

# Lyapunov Optimization: An Introduction

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# Outline

## 1 A Brief Introduction

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- 2 How it works
  - (Continuous) Optimization Problems
  - Stochastic Optimization Problems
  - How to Construct Virtual Queues
  - Lyapunov Function
  - Drift-Plus-Penalty Algorithm

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# A Brief Introduction

**Lyapunov optimization** refers to the use of a **Lyapunov function** to optimally control a **dynamical** system.

## Lyapunov function

Lyapunov functions are used extensively in control theory to ensure different forms of **system stability**. The state of a system at a particular time is often described by a multi-dimensional vector. A Lyapunov function is a **nonnegative scalar measure** of this multi-dimensional state. Typically, the function is defined to grow large when the system moves towards undesirable states. System stability is achieved by taking control actions that make **the Lyapunov function drift** in the negative direction towards zero.

## Lyapunov drift (the Lyapunov function drift)

Adding a weighted penalty term to the Lyapunov drift and **minimizing the sum** leads to the drift-plus-penalty algorithm for joint network stability and penalty minimization.

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# (Continuous) Optimization Problems

## Optimization Problem

The standard form of a continuous optimization problem is

$$\begin{aligned} \mathcal{P}_1 : \quad & \min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x}) \\ \text{s.t.} \quad & c_i(\mathbf{x}) \leq 0, i = 1, 2, \dots, k \\ & h_j(\mathbf{x}) = 0, j = 1, 2, \dots, l, \end{aligned}$$

where

- 1  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is the objective function to be minimized over the  $n$ -variable vector  $\mathbf{x}$ ;
- 2  $c_i(\mathbf{x}) \leq 0$  are called inequality constraints;
- 3  $h_j(\mathbf{x}) = 0$  are called equality constraints, and
- 4  $k, l \geq 0$ .

# Stochastic Optimization Problems

**Random events happen in every time slot  $t$  for  $t \in \mathcal{T}$ .**

In every time slot,

- ①  $\mathbf{w}(t) \triangleq [w_1(t), w_2(t), \dots, w_n(t)] \in \Omega^n$  are the **i.i.d.** random events;
- ②  $\boldsymbol{\alpha}(t) \triangleq [\alpha_1(t), \alpha_2(t), \dots, \alpha_m(t)] \in \mathcal{A}^m$  are the control actions.

According to the random events  $\mathbf{w}(t)$  already happened, the system (decision maker) takes control actions  $\boldsymbol{\alpha}(t)$  in a certain way. Therefore, for the optimization goal  $p(t)$ , we have

$$p(t) = P(\mathbf{w}(t), \boldsymbol{\alpha}(t)), \quad (1)$$

where  $P(\cdot)$  is a **certain** function (e.g., the way we calculate latency).

Besides the optimization goal  $p(t)$ , other variables in the system who can affect the optimality  $y_k(t), k \in \mathcal{K}$  (power consumption, available bandwidth, etc.) are also impacted by the taken control actions. Thus we have

$$y_k(t) = Y_k(\mathbf{w}(t), \boldsymbol{\alpha}(t)), k \in \{1, \dots, K\}, \quad (2)$$

where  $\forall k \in \{1, \dots, K\}, Y_k(\cdot)$  are all **certain** functions.

# Stochastic Optimization Problems

## Stochastic Optimization Problem

Minimize a **time average** optimization goal under several constraints in a time horizon which is slotted. The independent variables are the control actions to cope with the random events.

$$\mathcal{P}_2 : \min_{\forall t, \alpha(t) \in \mathcal{A}^m} \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[p(t)] \quad (3)$$

$$s.t. \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[y_k(t)] \leq 0, k \in \{1, \dots, K\}, \quad (4)$$

where  $p(t)$  is obtained by (1),  $y_k(t)$  is obtained by (2).

- ① Why **Expectation**  $\mathbb{E}[\cdot]$ ?
- ② Why time average?

# Virtual Queues

For every constraints  $y_k(t)$ ,  $k \in \mathcal{K}$  define a virtual queue with initial backlog 0:

$$Q_k(t+1) = \max\{Q_k(t) + y_k(t), 0\}, k \in \{1, \dots, K\}. \quad (5)$$

## How to control queues to ensure (2) always stand up?

According to (5), we have  $y_k(t) \leq Q_k(t+1) - Q_k(t)$ . Then we calculate the sum on time slots and take the Expectation:

$$\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[y_k(t)] \leq \frac{\mathbb{E}[Q_k(T)]}{T}, k \in \{1, \dots, K\}. \quad (6)$$

If the following constraint set up:

$$\lim_{T \rightarrow \infty} \frac{\mathbb{E}[Q_k(T)]}{T} = 0, k \in \{1, \dots, K\}, \quad (7)$$

The constraint (2) always set up.

# The Derivate Stochastic Optimization Problem

## The derivate problem

The new problem derivated from  $\mathcal{P}_2$  and (7) is defined as

$$\mathcal{P}_3 : \min_{\forall t, \alpha(t) \in \mathcal{A}^m} \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[p(t)] \quad (8)$$

*s.t.* (7).

Actually, a queue  $Q_k(t)$  that satisfies the above limit equation is said to be **mean rate stable**.

