Can we tame earthquakes?

Ioannis Stefanou & Filippo Masi

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CENTRALE NANTES SHAKE THE FUTURE.

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Anti-lock Braking System

Earthquakes and faults

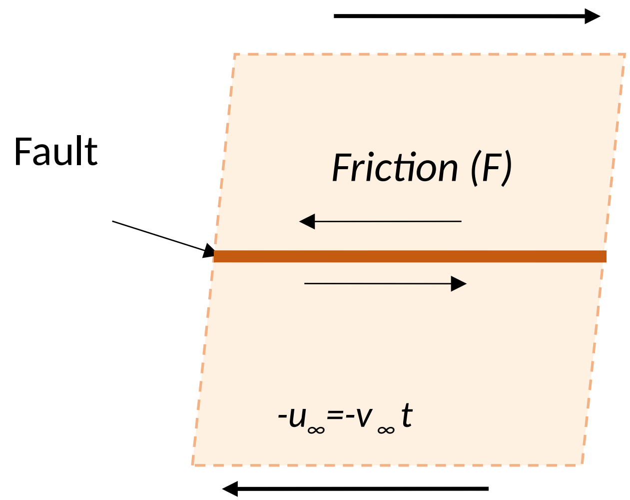

Greendale fault, New Zealand


Greendale fault, New Zealand

Earthquakes in simple words

Earthquakes in simple words

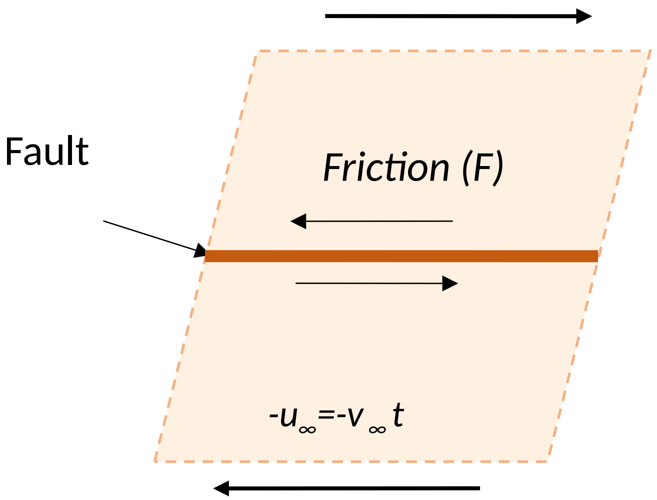
Far field tectonic displacements (~cm/yr), $u_\infty = v_\infty t$



Storage of elastic energy in the crust $U_{el}\uparrow$

Earthquakes in simple words

Far field tectonic displacements (~cm/yr), $u_\infty = v_\infty t$



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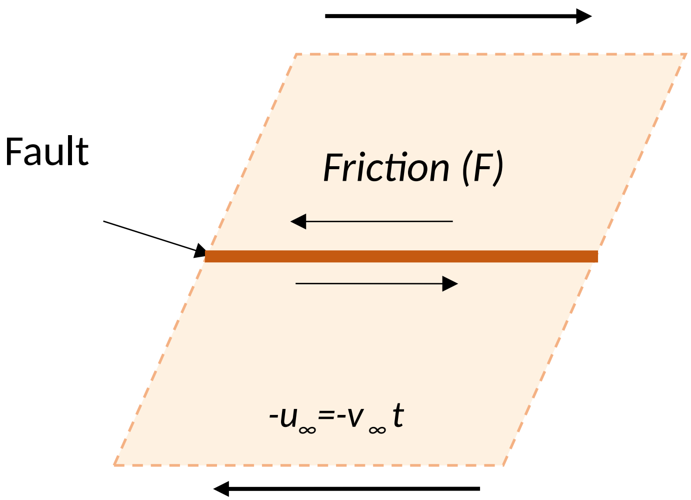

