

Evaluating the impact of eDoS attacks to cloud facilities

Gian-Luca Dei Rossi ¹ Mauro Iacono ² Andrea Marin ¹

¹Università Ca' Foscari Venezia ²Seconda Università di Napoli

November 18, 2015

The setting

Nowadays the use of cloud computing is widespread

- ▶ Infrastructure as a service
- ▶ Platform as a service
- ▶ Software as a service
- ▶ ...

Cloud services providers have to manage capacity within constraints such as

- ▶ Performance constraints (SLAs,...)
- ▶ Economic constraints (budgets, pricing policies,...)

Economic constraints impose *energy management* policies

- ▶ Hardware powered on and off *on demand*
- ▶ Policies have to take into account performance constraints
 - ▶ Strategies can be complex and at different granularities

eDoS attacks

Cloud facilities may be subject to *Denial of Service* (DoS) attacks

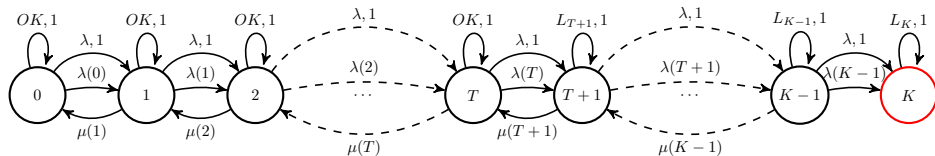
- ▶ aiming at degrading performance indices, e.g., average response time, and breaking SLAs
- ▶ easy to notice, but not so easy to counteract
- ▶ the attacker has a simple and noticeable goal

An *Energy oriented Denial of Service* (eDoS) attack, on the other hand

- ▶ aims at the maximisation of energy consumption
- ▶ using legitimate workload
- ▶ non-disruptive and long-term
 - ▶ it should not crash the system
 - ▶ it has to be hard to notice
- ▶ the attacker has not a feedback on the success of the attack
 - ▶ no knowledge about energy management policies of providers
 - ▶ lack of a simple correlation between load and energy consumption

We want to model the behaviour of those attacks with respect to different strategies.

A model for cloud infrastructures



Finite set of states $\mathcal{S}_C = \{0, 1, 2, \dots, K\}$

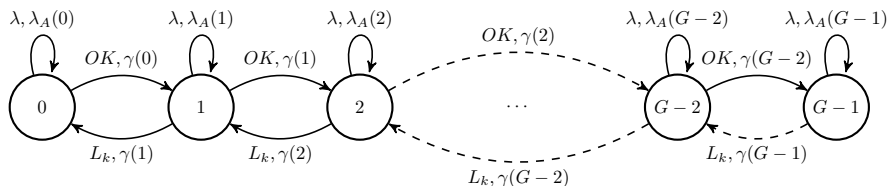
- ▶ states 0 to T : system dynamically scales its computational power
- ▶ states $T + 1$ to $K - 1$: system cannot scale, performance degradation
- ▶ state K : the system has crashed or the attack was discovered

Transitions:

$$\begin{aligned}
 \mathbf{C}_0(i, j) &= \lambda(i)[j = i + 1] + \mu(j)[j = i - 1][j \neq K] && \text{std. workload and services} \\
 \mathbf{C}_{OK}(i, j) &= [i = j][i \leq T], \quad 0 \leq i, j \leq K && \text{performance are OK} \\
 \mathbf{C}_{L_k}(i, j) &= [i = j][i = k], \quad T + 1 \leq k \leq K && \text{performances are degraded} \\
 \mathbf{C}_\lambda(i, j) &= [j = i + 1] && \text{workload from the attacker}
 \end{aligned}$$

Let $p: \mathcal{S}_C \rightarrow \mathbb{R}^+$, $p(K) = 0$, represent the power spent in each state of the cloud.

A model for e-attackers



Finite set of states $\mathcal{S}_A = \{0, \dots, G-1\}$

Transitions:

$$\mathbf{A}_\lambda(i, j) = [i = j] \lambda_A(i)$$

attack intensity

$$\mathbf{A}_{OK}(i, j) = \gamma(i) [j = i + 1]$$

increase intensity

$$\mathbf{A}_{L_k}(i, j) = \gamma(i) [j = i - 1], \quad T + 1 \leq k \leq K - 1$$

decrease intensity

Note: A_{OK} and A_{L_k} may vary with respect to the strategy adopted.

