

# Finite-Sample Error Bound

## I. FINITE-SAMPLE ERROR BOUND

The following result gives high-probability finite-sample error bounds for the average-value-at-risk constraint given a solution of the sample-based approximation  $\mathbf{SOCP}_M(\bar{\omega})$  of  $\mathbf{OCP}$ . For conciseness, we use notations from the main paper that we do not reintroduce.

*Lemma 1 (Error bound for solutions of  $\mathbf{SOCP}_M(\bar{\omega})$ ):*

Let  $M \in \mathbb{N}$  be a number of samples,  $\{\omega^i\}_{i=1}^M$  be independent and identically distributed (iid) samples of  $\omega$ , and formulate the sample average approximation  $\mathbf{SOCP}_M(\bar{\omega})$  of  $\mathbf{OCP}$ . Denote by  $u_M(\bar{\omega})$  the solution of  $\mathbf{SOCP}_M(\bar{\omega})$ . Then, under assumptions **(A1-A4)** (see the main paper), for some finite constants  $(\tilde{C}, \bar{h})$  and a compact set  $\mathcal{T} \subset \mathbb{R}$  large-enough, for  $(\epsilon_M, \delta_M)$  defined in (5), with probability at least  $1 - \delta_M$  over the  $M$  iid samples  $\omega^i$ ,

$$\text{AV@R}_\alpha \left( \sup_{s \in [0, T]} G(x_{u(\bar{\omega})}(s), \xi) \right) \leq \epsilon_M. \quad (1)$$

Lemma 1 gives a finite-sample high-probability error bound for the satisfaction of the risk constraint in  $\mathbf{OCP}$ . Specifically, replacing (16b) in  $\mathbf{SOCP}_M(\bar{\omega})$  (see the main paper) with

$$t + \frac{1}{\alpha M} \sum_{i=1}^M \max \left( \sup_{s \in [0, T]} G(x_u^i(s), \xi^i) - t, 0 \right) \leq -\epsilon_M$$

suffices to guarantee the satisfaction of the  $\text{AV@R}_\alpha$  constraint in  $\mathbf{OCP}$ . Note that  $\epsilon_M \rightarrow 0$  and  $\delta_M \rightarrow 0$  as  $M \rightarrow \infty$ , i.e., the error can be made arbitrarily small (with increasingly high probability) by increasing the number of samples  $M$ . It should not be surprising to the reader that no additional assumptions are required to derive the finite-sample error bound in Lemma 1, as it relies on concentration inequalities used to prove Theorem 1 in the main paper. The remainder of this document describes the proof of Lemma 1.

## II. EXPECTATIONS CONCENTRATION INEQUALITIES

The proof of Lemma 1 relies on a concentration inequality from [1]. Let  $(\Omega, \mathcal{G}, \mathbb{P})$  be a probability space,  $d \in \mathbb{N}$ ,  $\mathcal{U} \subset \mathbb{R}^d$  be a compact set,  $h : \mathcal{U} \times \Omega \rightarrow \mathbb{R}$  be a Carathéodory function (i.e.,  $h(u, \cdot)$  is  $\mathcal{G}$ -measurable for all  $u \in \mathcal{U}$  and  $h(\cdot, \omega)$  is continuous  $\mathbb{P}$ -almost-surely). We introduce the following two assumptions on  $h$ .

(B1)  $\mathbb{P}$ -almost-surely, the map  $u \mapsto h(u, \omega)$  is  $\alpha$ -Hölder continuous for some exponent  $\alpha \in (0, 1]$  and Hölder constant  $M(\omega)$  satisfying  $\mathbb{E}[M(\cdot)^2] < \infty$ , such that

$$|h(u_1, \omega) - h(u_2, \omega)| \leq M(\omega) \|u_1 - u_2\|_2^\alpha \quad (2)$$

for all  $u_1, u_2 \in \mathcal{U}$ .

(B2) For some constant  $0 \leq \bar{h} < \infty$ ,  $\mathbb{P}$ -almost-surely,

$$\sup_{u \in \mathcal{U}} |h(u, \omega)| \leq \bar{h}. \quad (3)$$

Let  $\{\omega^i\}_{i=1}^M$  be  $M \in \mathbb{N}$  independent and identically distributed (iid) samples of  $\omega$ . We have the following result.