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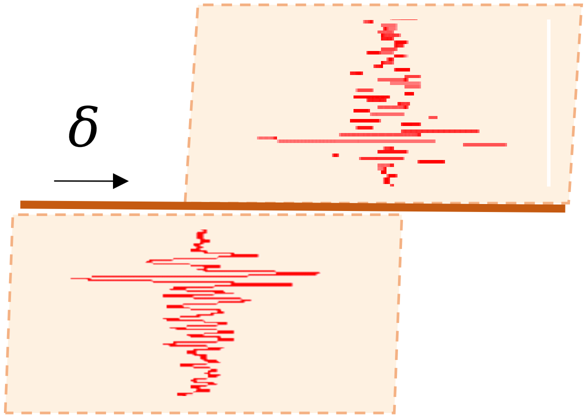
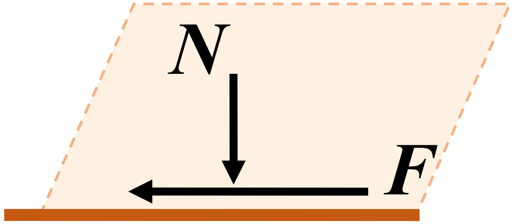
Earthquakes in simple words



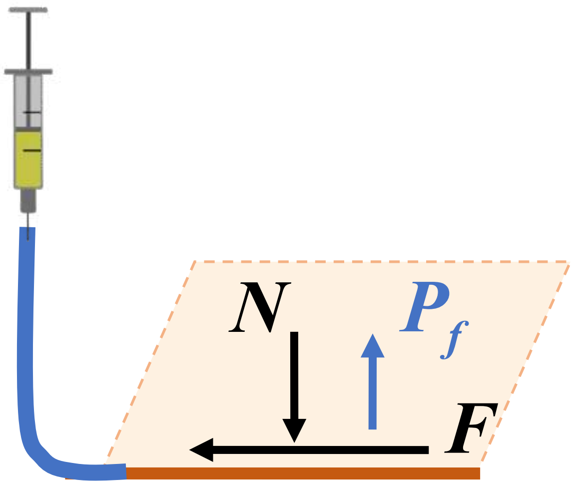
Injecting fluids and friction

$$F = \mu \cdot N$$



Injecting fluids and friction

$$F = \mu \cdot (N - P_f)$$



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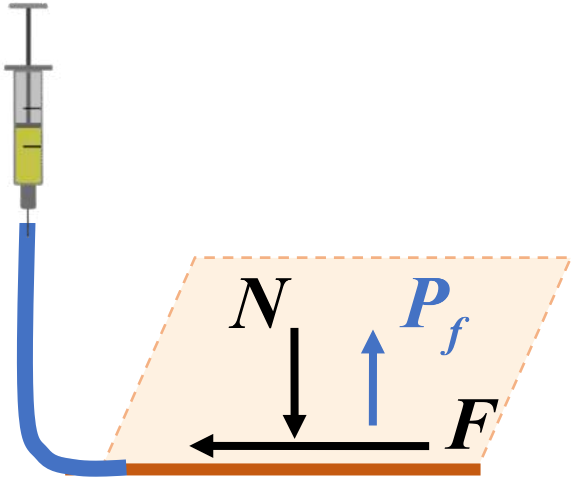
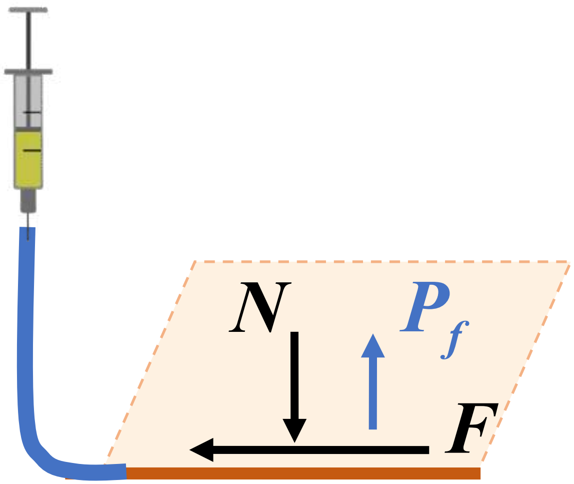
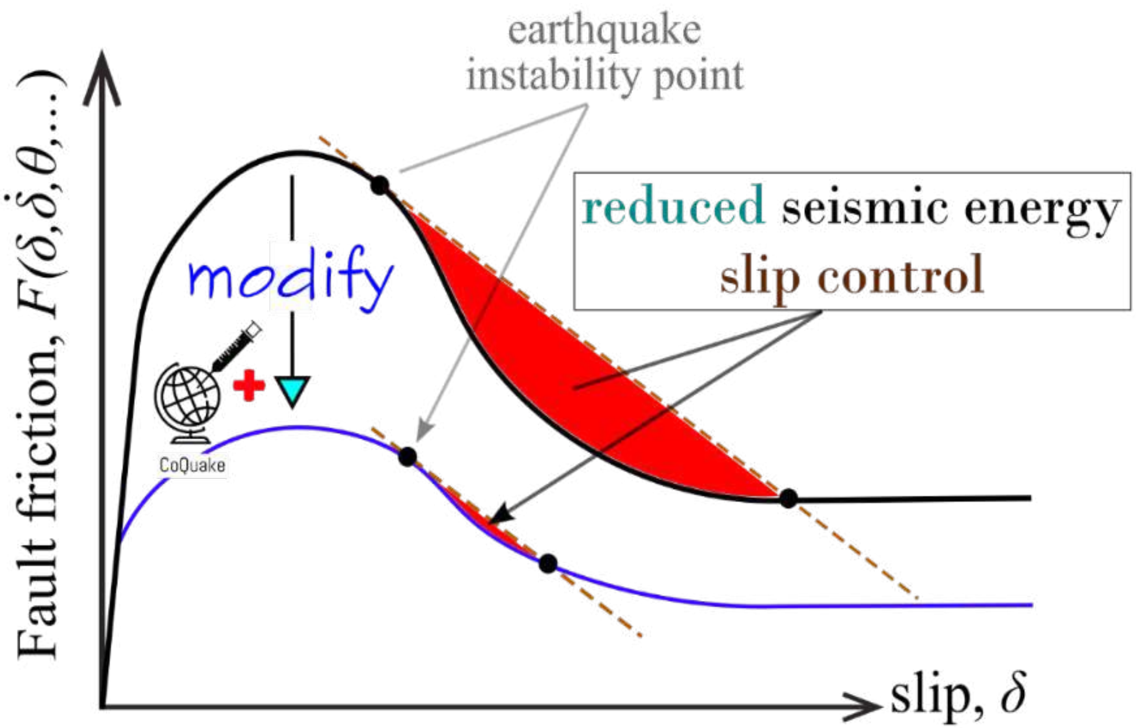