Cloud-Attacker interaction

We define the joint model between attacker and cloud using the $G(K+1) \times G(K+1)$ transition matrix

$$\mathbf{M} = \mathbf{C}_0 \otimes \mathbf{I}_G + \mathbf{C}_{OK} \otimes \mathbf{A}_{OK} + \sum_{k=T+1}^{K-1} \mathbf{C}_{L_k} \otimes \mathbf{A}_{L_k} + \mathbf{C}_\lambda \otimes \mathbf{A}_\lambda$$

The corresponding infinitesimal generator is

$$\mathbf{Q} = \mathbf{M} - \text{diag}(\mathbf{M}\mathbf{1})$$

and the associated Markov chain is $X(t)$

- ▶ states of $X(t)$ are pairs (k, g) with $0 \leq k \leq K$ and $0 \leq g \leq G-1$
- ▶ we write $|X(t)|_1$ ($|X(t)|_2$) to denote the first (second) component of the pair.

Quantitative Indices

States of \mathbf{M} does not describe an ergodic CTMC

- Once the cloud is in state K (failure or attack detection) it cannot leave
- In the joint model all states (K, g) with $g = 0, \dots, G - 1$ form an *absorbing subset* of the states

τ is the r.v. representing the time required by the chain to reach an absorbing state:

$$\tau = \inf\{t \geq 0 | X(t) = (K, g), g \in [0, G - 1]\}$$

$\bar{\tau} = E[\tau]$ is the finite *expected time to absorption*.

The energy consumed up to absorption is the r.v. defined as:

$$R = \int_0^\infty p(|X(t)|_1) dt,$$

Since $p(k)$ is bounded then $P\{R < \infty\} = 1$ and we define $\bar{R} = E[R]$ as the expected energy consumed by the cloud before the absorption.

Exact computation of the indices

Let $\mathbf{M}' = [\mathbf{M}]_{KG}$ be the transition rate matrix formed with the first $K \cdot G$ rows and columns of \mathbf{M} , and let \mathbf{P} be defined as:

$$\mathbf{P} = ([\text{diag}(\mathbf{M}\mathbf{1})]_{KG})^{-1} \mathbf{M}' ,$$

i.e., the DTMC embedded in $X(t)$ reduced to the transient states.

Let \mathbf{r} be the vector s.t. $\mathbf{r}(s) = E[R|X(0) = s]$, computed as

$$\mathbf{r} = (\mathbf{I} - \mathbf{P})^{-1} \mathbf{v} ,$$

where \mathbf{v} is a column vector whose s -th component is

$$\mathbf{v}(s) = \frac{p(|s|_1)}{\sum_{\substack{j \in [0, K] \times [0, G-1] \\ j \neq s}} q_{sj}} .$$

Let $\boldsymbol{\pi}(s)$ be the column vector with the initial distribution, then \overline{R} is:

$$\overline{R} = \boldsymbol{\pi}^T \mathbf{r} .$$

The computation of $\overline{\tau}$ is analogous, fixing the numerator of \mathbf{v} to 1

Approximate computation

When the attack is very long, $\mathbf{I} - \mathbf{P}$ is almost singular \implies **numerical instability**

- ▶ We propose an approximation based on *quasi stationarity* theory
- ▶ If $\bar{\tau} \gg$ trans. times of $X(t)$, transient part may have a stationary behaviour.

Let \mathcal{U} be the set of the transient states of $X(t)$

$$\mathcal{U} = \{(k, g) : k \in [0, K - 1] \wedge g \in [0, G - 1]\},$$

and $\mathbf{Q}_U = [\mathbf{Q}]_{KG}$ be the infinitesimal generator matrix reduced to the states in \mathcal{U} .

Definition

A distribution \mathbf{u} is to be quasi-stationary for $X(t)$ if

$$Pr_{\mathbf{q}}\{X(t) = s | \tau > t\} = \mathbf{q}(s),$$

where $Pr_{\mathbf{q}}$ denotes that the distribution of $X(0)$ is \mathbf{q} .

\mathbf{Q}_U has a unique eigenvalue $-\alpha$ with maximal real part. \mathbf{q} is the unique vector s.t.

$$\mathbf{q}^T \mathbf{Q}_U = -\alpha \mathbf{q}^T,$$

with $\mathbf{1}^T \mathbf{q} = 1$. \mathbf{q} is the unique distribution that satisfies the Definition above.