*Lemma 2 (Concentration inequality [1]):* Assume that  $h$  satisfies (B1) and (B2). Let  $D = 2 \sup_{u \in \mathcal{U}} \|u\|_2$ ,  $C = 32$ ,  $u_0 \in \mathcal{U}$ , and  $\Sigma_0$  denote the covariance matrix of  $h(u_0, \cdot)$ , and define the constant

$$\tilde{C} = \left( 8CD^{\frac{\alpha+1}{2}} d^{\frac{1}{2}} \mathbb{E}[M^2]^{\frac{1}{2}} \alpha^{-\frac{1}{2}} + \text{Trace}(\Sigma_0)^{\frac{1}{2}} \right). \quad (4)$$

Let  $M \in \mathbb{N}$  be the number of iid samples  $\omega^i$  and define

$$\epsilon_M = 2\tilde{C}M^{-\frac{1}{4}}, \quad \delta_M = \exp \left( -\frac{\tilde{C}^2}{2\bar{h}^2} M^{\frac{1}{4}} \right). \quad (5)$$

Then, with probability at least  $1 - \delta_M$  over the  $M$  iid samples  $\omega^i$ ,

$$\sup_{u \in \mathcal{U}} \left| \frac{1}{M} \sum_{i=1}^M h(u, \omega^i) - \mathbb{E}[h(u, \cdot)] \right| \leq \epsilon_M. \quad (6)$$

Lemma 2 provides a high-probability finite-sample error bound for the sample average approximation of the expected value of  $h(u, \cdot)$  that holds uniformly over all  $u \in \mathcal{U}$ . It corresponds to Proposition 3.6 in [1] with  $\epsilon = 1/4$ . Note that  $\epsilon_M \rightarrow 0$  and  $\delta_M \rightarrow 0$  as  $M \rightarrow \infty$ .

## III. PROOF OF LEMMA 1

For conciseness, we use notations from the main paper that we do not reintroduce. As a preliminary step, we define the function  $Z : \mathcal{U} \times \Omega \rightarrow \mathbb{R}$  by

$$Z_u(\omega) = \sup_{s \in [0, T]} G(x_u(s, \omega), \xi(\omega)), \quad (7)$$

which is clearly bounded and Hölder continuous under assumptions **(A1-A4)** (see the main paper and the proof of Theorem 1). Then, given a large-enough compact set  $\mathcal{T} \subset \mathbb{R}$ , we define the measurable function  $g : (\mathcal{T} \times \mathcal{U}) \times \Omega \mapsto \mathbb{R}$ ,

$$g((t, u), \omega) \mapsto t + \alpha^{-1} \max(Z_u(\omega) - t, 0). \quad (8)$$

Note that, since  $g$  is a composition of  $\alpha$ -Hölder-continuous functions (note that  $\max$  is Lipschitz) and  $\mathcal{T}$  is bounded,  $g$  is also bounded and  $\alpha$ -Hölder continuous, i.e.,  $g$  satisfies assumptions (B1) and (B2) over  $(t, u) \in \mathcal{T} \times \mathcal{U}$ . We thus have the following result.

*Corollary 1 (Finite-sample error bound):* Given  $M$  iid samples  $\omega^i \in \Omega$ , formulate the sample average approximation  $\mathbf{SOCP}_M$  of  $\mathbf{OCP}$ . Define the map  $g$  as in (8). Then, under assumptions **(A1-A4)** (see the main paper), for some

finite constants  $(\tilde{C}, \bar{h})$  large-enough, for  $(\epsilon_M, \delta_M)$  defined in (5), with probability at least  $1 - \delta_M$  over the  $M$  samples,

$$\sup_{(t,u) \in \mathcal{T} \times \mathcal{U}} \left| \frac{1}{M} \sum_{i=1}^M g((t,u), \omega^i) - \mathbb{E}[g((t,u), \cdot)] \right| \leq \epsilon_M. \quad (9)$$

*Proof:* Under assumptions **(A1-A4)**, the function  $g$  defined above satisfies Assumptions (B1) and (B2). The conclusion follows from Lemma 2. ■

The desired result (Lemma 2) follows directly from Corollary 1, i.e., we obtain high-probability finite-sample error bounds for the risk constraints given a solution of the sample-based approximation **SOCP** <sub>$M$</sub> ( $\bar{\omega}$ ) of **OCP**.