Injecting fluids and friction

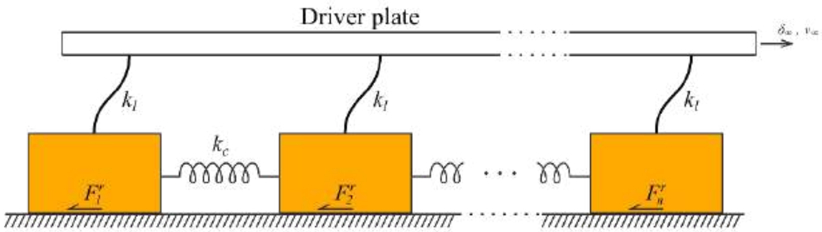
$$F = \mu \cdot (N - P_f)$$

[Terzaghi, 1925]

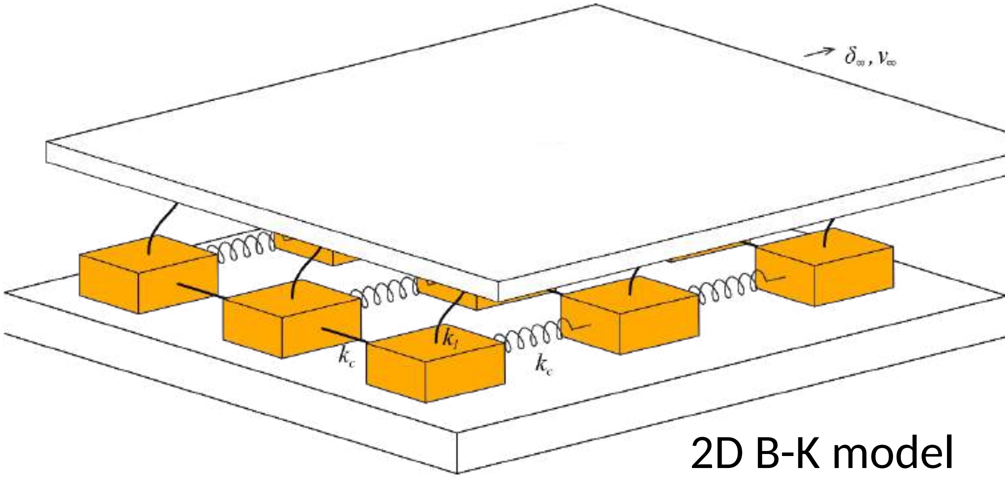




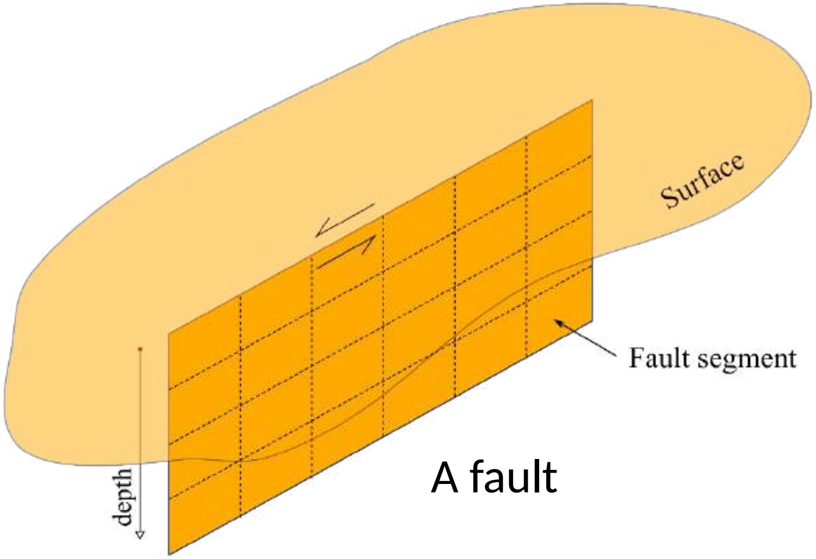
Increasing complexity: Burridge-Knopoff & Faults