Approximate computation: absorption time

Proposition (Time to absorption)

Let \mathbf{q} be the quasi-stationary distribution of $X(t)$ for the subset of states \mathcal{U} , then:

$$Pr_{\mathbf{q}}\{\tau > t + \Delta_t | \tau > t\} = e^{-\alpha \Delta_t} \quad t, \Delta_t \geq 0.$$

i.e., the absorption time from a q.s. distribution is exponentially distributed with parameter given by the highest (negative) real (left) eigenvalue of \mathbf{Q}_U .

Therefore $\bar{\tau} = \alpha^{-1}$ when the chain at time 0 is q.s. distributed.

In general we cannot make that assumption, however the following results hold

Proposition

Let \mathbf{w} be any probability distribution over \mathcal{U} , then

- ▶ $\lim_{t \rightarrow \infty} Pr_{\mathbf{w}}\{\tau > t + \Delta_t | \tau > t\} = e^{-\alpha \Delta_t} ;$
- ▶ $\lim_{t \rightarrow \infty} Pr_{\mathbf{w}}\{X(t) = s | \tau > t\} = \mathbf{q}(s).$

Therefore, for large absorption times, regardless to the initial distribution of $X(t)$,

$$\bar{\tau} \simeq \alpha^{-1}$$

Approximate computation: energy consumption

The computation of the approximate average energy consumption is given by

$$\overline{R} \simeq \alpha^{-1} \sum_{s \in \mathcal{U}} p(|s|_1) \mathbf{q}(s).$$

In practice the precision of the approximation depends on the spectral gap η between α and α_2 , where α_2 is the eigenvalue with the next largest real part after α :

$$\eta = \operatorname{Re}(\alpha_2) - \alpha.$$

The convergence of the initial distribution of $X(t)$ to the quasi-stationary distribution is fast if $\eta \gg \alpha$.

Since \mathbf{Q}_U is a diagonal dominant M-matrix, the computation of the eigenvalue with the smallest real part can use fast and stable algorithms.

Experimenting with the model

The presented model can be used to

- ▶ evaluate the energy consumption of a cloud infrastructure given a (legitimate or not) load
- ▶ evaluate the behaviour and the effectiveness of an eDoS attacker using a particular strategy
- ▶ evaluate the quality of the quasi-stationarity based approximation

In order to perform those evaluations, we use a MATLAB[®] custom-made implementation of the described methods.

In the following examples, the initial distribution $\pi(s)$ is assumed to be

$$\pi(s) = \begin{cases} \pi(s)_{[\mathbf{C}]_K} \left(\lfloor \frac{s}{G} \rfloor \right) & \text{if } s \bmod G = 0 \\ 0 & \text{otherwise} \end{cases}$$

where $\pi(s)_{[\mathbf{C}]_K}$ is the stationary distribution of the cloud \mathbf{C} , conditioned on the fact that the absorbing states have not been visited, considered in isolation.

Attack strategies

- Strategy 1
- ▶ The attacker moves from state g to state $g + 1$, i.e., it increases the arrival intensity at the cloud system whenever it observes a QoS of type OK.
 - ▶ The attacker moves from state g to state $g - 1$ whenever it observes a QoS of type L_k .
- Strategy 2
- ▶ The attacker moves from state g to state $g + 1$ whenever it observes a QoS of type OK.
 - ▶ The attacker goes back to state 0 whenever it observes a QoS of type L_k .
- Strategy 3
- ▶ The attacker moves from state g to state $g + 1$ whenever it observes a QoS of type OK.
 - ▶ When a QoS of type L_k is observed, the attacker moves from state g to state $\max(g - k + T, 0)$.

Parameters

Parameter	Approx. Validation	Strategies comparison
K	20	20
T	14	14
G	6	6
λ	$[1.3, 7.0]$	1
μ	1.2	0.5
$\gamma(g)$	$\mu/30$	$\min(\max(\lambda_A(g), \lambda), T\mu)/30$
$\lambda_A(g)$	Fg	$Fg\mu$
F	0.8	$[2.0, 8.0]$
$p(k)$	$\min(k, T)$	$\min(k, T)$

