

Optimization of an energy harvesting device via cross-entropy method

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1 Introduction

2 Nonlinear Dynamics

3 Optimization Problem

4 Numerical Experiments

5 Final Remarks

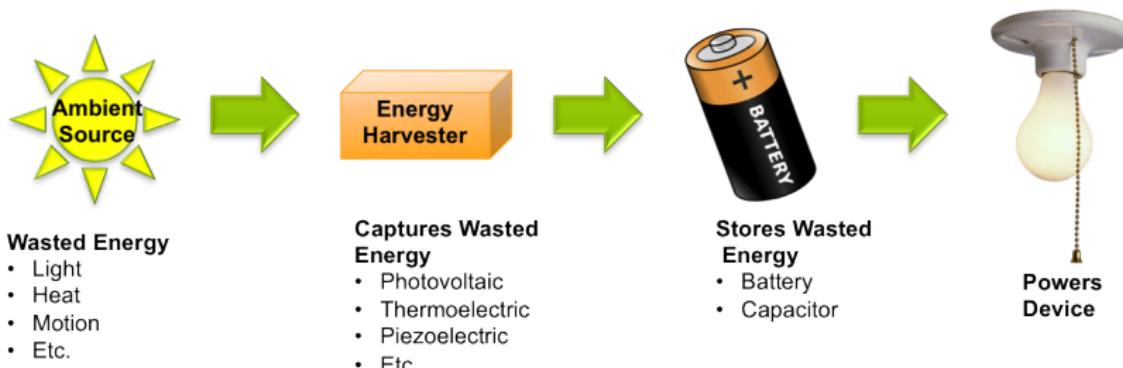


Section 1

Introduction



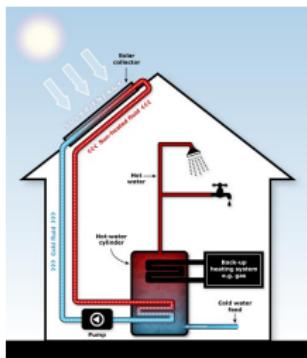
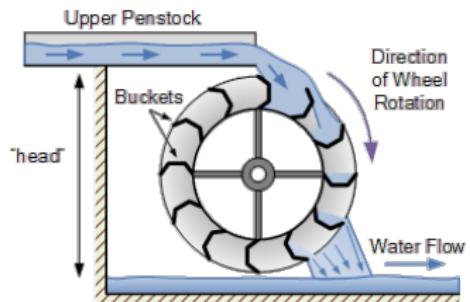
Energy Harvesting



- Capture wasted energy from external sources
- Store this wasted energy for future use
- Use the stored energy to supply other devices

*Picture from <http://hiddenjoules.com/intro/what/>

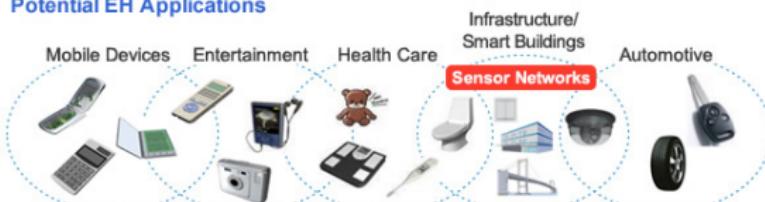
Classical Technologies in Energy Harvesting



*Pictures obtained from Google Images, several sources. If you are the owner of any one of these images, consider its use a compliment.

Emergent Technologies in Energy Harvesting

Potential EH Applications



Energy
Storage



Alkaline Batteries



Lithium Batteries



Super capacitors



Solar (Photovoltaic)



Industrial Solar Solns.



Heat - Thermo

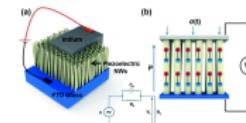
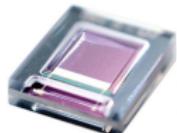


Vibration -
Magnetic
Induction



Piezoelectric

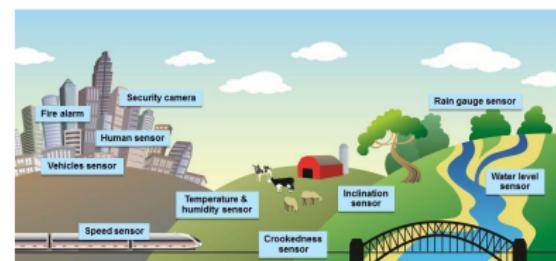
Commodity Products



*Pictures obtained from Google Images, several sources. If you are the owner of any one of these images, consider its use a compliment.

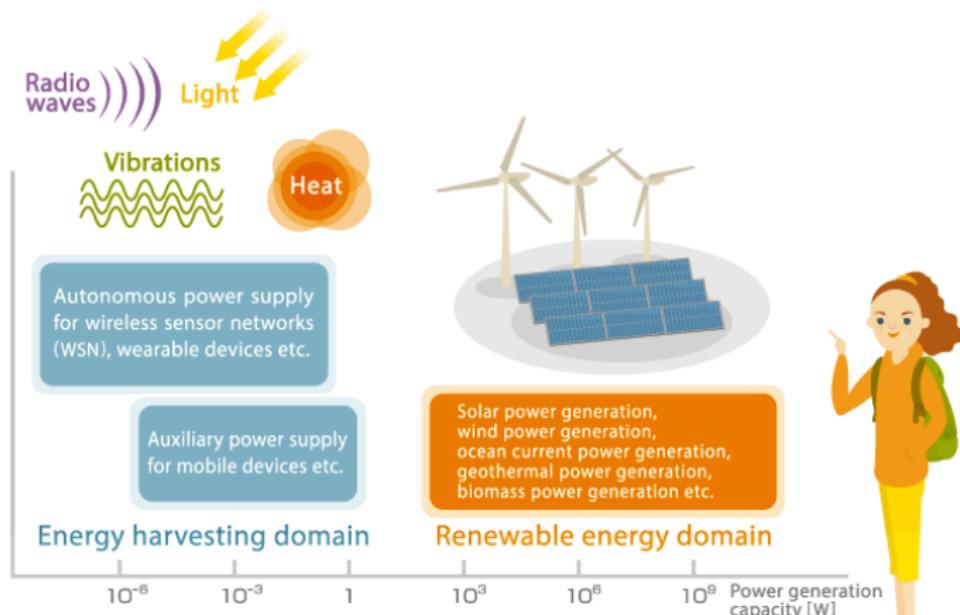


Spansion Energy Harvesting Technology Can Power the IoT



Energy Scale for Modern Harvesting Devices

- Power generation capacity and main applications of energy harvesting



*Picture from <http://www.global.tdk.com/techmag/knowledgebox/vol1.htm>

Research objectives

This research has several objectives:

- Investigate in detail the underlying nonlinear dynamics
- Propose strategies to enhance the recovered energy
- Model the underlying uncertainties and study their influence