1D B-K model

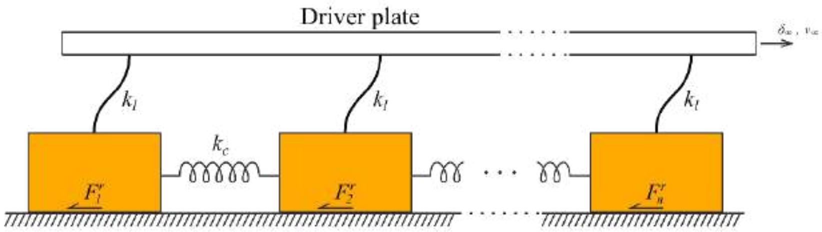


2D B-K model



A fault

Increasing complexity: Burridge-Knopoff & Faults



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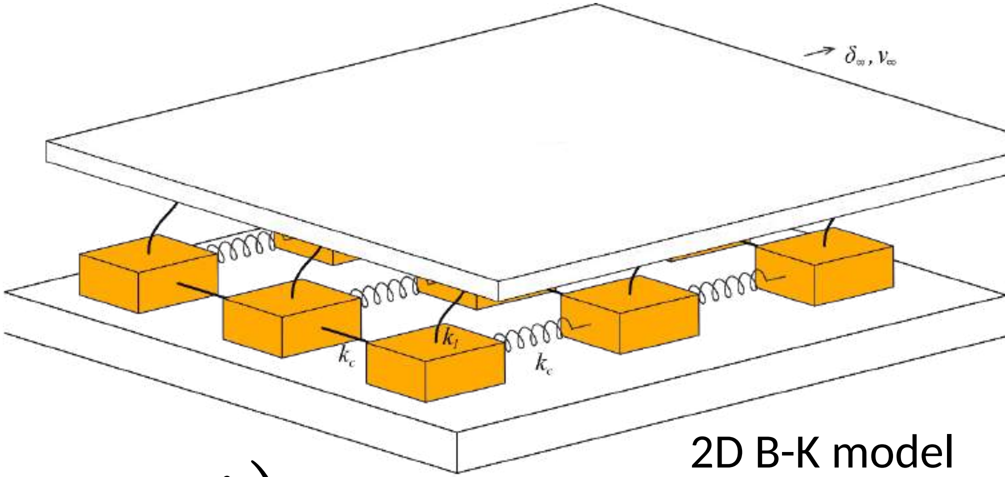
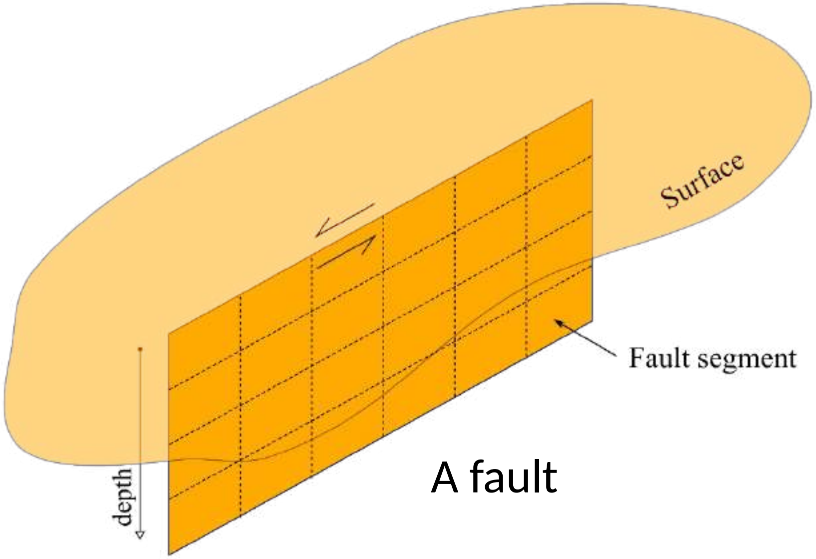