*Proof of Lemma 2:* For any  $u \in \mathcal{U}$ , define the random variable  $Z_u(\omega) = (7)$  (as in the paper), so that

$$\text{AV@R}_\alpha \left( \sup_{s \in [0, T]} G(x_{u(\bar{\omega})}(s), \xi) \right) = \text{AV@R}_\alpha (Z_{u(\bar{\omega})}).$$

Then, define the function  $g : (\mathcal{T} \times \mathcal{U}) \times \Omega \mapsto \mathbb{R}$  as in (8). Denote the solution to **SOCP** <sub>$M$</sub> ( $\bar{\omega}$ ) by  $(t(\bar{\omega}), u(\bar{\omega}))$ , and note that

$$g((t(\bar{\omega}), u(\bar{\omega})), \omega) = t(\bar{\omega}) + \frac{1}{\alpha} \max(Z_{u(\bar{\omega})}(\omega) - t(\bar{\omega}), 0).$$

By the feasibility of **SOCP** <sub>$M$</sub> ( $\bar{\omega}$ ), we have that

$$\begin{aligned} \frac{1}{M} \sum_{i=1}^M g((t(\bar{\omega}), u(\bar{\omega})), \omega^i) \\ = t(\bar{\omega}) + \frac{1}{\alpha M} \sum_{i=1}^M \max(Z_{u(\bar{\omega})}(\omega^i) - t(\bar{\omega}), 0) \\ \leq 0. \end{aligned}$$

Moreover, by Corollary (1), with probability at least  $1 - \delta_M$  over the  $M$  samples  $\omega^i$ ,

$$\sup_{(t,u) \in \mathcal{T} \times \mathcal{U}} \left| \frac{1}{M} \sum_{i=1}^M g((t,u), \omega^i) - \mathbb{E}[g((t,u), \cdot)] \right| \leq \epsilon_M.$$

By combining the last two inequalities, we conclude that

$$\mathbb{E}[g((t(\bar{\omega}), u(\bar{\omega})), \cdot)] \leq \epsilon_M$$

with probability at least  $1 - \delta_M$ .

Finally, for  $\mathcal{T}$  large-enough (this bounded set  $\mathcal{T}$  exists as discussed in the proof of Theorem 1 in the main paper, see also [2]), by definition,

$$\begin{aligned} \text{AV@R}_\alpha(Z_{u(\bar{\omega})}) &= \inf_{t \in \mathbb{R}} \left( t + \frac{1}{\alpha} \mathbb{E}[\max(Z_{u(\bar{\omega})} - t, 0)] \right) \\ &= \inf_{t \in \mathcal{T}} \left( t + \frac{1}{\alpha} \mathbb{E}[\max(Z_{u(\bar{\omega})} - t, 0)] \right) \\ &\leq t(\bar{\omega}) + \frac{1}{\alpha} \mathbb{E}[\max(Z_{u(\bar{\omega})} - t(\bar{\omega}), 0)]. \\ &= \mathbb{E}[t(\bar{\omega}) + \alpha^{-1} \max(Z_{u(\bar{\omega})} - t(\bar{\omega}), 0)]. \\ &= \mathbb{E}[g((t(\bar{\omega}), u(\bar{\omega})), \cdot)] \\ &\leq \epsilon_M \end{aligned}$$

with probability at least  $1 - \delta_M$ , concluding the proof. ■

## REFERENCES

- [1] T. Lew, R. Bonalli, and M. Pavone. Sample average approximation for stochastic programming with equality constraints. Available at <https://arxiv.org/abs/2206.09963>, 2022.
- [2] A. Shapiro, D. Dentcheva, and A. Ruszczyński. *Lectures on Stochastic Programming: Modeling and Theory, Second Edition*. Society for Industrial and Applied Mathematics, 2014.