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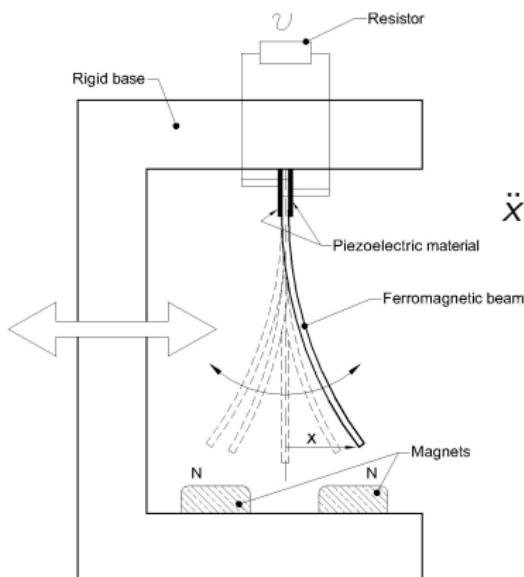


Section 2

Nonlinear Dynamics



Bi-stable energy harvesting device



$$\ddot{x} + 2\xi\dot{x} - \frac{1}{2}x(1-x^2) - \chi v = f \cos \Omega t$$

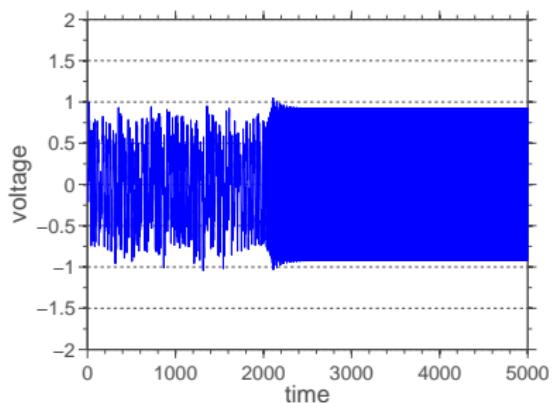
$$\dot{v} + \lambda v + \kappa \dot{x} = 0$$

$$x(0) = x_0, \quad \dot{x}(0) = \dot{x}_0, \quad v(0) = v_0$$

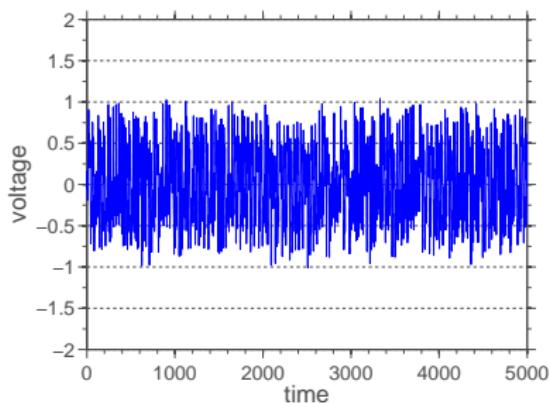


A. Erturk, J. Hoffmann and D. J. Inman, *A piezomagnetoelastic structure for broadband vibration energy harvesting*. **Applied Physics Letters**, 94: 254102, 2009.

Nonlinear dynamics: time series

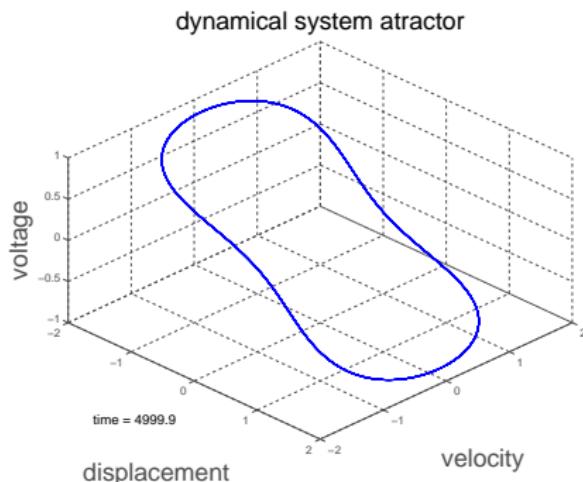
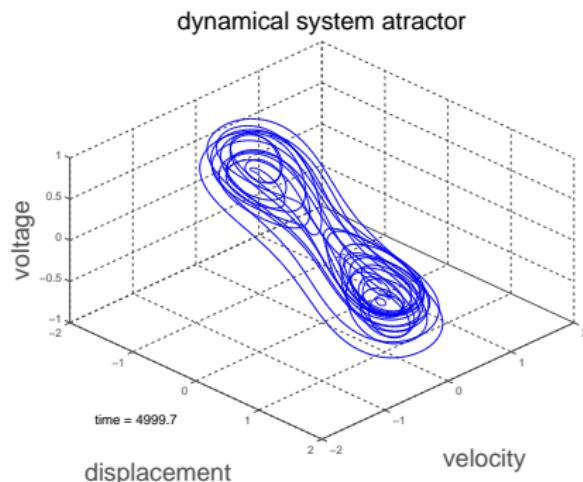


(a) $f = 0.11$

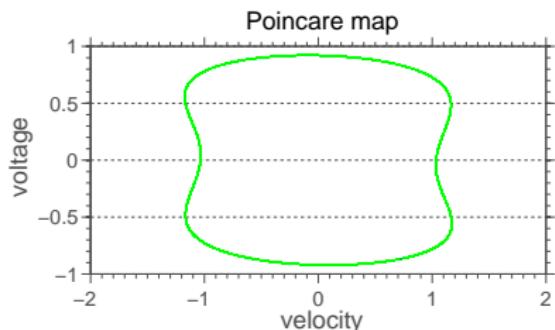
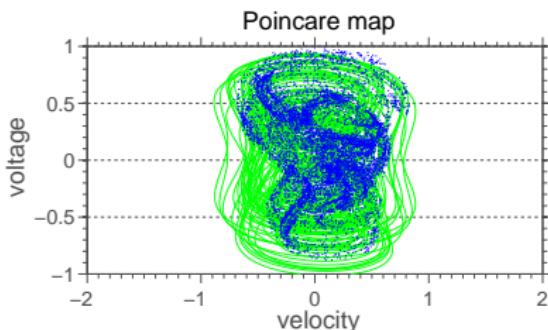


(b) $f = 0.10$

Nonlinear dynamics: system attractor

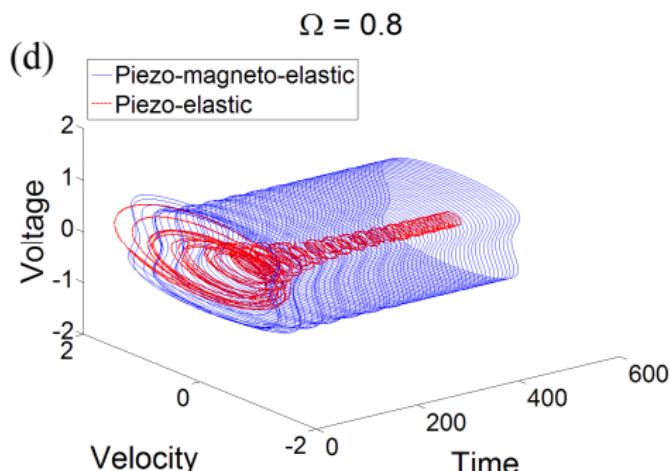
(a) $f = 0.11$ (b) $f = 0.10$

Nonlinear dynamics: Poincaré maps

(a) $f = 0.11$ (b) $f = 0.10$

Nonlinearity and efficiency

Nonlinearity of this dynamical system may enhance output power.