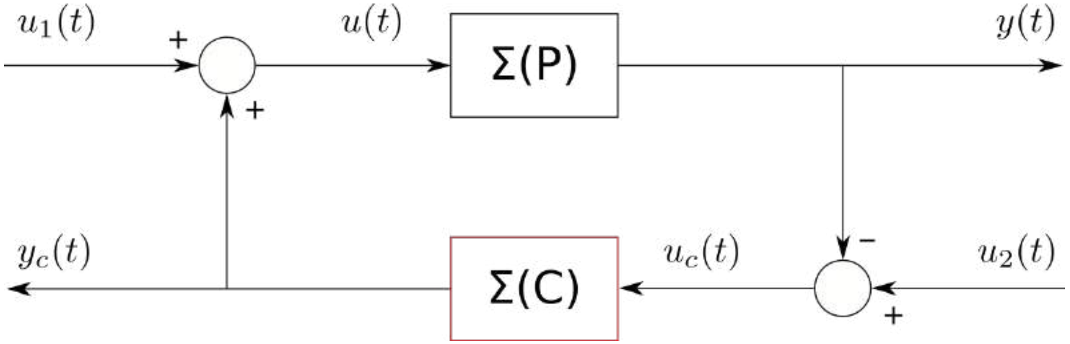
2D B-K model

$$\dot{x} = f(x, p_f, t)$$



A fault

The mathematical theory of control



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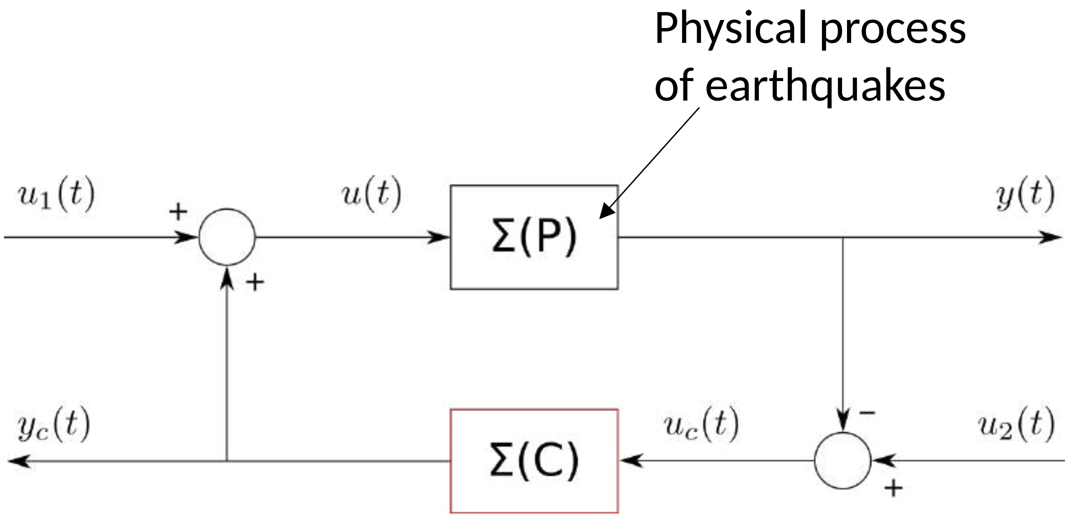