Table: Parameter values for the experiments

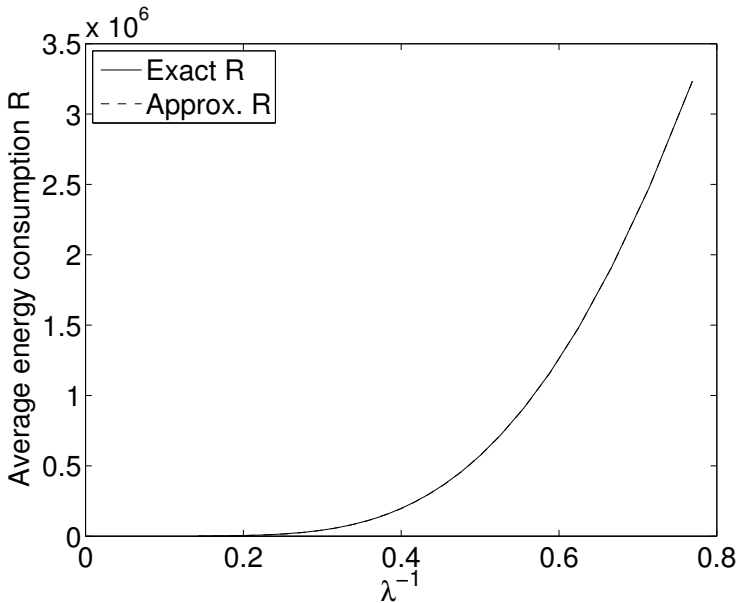


Figure: Exact and approximate computation of \bar{R}

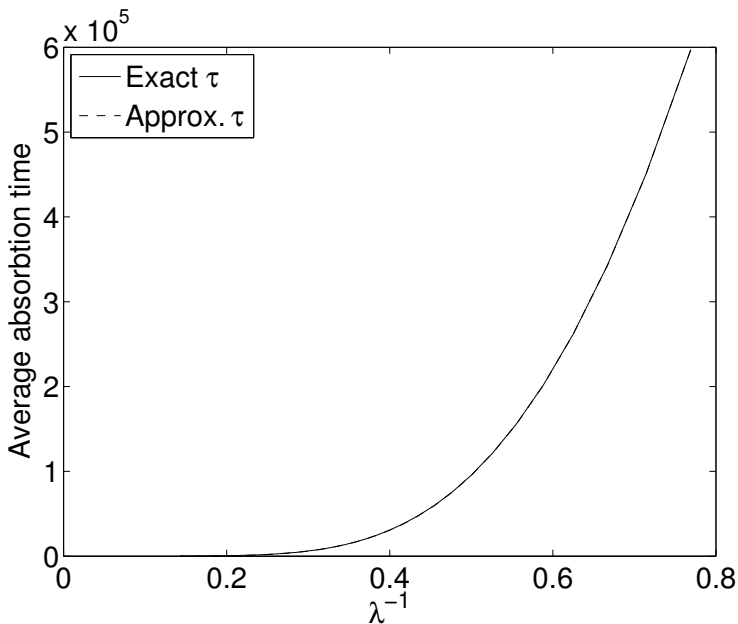


Figure: Exact and approximate computation of $\bar{\tau}$

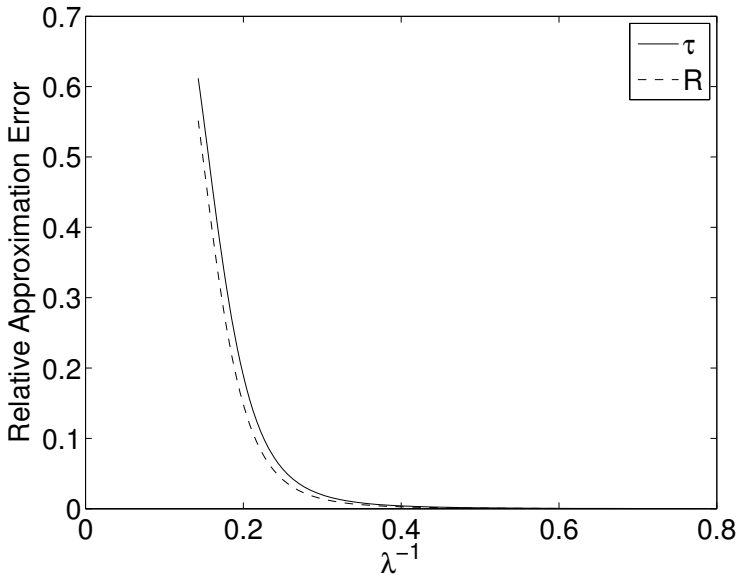


Figure: Relative approximation error for \bar{R} and $\bar{\tau}$, Strategy 1