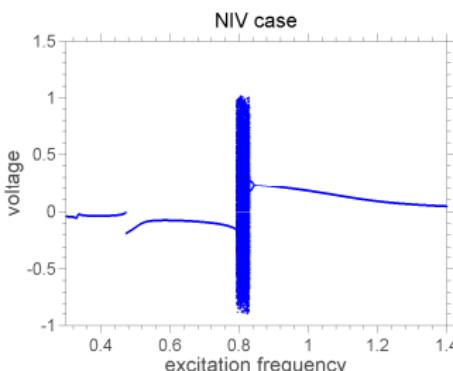
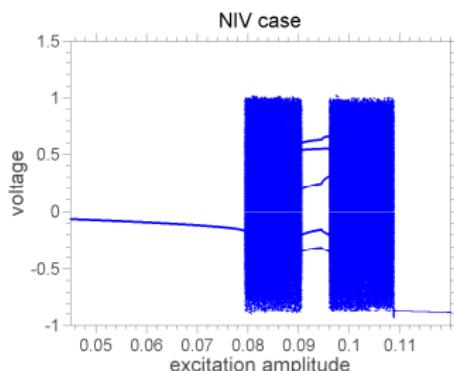
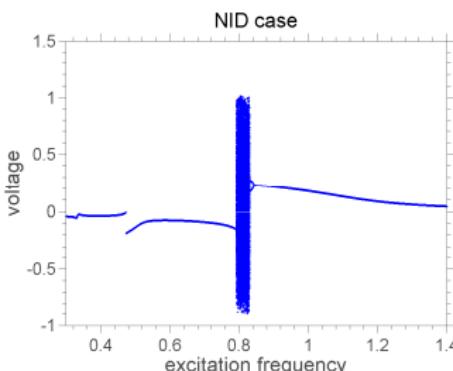
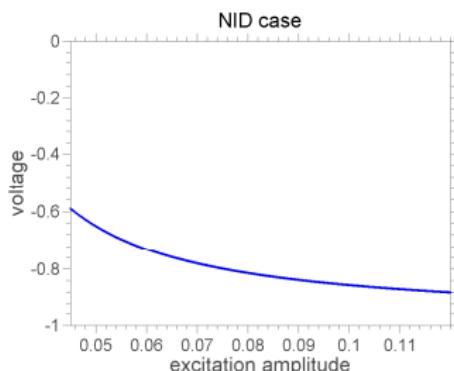


A. Erturk, *Electromechanical Modeling of Piezoelectric Energy Harvesters*, PhD Thesis, Virginia Tech, 2009.

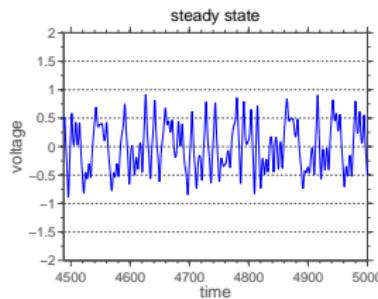
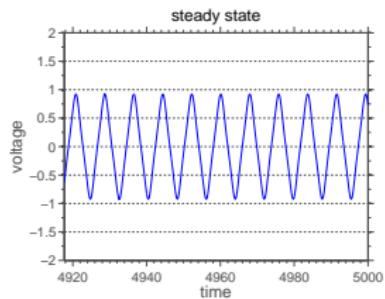
*Picture from the above reference.

Nonlinearity and chaos

Nonlinearity of this dynamical system may also induce chaos.

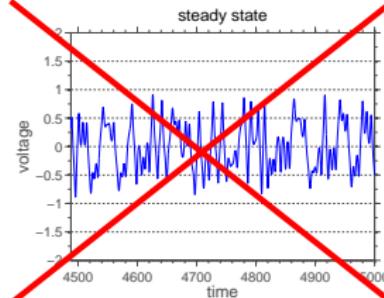
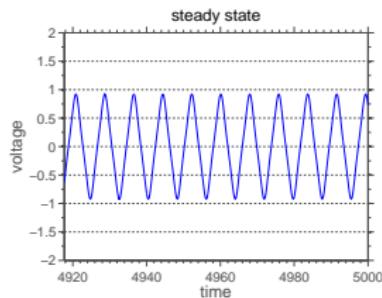


For practical use of the electrical energy ...



*Phone picture from <http://freevector.co/vector-icons/technology/charging-phone.html>

For practical use of the electrical energy ...



... irregular voltage is undesirable!

*Phone picture from <http://freevector.co/vector-icons/technology/charging-phone.html>

Detection of chaos: 0-1 test

Given a time series (x_1, \dots, x_N) , for several $c \in (0, 2\pi)$:

- ➊ change from coordinates (x, \dot{x}) to (p, q) :

$$p(n) = \sum_{j=1}^n x_j \cos(jc), \quad q(n) = \sum_{j=1}^n x_j \sin(jc)$$

- ➋ compute mean square displacement (for $0 \ll n \ll N$):

$$M(n) = \frac{1}{N} \sum_{j=1}^N \left([p(j+n) - p(j)]^2 + [q(j+n) - q(j)]^2 \right)$$

- ➌ compute correlation:

$$K_c = \text{corr} \{(1, 2, \dots, n), (M(1), M(2), \dots, M(n))\}$$

- ➍ compute median:

$$K = \text{median}\{K_c\}$$

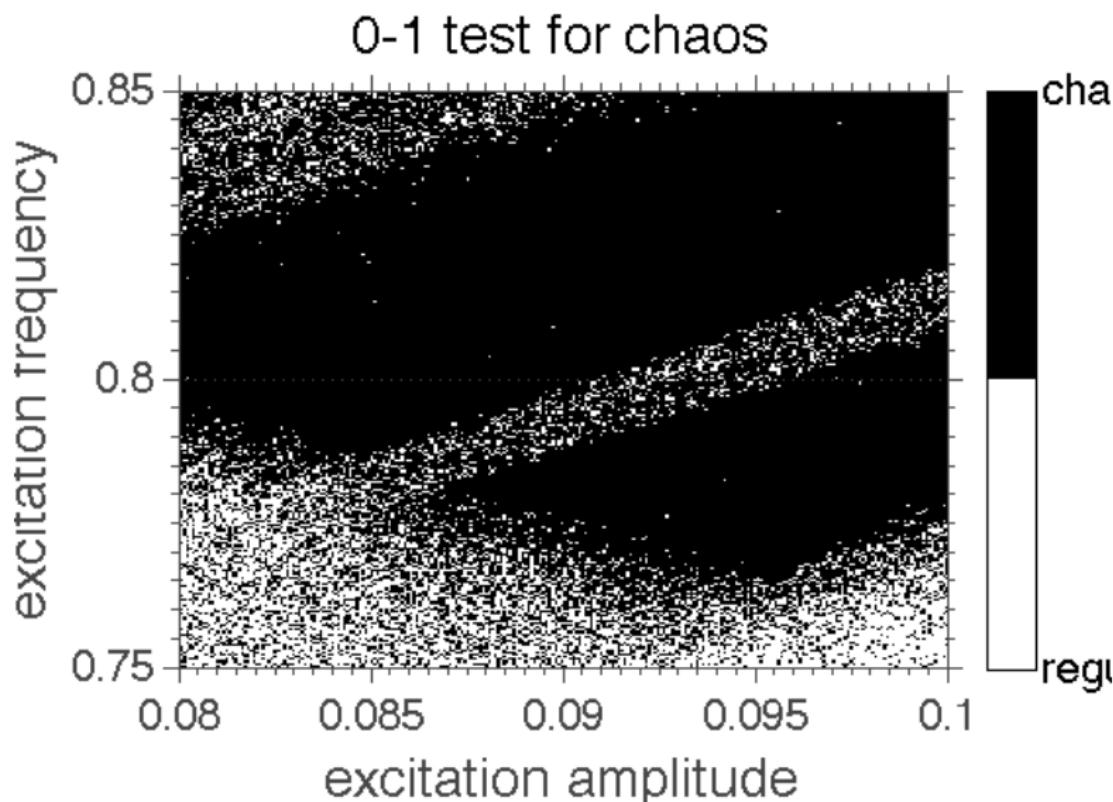
Numerical indicator:

