi_0}, \quad \beta = 1 - \alpha.
\]
- For \( \tau_{th} \geq d \), as the value of \( d \) is either 0 or 1, thus it follows that
\[
\beta = \frac{\pi_2}{\pi_2|_{\beta=1}} \cdot \frac{1 - \pi_0 - \pi_1}{\lambda_{\infty,1} \pi_1}, \quad \alpha = 1 - \beta.
\]

**Case 3** (\( \tau_{th} \geq 2 \)):
- For \( \tau_{th} < d \),
\[
\beta = \frac{\pi_{\tau_{th}+1}}{\pi_{\tau_{th}+1}|_{\beta=1}} = \frac{1 - \sum_{i=0}^{\tau_{th}} \pi_i}{\lambda_{\infty,\tau_{th}} \pi_{\tau_{th}} + (1 - \sum_{i=0}^{\tau_{th}} \pi_i - \pi_T) \lambda_{\tau_{th}+1}}.
\]
- For \( \tau_{th} \geq d \),
\[
\beta = \frac{\pi_{\tau_{th}+1}}{\pi_{\tau_{th}+1}|_{\beta=1}} \cdot \frac{1 - \sum_{i=0}^{\tau_{th}} \pi_i}{\lambda_{\tau_{th}+d} \pi_{\tau_{th}}}.
\]

Based on these analysis, we present the optimal on-line schedule in a closed form as follows.

**Theorem 6.** (Optimal on-line schedule). The optimal on-line schedule \( \theta_{on}^* \) over infinite-time horizon with respect to \( \mu \) is explicitly given as follows:
- For \( \mu \in (0, \mu_0), \varpi \triangleq \Delta.
- For \( \mu \in (\mu_i, \mu_{i+1}] (i \geq 0) \),
\[
\varpi_i \triangleq \arg \max_{\overline{\varpi}} \{ \tau_{th} = i + 1 \},
\]
where \( \{\mu_i\}_{i=0}^\infty \) is determined by
\[
\nu_i \triangleq - \sum_{k=0}^{i+1} \frac{d\pi_k}{d\varpi} \text{Tr} \left[ h^k (\overline{P}) \right].
\]

**Proof.** The proof is omitted because of the limited space.

Based on the above conclusions, we will present the convergence condition shown as the following corollary.

**Corollary 7.** (Convergence analysis). For \( \varpi = \delta \), the estimator converges if \( \lambda_{\infty,d} < \frac{1}{\rho^2(A)} \), where \( \rho(A) \) represents the spectral radius of matrix \( A \).

**Proof.** According to Lemma 2, \( H^i (\overline{P}) \) can be rewritten as
\[
H^i (\overline{P}) = \sum_{i=1}^\infty (H^i (\overline{P}) - H^{i-1} (\overline{P})) = \sum_{i=1}^\infty c_{i,i} (h^i (\overline{P}) - h^{i-1} (\overline{P})),
\]
where \( c_{i,i} \) equals to
\[
c_{i,i} = \begin{cases} 
\prod_{j=0}^{i-1} \lambda_{\infty,j}, & i \leq d, \\
\lambda_{\infty,d} \prod_{j=0}^{d-i} \lambda_{\infty,j}, & i > d.
\end{cases}
\]

Thus we consider the convergence of \( \{H^i (\overline{P})\}_{i=0}^\infty \), it is noticed that for \( \rho(A) > 1 \), we have to ensure
\[
\lim_{i \to \infty} \frac{\text{Tr} \left[ H^{i+1} (\overline{P}) - H^i (\overline{P}) \right]}{\text{Tr} \left[ H^i (\overline{P}) - H^{i-1} (\overline{P}) \right]} = \lim_{i \to \infty} \lambda_{\infty,d} \cdot \frac{\text{Tr} \left[ h^{i+1} (\overline{P}) - h^i (\overline{P}) \right]}{\text{Tr} \left[ h^i (\overline{P}) - h^{i-1} (\overline{P}) \right]} = \lambda_{\infty,d} \rho^2 (A) < 1 \Rightarrow \lambda_{\infty,d} < \frac{1}{\rho^2 (A)},
\]
which derives out the property.

4. NUMERICAL SIMULATIONS

**Parameter setup:** \( A = \begin{pmatrix} 1 & 0.4 \\ 0.2 & 0.5 \end{pmatrix} \), \( C = (0.5, 0.8) \), \( Q = \begin{pmatrix} 0.15 & 0 \\ 0 & 0.1 \end{pmatrix} \), \( R = 0.1 \), \( d = 2 \). The higher level \( \Delta = 4 \) and the lower level \( \delta = 1 \).

We first verify the convergence condition presented in Remark 7. It is obvious that the convergence can be satisfied if \( \lambda_{\infty,2} < \frac{1}{\rho(A)} \approx 0.78 \). We choose \( \lambda_{\infty,2} = 0.7 \) and 0.85 as examples for simulations shown in Fig. 3. From the result, when \( \lambda_{\infty,2} = 0.7 \), the estimator converges; when \( \lambda_{\infty,2} = 0.85 \), the estimator diverges.

Next, we compare the performance of different proposed schedules under the same power budget. Let the param-
Fig. 4. Stability analysis with $\lambda_{\infty, 2} = 0.7$ and 0.85.

At the same time, the relative parameters, i.e., $\pi_T$, $l$, $\tau_{th}$ and $\beta$ are listed in Tab. 1. From the table it can be seen that both $l$ and $\tau_{th}$ decrease as the power budget $\pi_T$ increases. Moreover, $\tau_{th}$ is smaller than $l$ for all range of $\pi_T$, which is consistent with our former analysis.

Based on the above results, we finally validate the global optimality with respect to different values of $\mu$. Let $\mu = 0.05, 0.1, 0.15$ and 0.2. We plot the global optimal $J(\theta_{on})$ and $J(\theta_{off})$ with $\omega^*$ as shown in Tab. 2. It is conspicuously seen that $J(\theta_{on})$ is superior to that of $J(\theta_{off})$ with the smaller cost.

Table 1. Parameters with respect to different $\pi_T$

| $\pi_T$ | 0 | 0.05 | 0.1 | 0.15 | 0.2 | 0.25 | 0.3 |
|---------|---|------|-----|------|-----|------|-----|
| $l$     | +\infty | 19 | 9 | 5 | 4 | 3 | 2 |
| $\tau_{th}$ | +\infty | 3 | 2 | 2 | 1 | 1 | 1 |
| $\beta$ | 0.187 | 0.784 | 0.475 | 0.093 | 0.824 | 0.605 |
| $\pi_T$ | 0.35 | 0.4 | 0.45 | 0.5 | 0.55 | 0.6 | 0.65 |
| $l$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $\tau_{th}$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| $\beta$ | 0.391 | 0.182 | 0.982 | 0.833 | 0.703 | 0.588 | 0.486 |

Table 2. Comparisons of $J(\theta_{on})$ and $J(\theta_{off})$ with respect to different $\mu$

| $\mu$ | 0.05 | 0.1 | 0.15 | 0.2 |
|-------|------|-----|------|-----|
| $\pi_T$ | 0.439 | 0.571 | 0.684 | 0.747 |
| $\tau_{th}$ | 4 | 2.33 | 1.63 | 1.17 |
| $\beta$ | 0.393 | 0.563 | 0.669 | 0.740 |

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