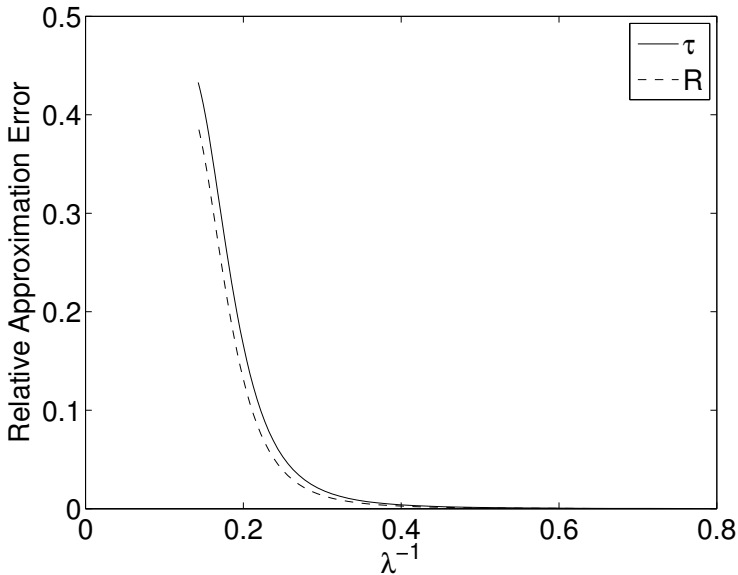


Figure: Relative approximation error for \bar{R} and $\bar{\tau}$, Strategy 2

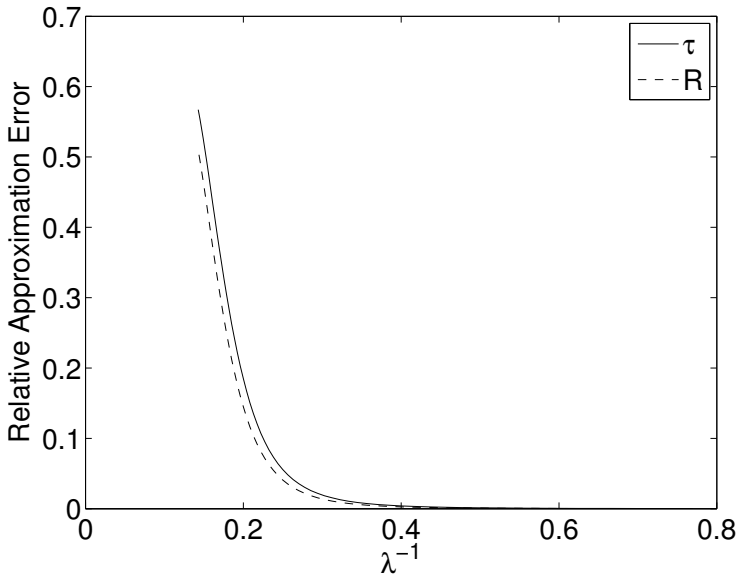


Figure: Relative approximation error for \bar{R} and $\bar{\tau}$, Strategy 3

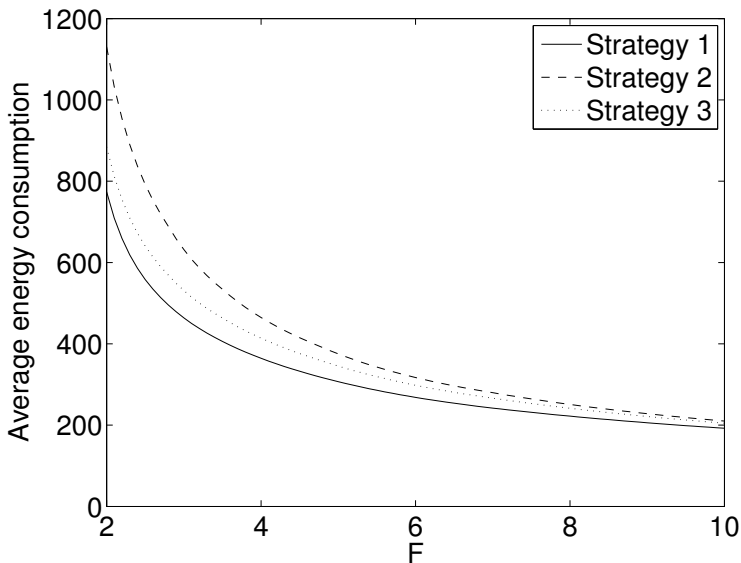


Figure: Computation of \bar{R} for different strategies