$K \approx 0$: regular dynamics

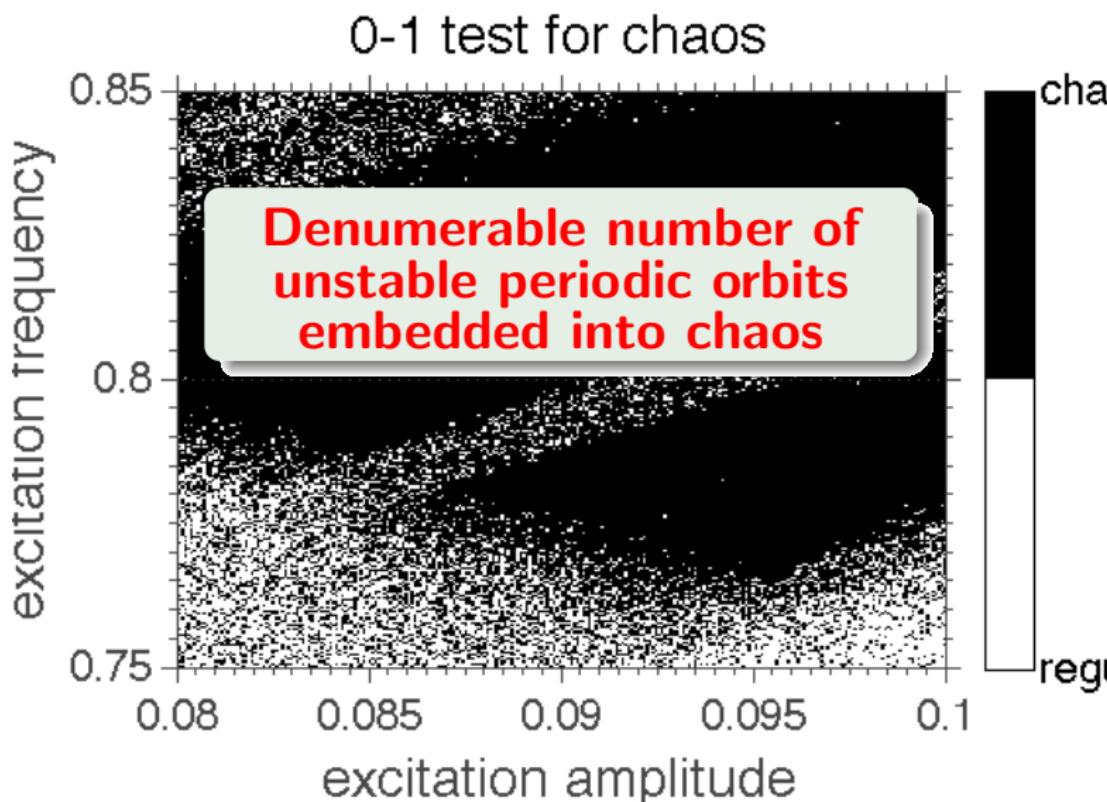
$K \approx 1$: chaotic dynamics



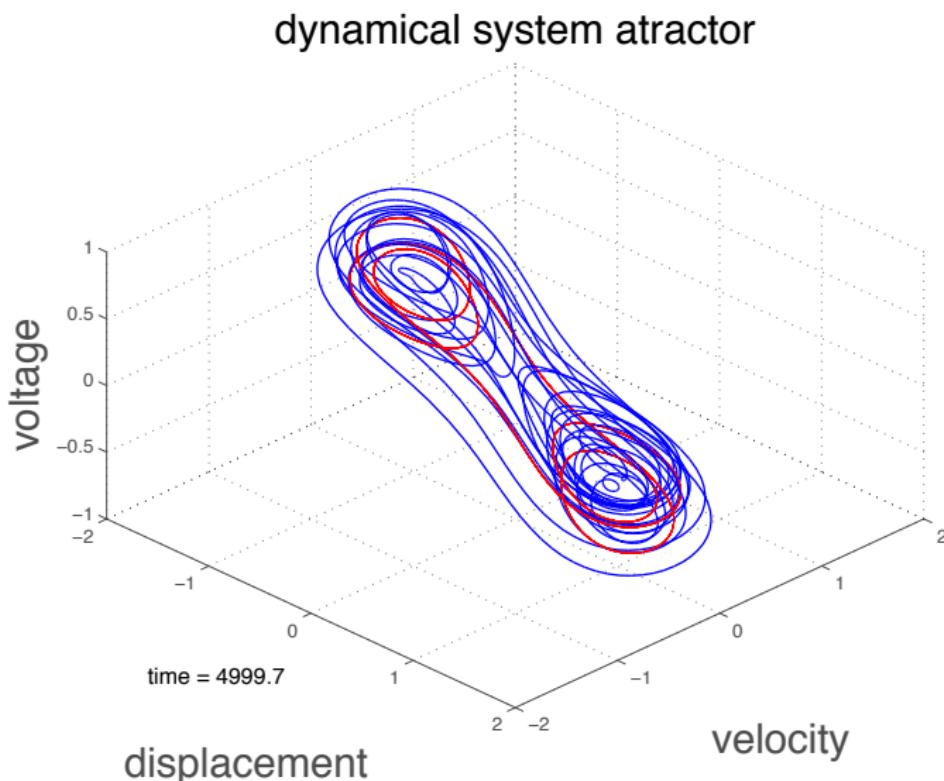
Characterization of chaos



Characterization of chaos



UPO embedded into a chaotic attractor



How to explore these unstable periodic orbits?

- Control of chaos
 - OGY method
 - Pyragas method
- Nonlinear optimization
 - Direct search on a fine grid
 - Genetic algorithm
 - Particle swarm optimization
 - Cross-Entropy method
 - Many other ...



How to explore these unstable periodic orbits?

- Control of chaos → **known UPO is required**
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How to explore these unstable periodic orbits?