## Other degree of Stability:

$$\exists \delta \leq 0, \lim_{T \rightarrow \infty} \frac{\mathbb{E}[Q_k(T)]}{T} \leq \delta, k \in \{1, \dots, K\}. \quad (9)$$

# How to solve $\mathcal{P}_3$ with asymptotically optimality?

## Lyapunov function

A Lyapunov function is a **nonnegative scalar measure** of this multi-dimensional state. Denote the queue vector as  $\Theta(t) \triangleq [Q_1(t), \dots, Q_K(t)]$ , the Lyapunov function is defined by

$$L(\Theta(t)) \triangleq \frac{1}{2} \sum_{k=1}^K Q_k(t)^2. \quad (10)$$

**Lyapunov drift** is defined as  $\Delta(\Theta(t)) \triangleq L(\Theta(t+1)) - L(\Theta(t))$ .

Because of (5),  $Q_k(t+1)^2 \leq (Q_k(t) + y_k(t))^2, k \in \{1, \dots, K\}$ . Calculate the sum of all queues' backlog, we can obtain that

$$\begin{aligned} \Delta(\Theta(t)) &= \frac{1}{2} \sum_{k=1}^K Q_k(t+1)^2 - \frac{1}{2} \sum_{k=1}^K Q_k(t)^2 \\ &\leq \frac{1}{2} \sum_{k=1}^K y_k(t)^2 + \sum_{k=1}^K Q_k(t)y_k(t) \leq B + \sum_{k=1}^K Q_k(t)y_k(t). \end{aligned} \quad (11)$$

## Drift-Plus-Penalty Expression

In order to keep the queue stable, we have to minimize the optimization goal  $p(t)$  and Lyapunov drift simultaneously, tuned by parameter  $V$ .

### Drift-plus-penalty problem

$$\mathcal{P}_4 : \min_{\forall t, \alpha(t) \in \mathcal{A}^m} \mathbb{E}[\Delta(\Theta(t)) + V \cdot p(t) | \Theta(t)] \quad (12)$$

*s.t.* (7).

**We cannot solve  $\mathcal{P}_4$  in every independent time slot!** Thus we have

### The upper bound of drift-plus-penalty

$$\mathcal{P}_5 : \min_{\forall t, \alpha(t) \in \mathcal{A}^m} \mathbb{E}[B + V \cdot p(t) + \sum_{k=1}^K Q_k(t) y_k(t) | \Theta(t)] \quad (13)$$

*s.t.* (7).

# Drift-plus-penalty algorithm

In every time slot take the following procedure:

- ① At the beginning of the  $t$ th time slot, obtain random events and queues' backlog:  $\mathbf{w}(t), \Theta(t)$ .
- ② Solve the following problem to obtain the optimal control action  $\alpha^*(t)$ :

$$\alpha^*(t) = \operatorname{argmin}_{\alpha(t) \in \mathcal{A}^m} \mathbb{E}[B + V \cdot p(t) + \sum_{k=1}^K Q_k(t) y_k(t) | \Theta(t)]. \quad (14)$$

- ③  $\forall k \in \{1, \dots, K\}$ , according to (5) to update  $Q_k(t)$ .
- ④  $t \leftarrow t + 1$ .

- ▷ Why constraint (7) is not considered in the algorithm?
- ▷ How to solve the problem in **Step. 2**?



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# Average Penalty Analysis

**w-only policy** is a stationary and random method to obtain  $\alpha^\dagger(t)$  depend only on the observed  $\mathbf{w}(t)$ . i.e., for every possible random event  $\mathbf{w}(t) \in \Omega^n$ , w-only policy decide  $\alpha^\dagger(t)$  according to a conditional probability distribution:

$$\alpha^\dagger(t) = \operatorname{argmax}_{\alpha(t) \in \mathcal{A}^m} \Pr(\alpha(t) | \mathbf{w}(t)). \quad (15)$$

## Optimal w-only policy

Optimal w-only policy is an w-only policy under the following conditions:

$$P(\mathbf{w}(t), \alpha^*(t)) = p^*, \quad (16)$$

$$Y_k(\mathbf{w}(t), \alpha^*(t)) \leq 0, k \in \{1, \dots, K\}, \quad (17)$$

where

$$p^* = \min \left( \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[p(t)] \right). \quad (18)$$

# Performance Analysis

## Analysis on optimality and queue size (proof on [link](#))

▷ Optimality gap:  $O(\frac{1}{V})$

$$\sum_{t=0}^{T-1} \mathbb{E}[p(t)|\Theta(t)] \leq p^* + \frac{B}{V}. \quad (19)$$

▷ Average queue size:  $O(V)$

$$\begin{aligned} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{k=1}^K \mathbb{E}[Q_k(t)|\Theta(t)] &\leq \frac{B'}{\epsilon} + \mathbb{E}[L(\Theta(0))] - \mathbb{E}[L(\Theta(T))] \\ &\leq \frac{B + V(p_{max} - p_{min})}{\epsilon}. \end{aligned} \quad (20)$$

▷ Constraint (7) can always be satisfied:

$$\forall k \in \{1, \dots, K\}, \lim_{T \rightarrow \infty} \frac{\mathbb{E}[Q_k(T)]}{T} = 0.$$

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# Conclusions

- 1 Lyapunov Optimization can only obtain asymptotically optimality, i.e.  $O(\frac{1}{V})$ .
- 2 A longer time horizon is needed to obtain a better solution.
- 3 Relation between the length of time horizon and the time average queue size?

**Time for Case Study :-)**