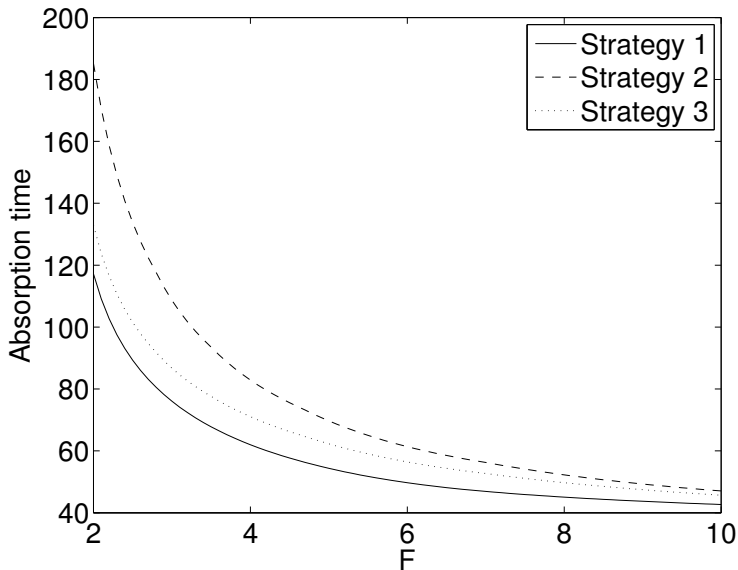


Figure: Computation of $\bar{\tau}$ for different strategies

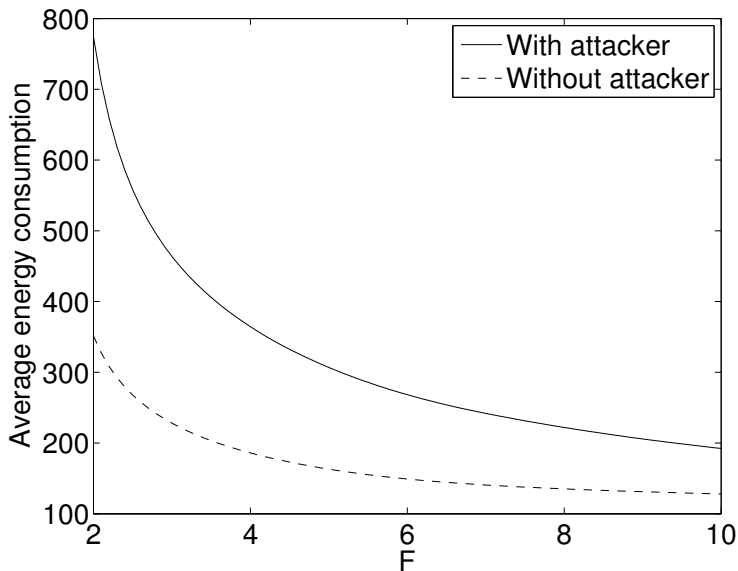


Figure: Comparison of \bar{R} with or without attacker. Strategy 1

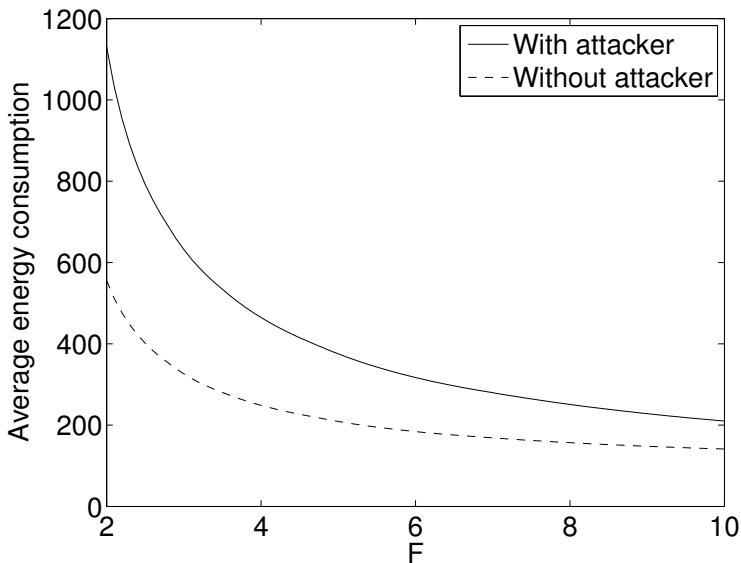


Figure: Comparison of \bar{R} with or without attacker. Strategy 2