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Section 3

Optimization Problem

Optimization of recovered power

Find a pair (f, Ω) which maximize

$$P = \frac{1}{T} \int_{\tau=0}^T \lambda v^2(\tau) d\tau$$

(mean power)

such that

$$f_{min} \leq f \leq f_{max}$$

$$\Omega_{min} \leq \Omega \leq \Omega_{max}$$

(control parameters are acceptable)

$$K \leq \text{tolerance}$$

(system dynamics is regular, i.e., not chaotic)



Optimization framework

- constrained problem

Find $\mathbf{x}^* = \arg \max \mathcal{S}(\mathbf{x})$ s.t. $\mathcal{G}_m(\mathbf{x}) \leq 0, m = 1, \dots, M$

- penalized problem

Find $\mathbf{x}^* = \arg \max \left\{ \mathcal{S}(\mathbf{x}) + \sum_{m=1}^M H_m \max [0, \mathcal{G}_m(\mathbf{x})] \right\}$

Characteristics:

- Test 0-1 for chaos constraint is a discontinuous function of \mathbf{x}
- Gradient-based methods are not applicable
- Evolutionary algorithms/metaheuristics can be used
(but we prefer not!)



An Idea

Solve this optimization problem through the calculation of a rare-event probability (Cross-Entropy Method)



Cross-entropy method

Hypothesis: There is a single maximum

$$\mathcal{S}(\mathbf{x}^*) = \gamma^* = \max_{\mathbf{x} \in \mathcal{X}} \mathcal{S}(\mathbf{x})$$

The optimization problem is randomized

$$\mathcal{P}\{\mathcal{S}(\mathbf{X}) \geq \gamma\} = \mathbb{E}\left\{\mathcal{I}_{\{\mathcal{S}(\mathbf{X}) \geq \gamma\}}\right\}$$

where \mathbf{X} is a random vector with probability density $f(\mathbf{x}; \mathbf{v})$

$\mathcal{S}(\mathbf{X}) \geq \gamma$ is a rare-event when $\gamma \approx \gamma^*$



R. Y. Rubinstein, and Dirk P. Kroese, **Simulation and the Monte Carlo Method**, Wiley, 3rd Edition, 2017.



Cross-entropy method

CE method generates an “optimal sequence” of estimators $(\hat{\gamma}_t, \hat{\mathbf{v}}_t)$ such that $\hat{\gamma}_t \rightarrow \gamma^*$ and $f(\mathbf{x}, \hat{\mathbf{v}}_t) \rightarrow \delta(\mathbf{x} - \mathbf{x}^*)$

“minimize KL divergence between $\mathcal{I}_{\{\mathcal{S}(\mathbf{x}) \geq \gamma\}}$ and $f(\cdot, \mathbf{v})$ ”

This method has two main steps:

- ① **Generate** an iid sample of objects in the search space \mathcal{X} according to a specified probability distribution $f(\cdot; \mathbf{v})$
- ② **Update** distribution parameters, based on the best performing samples (elite samples), using cross-entropy minimization



R. Y. Rubinstein, and Dirk P. Kroese, **Simulation and the Monte Carlo Method**, Wiley, 3rd Edition, 2017.



Cross-entropy algorithm

- ① Define N , N^e , t_{max} , $t = 0$, $f(\cdot, \mathbf{v})$ and $\hat{\mathbf{v}}_0$
- ② Update level $t = t + 1$
- ③ Generate $\mathbf{X}_1, \dots, \mathbf{X}_N$ (iid) samples from $f(\cdot, \hat{\mathbf{v}}_{t-1})$
- ④ Evaluate performance function $\mathcal{S}(\mathbf{X}_n)$ at samples $\mathbf{X}_1, \dots, \mathbf{X}_N$ and sort the results $\mathcal{S}_{(1)} \leq \dots \leq \mathcal{S}_{(N)}$
- ⑤ Update estimators $\hat{\gamma}_t$ and $\hat{\mathbf{v}}_t$
- ⑥ Repeat ② — ⑤ while stopping criterion is not met



R. Y. Rubinstein, and Dirk P. Kroese, **Simulation and the Monte Carlo Method**, Wiley, 3rd Edition, 2017.



Cross-Entropy Estimators

- Level estimator:

$$\hat{\gamma}_t = \mathcal{S}_{(N-N^e+1)}$$

- Elite samples:

$$\mathcal{E}_t = \left\{ \mathbf{X}_k : \mathcal{S}(\mathbf{X}_k) \geq \hat{\gamma}_t \right\}$$

- Parameter estimator:

$$\hat{\mathbf{v}}_t = \arg \max_{\mathbf{v}} \sum_{\mathbf{X}_k \in \mathcal{E}_t} \ln f(\mathbf{X}_k; \mathbf{v})$$

(maximum likelihood estimator)

- For $f(\cdot; \mathbf{v}) \sim \mathcal{N}(\mu, \sigma)$ one has

$$\hat{\mu}_t = \frac{\sum_{\mathbf{X}_k \in \mathcal{E}_t} \mathbf{X}_k}{|\mathcal{E}_t|} \quad \text{and} \quad \hat{\sigma}_t = \sqrt{\frac{\sum_{\mathbf{X}_k \in \mathcal{E}_t} (\mathbf{X}_k - \hat{\mu}_t)^2}{|\mathcal{E}_t|}}$$

Section 4

Numerical Experiments

Reference solution

- Domain:

$$0.08 \leq f \leq 0.1$$

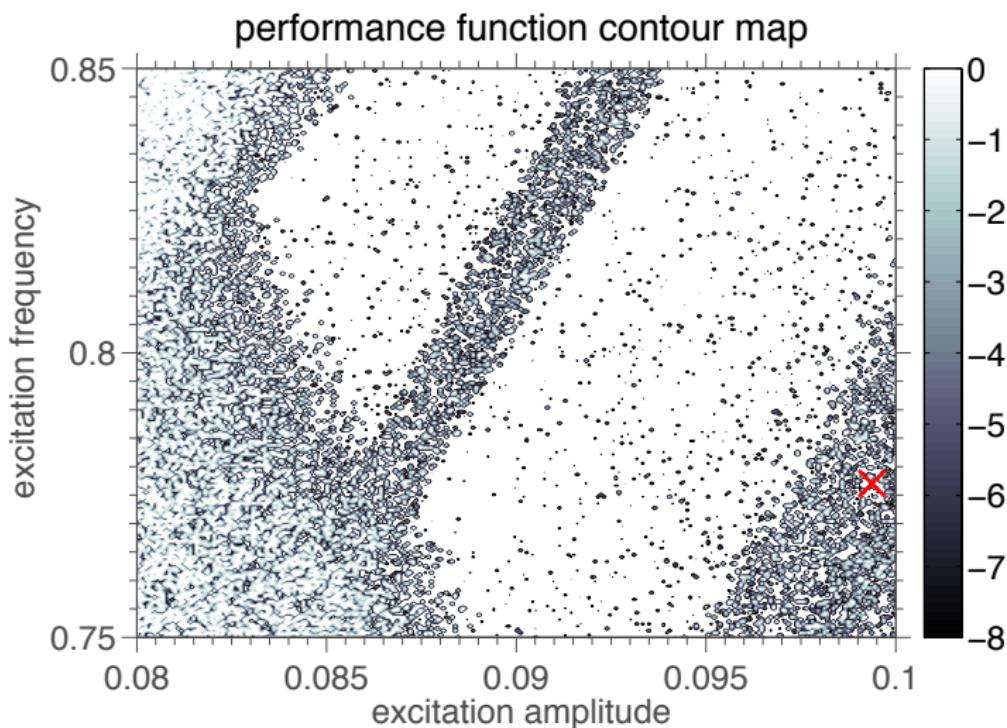
$$0.75 \leq \Omega \leq 0.85$$

- Penalty parameter: 10
- Direct search on a uniform grid: 256×256 points
- CPU time:¹ ≈ 14 hours