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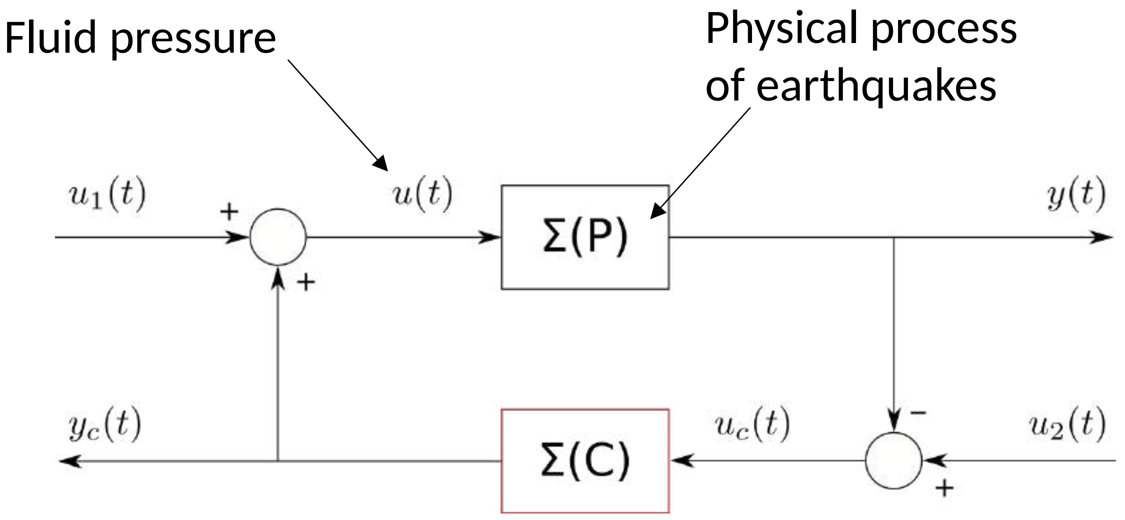