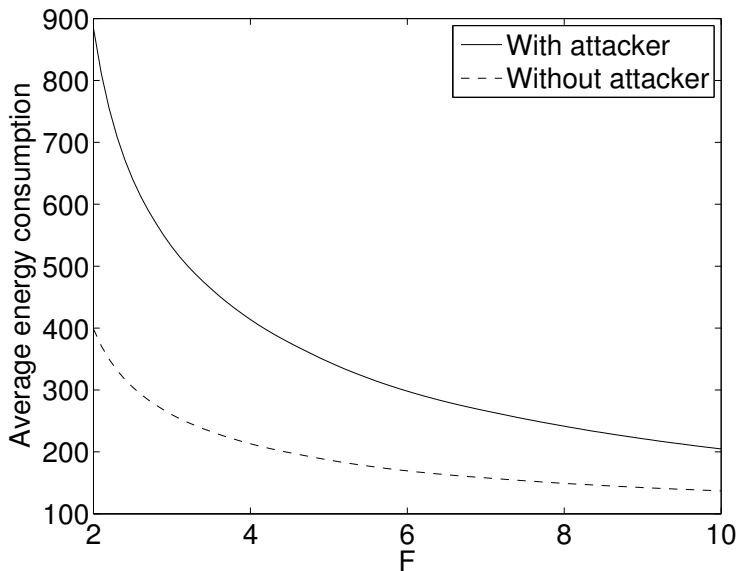


Figure: Comparison of \bar{R} with or without attacker. Strategy 3

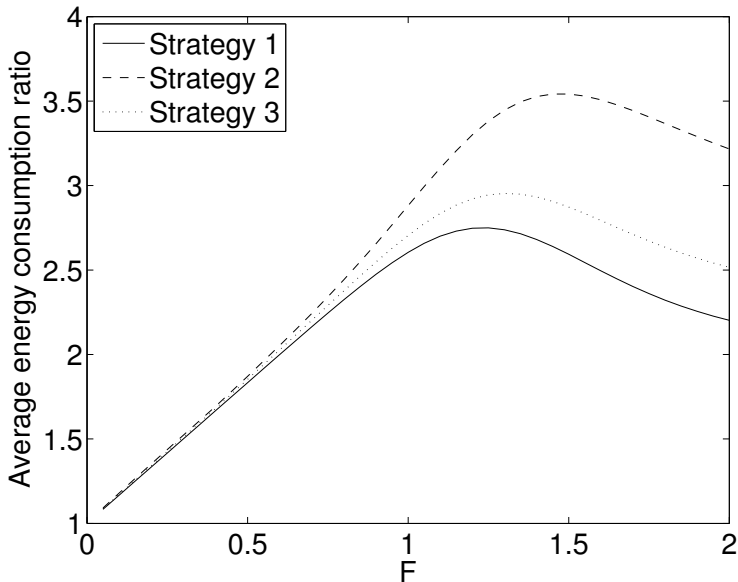


Figure: Ratio between values of \overline{R} with and without attacker, $F \in (0, 2]$

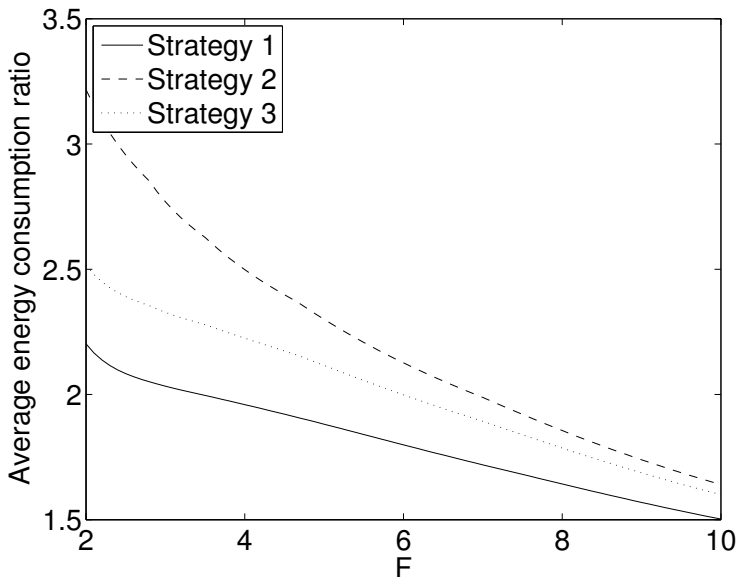


Figure: Ratio between values of \bar{R} with and without attacker, $F \in [2, 10]$