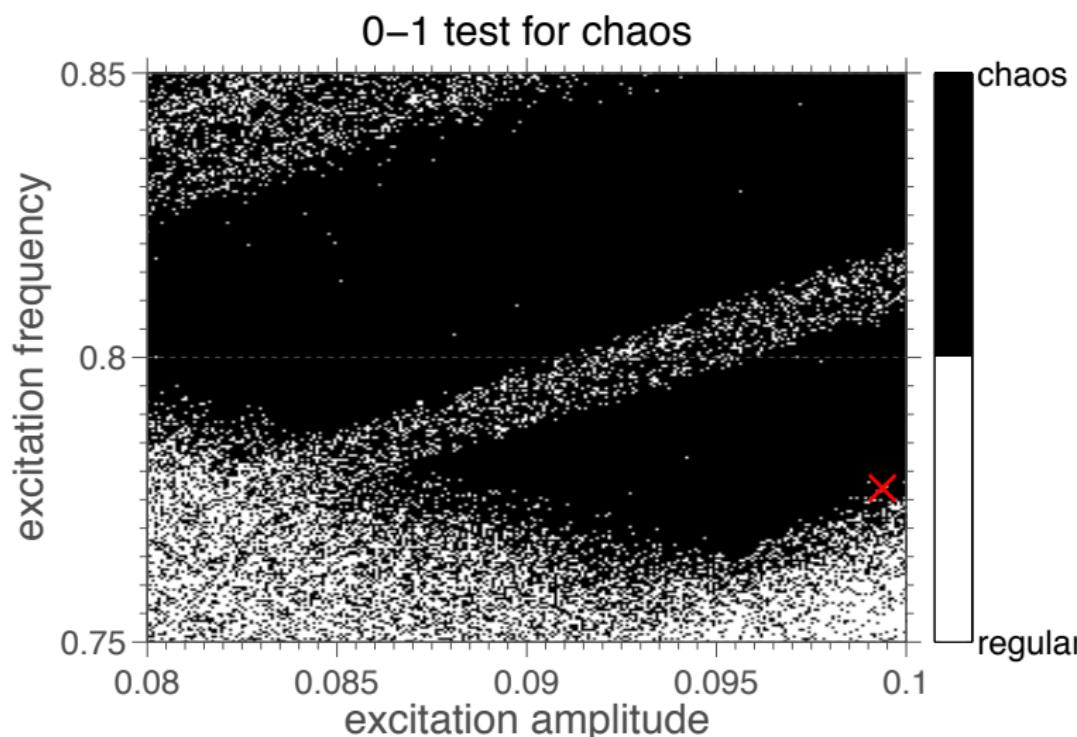


¹MacBook Pro “Core i7” 2.2 GHz 16GB 1333 MHz DDR3

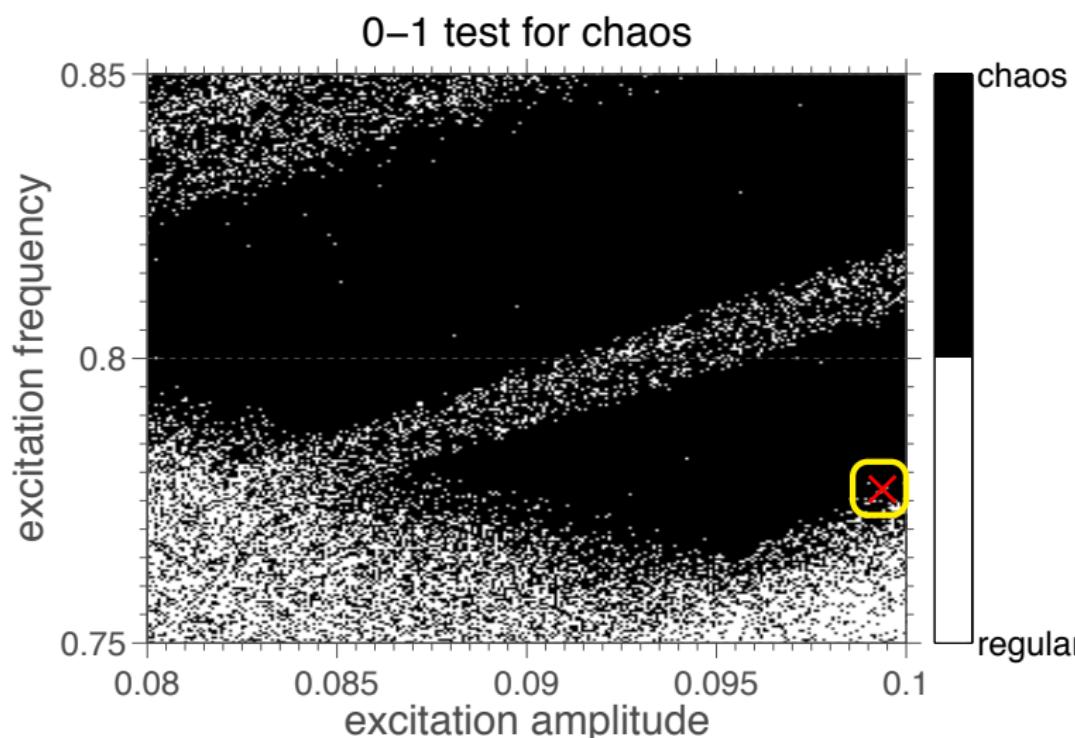
Reference solution: performance function