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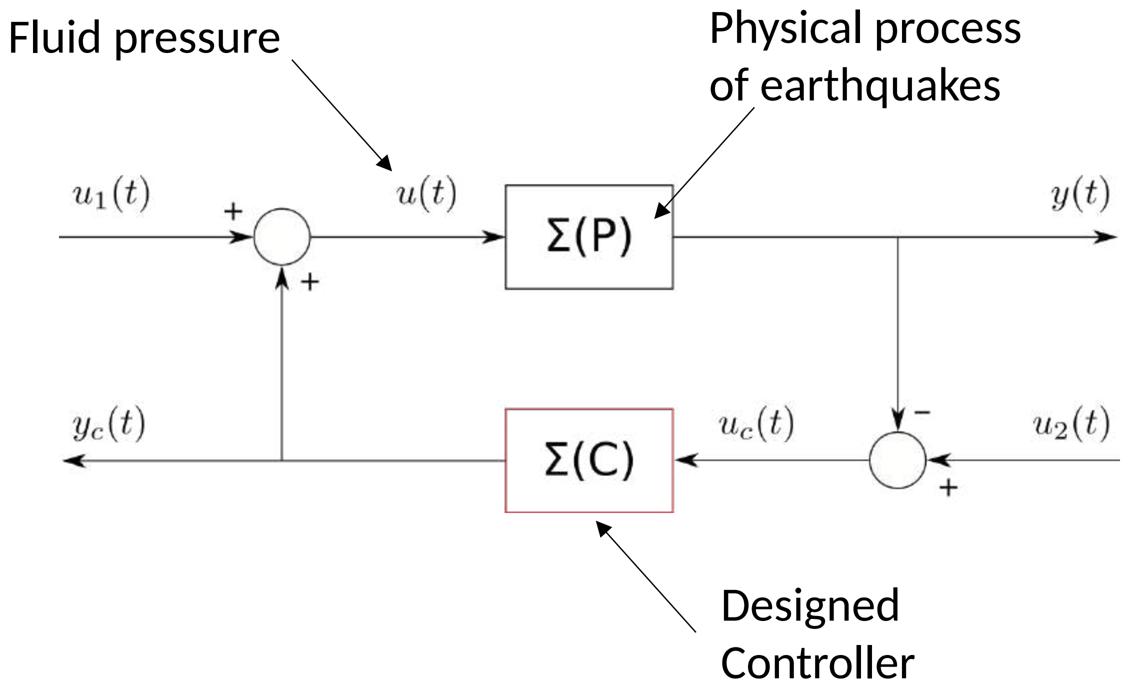
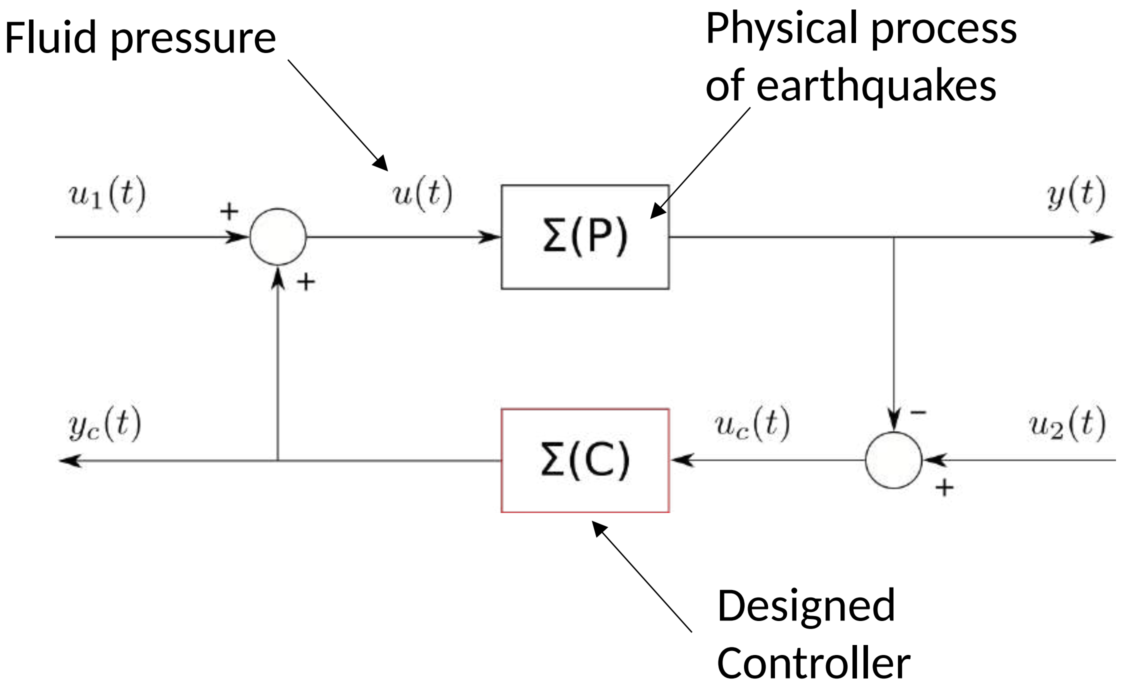


The mathematical theory of control



Target: stabilization, tracking,
optimization & robustness

Robust non-linear control

If:

1) The friction coefficient is Lipschitz continuous w.r.t the states x:

$$|\mu(x,t) - \mu(0)| < \beta\,|x|,\ \beta > 0$$

2) The friction coefficient has a lower bound: $\mu(x,t) > c > 0$

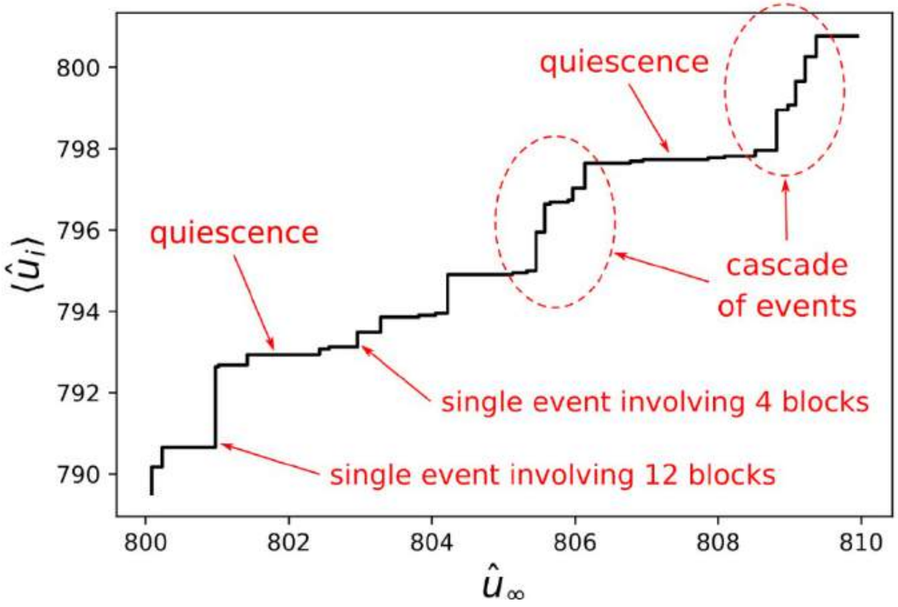
3) Elasticity and viscosity of the surrounding rocks are bounded