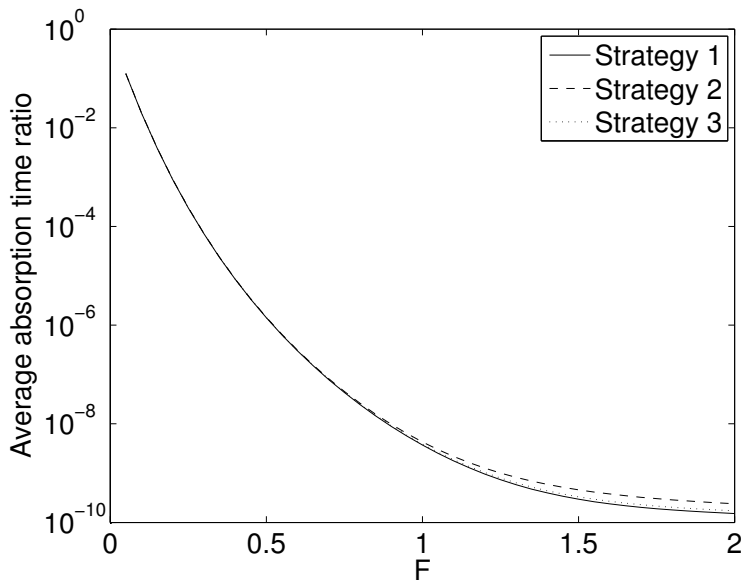


Figure: Ratio between values of $\bar{\tau}$ with and without attacker, $F \in (0, 2]$

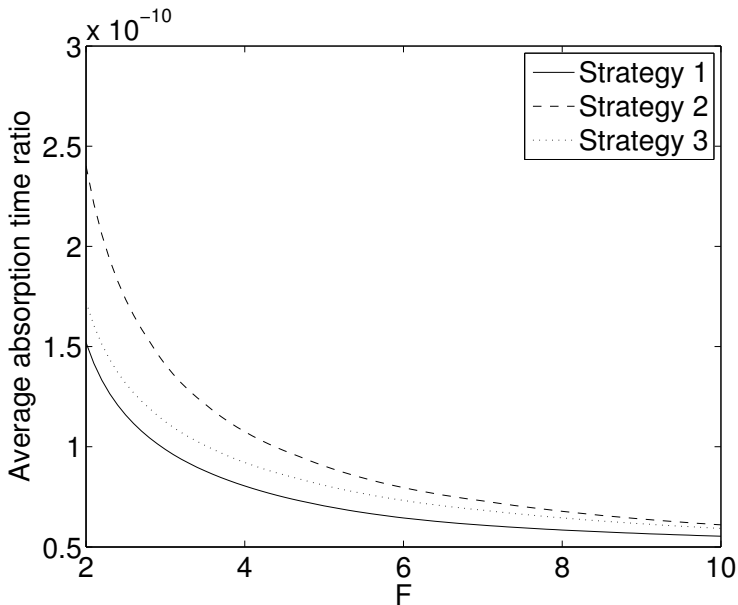


Figure: Ratio between values of $\bar{\tau}$ with and without attacker, $F \in [2, 10]$

Conclusions

- ▶ We proposed a Markovian model to study the impact of eDoS attacks to cloud infrastructures.
- ▶ We analysed the mean time to absorption and on the expected cumulated rewards in a CTMC describing the attacker strategy and the cloud state.
- ▶ We gave numerically stable methods to compute (or approximate for long-lasting attacks) the performance indices that allow us to evaluate the impact of an attack.
- ▶ We found that low-aggressive strategies of the attackers are more dangerous for the cloud since they do not change significantly the life-time of the systems while they maintain a higher energy consumption.

Future works:

- ▶ give a more detailed model of the cloud infrastructure
- ▶ give a model for non-coordinated attackers performing a distributed eDoS
- ▶ perform a validation of the analysis on real data
- ▶ design a statistic approach to estimate the probability of being in presence of an eDoS attack in a cloud infrastructure
- ▶ ...

Thanks!

Thanks for your attention

⋮

(even if you slept during the whole presentation)

any question?