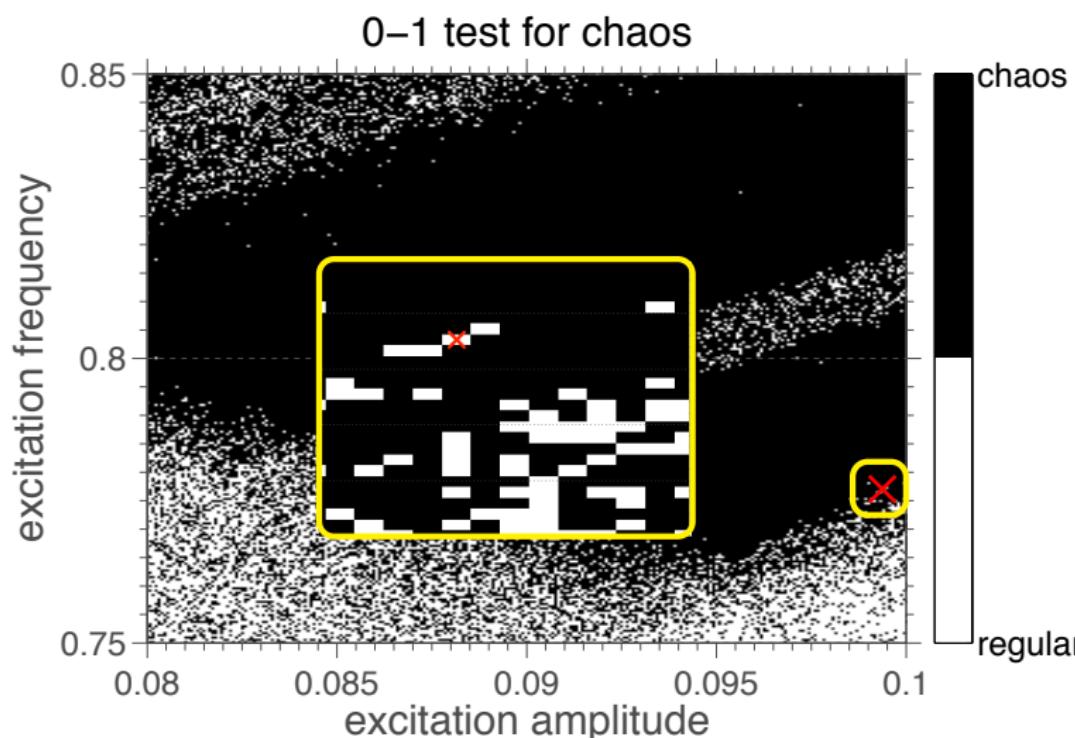
Reference solution: chaos indicator



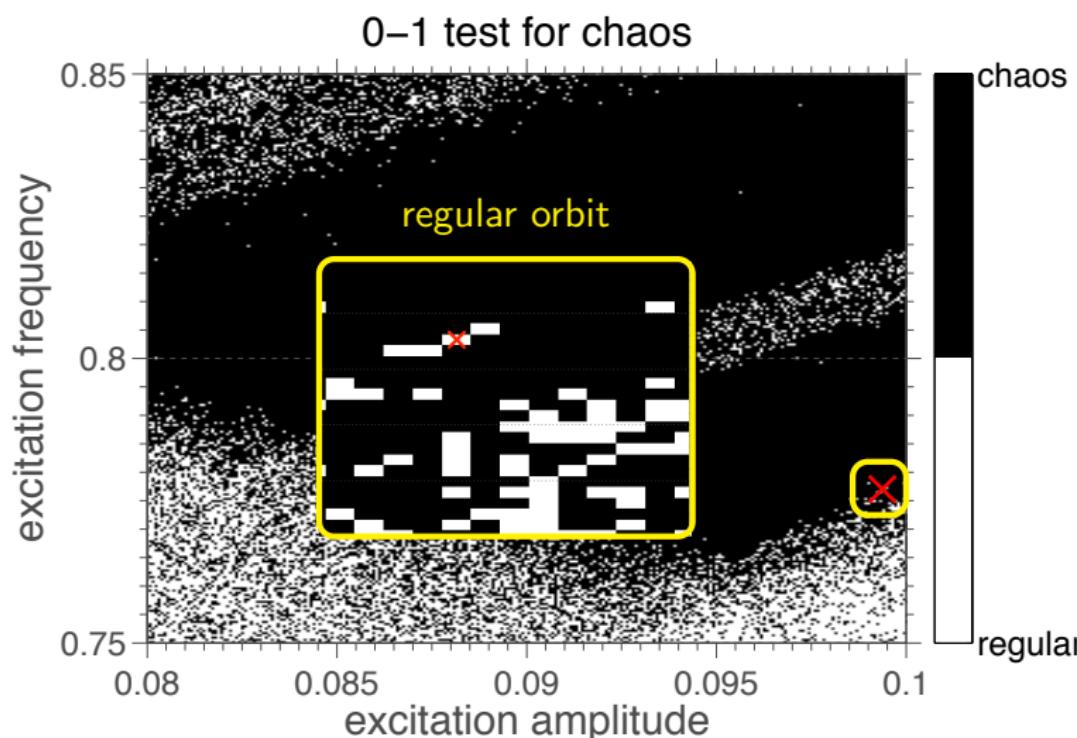
Reference solution: chaos indicator



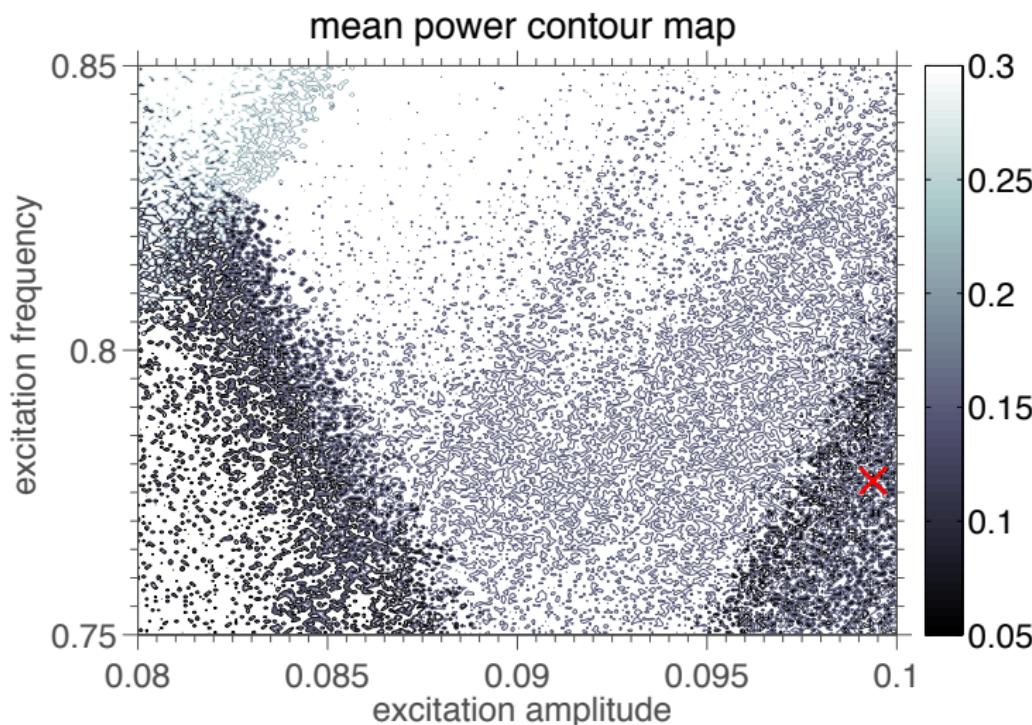
Reference solution: chaos indicator



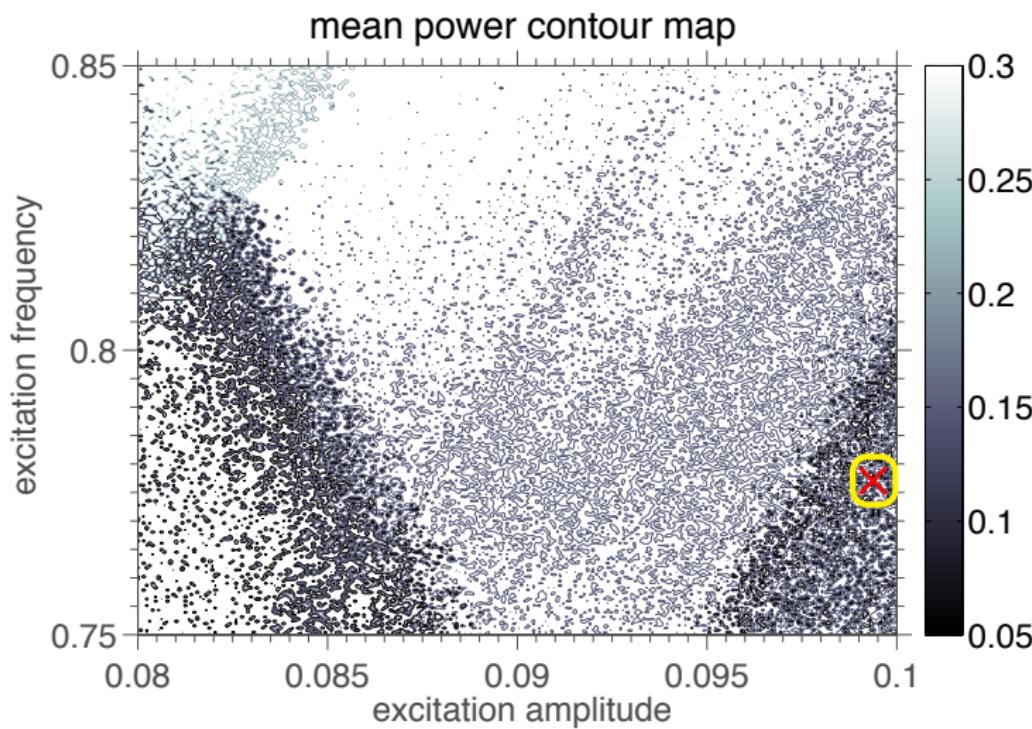
Reference solution: chaos indicator



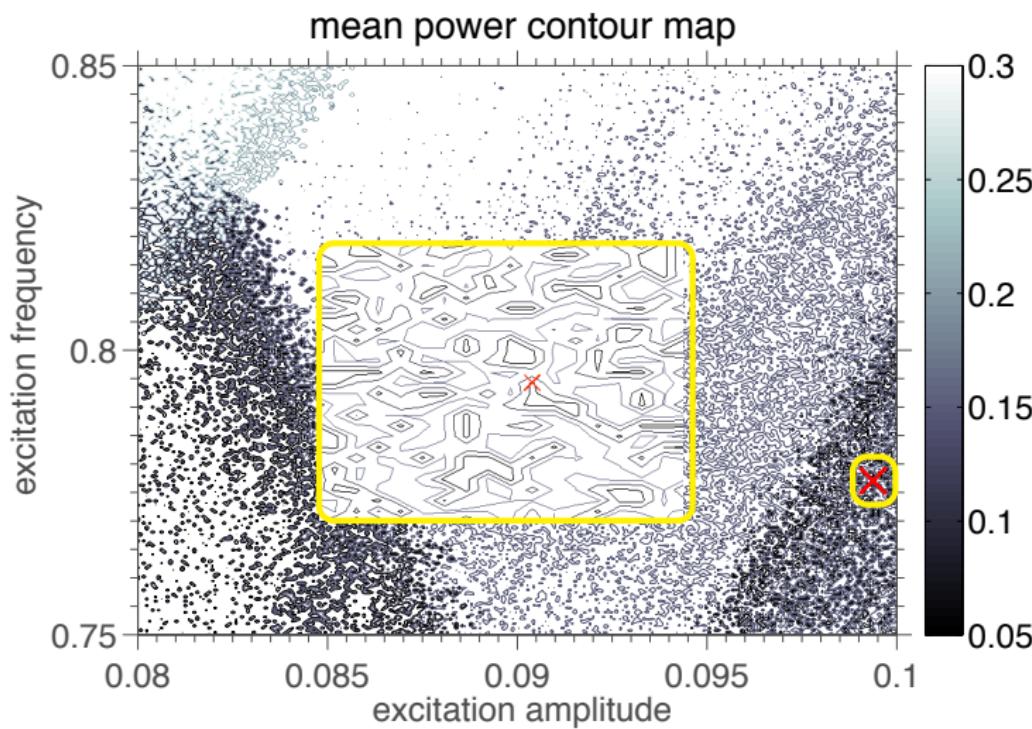
Reference solution: mean power



Reference solution: mean power



Reference solution: mean power



Cross-entropy solution

- Domain:

$$0.08 \leq f \leq 0.1$$

$$0.75 \leq \Omega \leq 0.85$$

- Penalty parameter: 10
- Number of CE samples: 50
- Percentage of elite samples: 10%
- CE samples distribution: Truncated Gaussian
- Convergence criterium: $\|\sigma\|_\infty < 1 \times 10^{-3}$
- Levels until convergence: 17
- CPU time:² ≈ 12 minutes

²MacBook Pro “Core i7” 2.2 GHz 16GB 1333 MHz DDR3

Cross-entropy animation (50 samples)

Cross-entropy animation (75 samples)

Cross-entropy animation (25 samples)



Cross-entropy performance

- Percentage of elite samples: 10%
- Convergence criterium: $\|\sigma\|_\infty < 1 \times 10^{-3}$

CE samples	CE levels	CPU time ³ (seconds)	speed-up
reference	—	50 632	—
25	15	304	167
50	17	696	73
75	29	1736	29
100	42	3286	15

³MacBook Pro “Core i7” 2.2 GHz 16GB 1333 MHz DDR3

Section 5

Final Remarks



Concluding remarks

Contributions:

- Formulation of a nonlinear optimization problem to enhance power recovered by a bi-stable energy harvesting device
- Efficient solution of this optimization problem by means of cross-entropy method

Ongoing research:

- Study the effect of sampling from non-Gaussian distributions on the proposed cross-entropy approach
- Combine this cross-entropy approach with techniques of chaos control to enhance energy harvesting performance



Acknowledgments

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- Prof. Welington Oliveira (MINES ParisTech)

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- Prof. Antônio José da Silva Neto (UERJ)
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Thank you for your attention!

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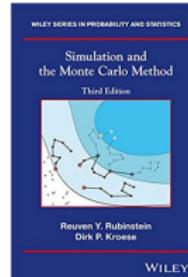
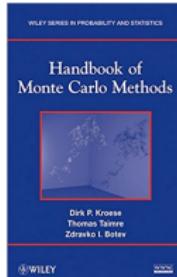
A. Cunha Jr Enhancing the performance of a bi-stable energy harvesting device via cross-entropy method
(under review).

<https://hal.archives-ouvertes.fr/hal-01531845>



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-  D. P. Kroese, T. Taimre and Z. I. Botev, **Handbook of Monte Carlo Methods**, Wiley, 2011.
-  R. Y. Rubinstein, and Dirk P. Kroese, **Simulation and the Monte Carlo Method**, Wiley, 3rd Edition, 2017.



Physical system parameters

parameter	value
ξ	0.01
χ	0.05
f	0.083
Ω	0.8
λ	0.05
κ	0.5
x_0	1.0
\dot{x}_0	0.0
v_0	0.0