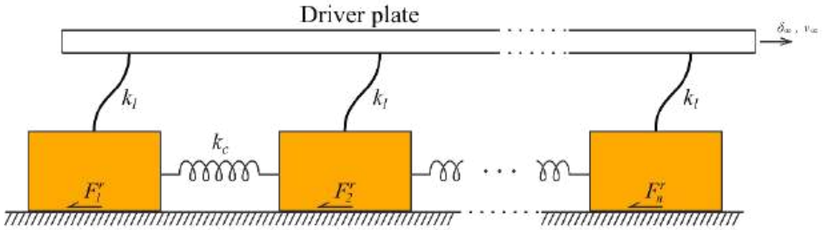
4) Diffusivity has a lower bound greater than zero

then we can design an output feedback stabilizing controller and we can achieve asymptotic tracking.

[Stefanou, 2020, pre-print
Stefanou & Tzortzopoulos, 2021, submitted
Tzortozopoulos & Stefanou, under preparation]

Example of control of a complex frictional system





24 blocks

[see also Turcotte, 1992,
– among many others]

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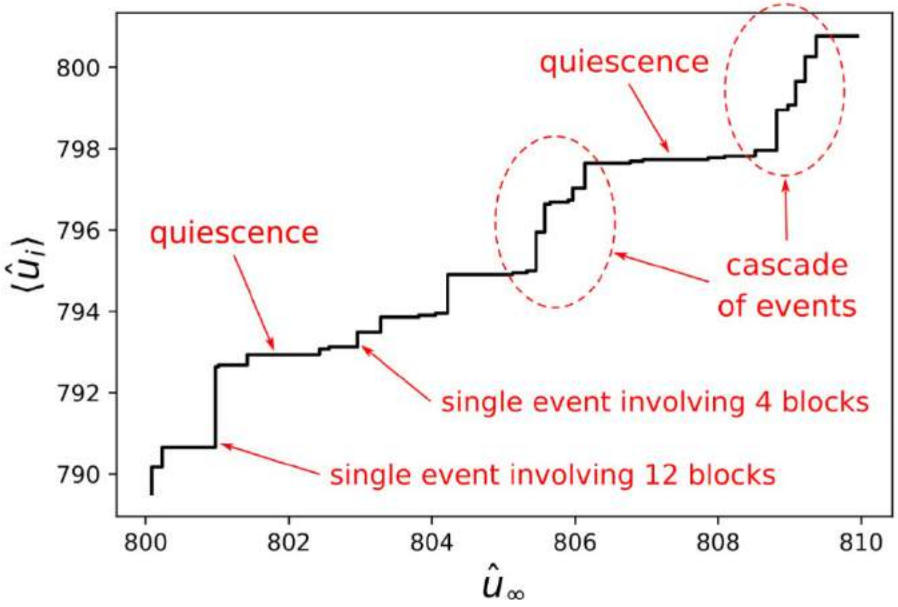

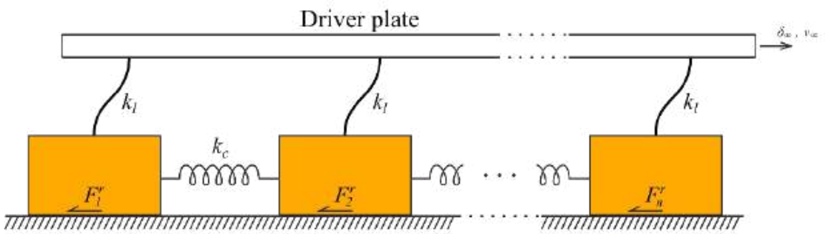

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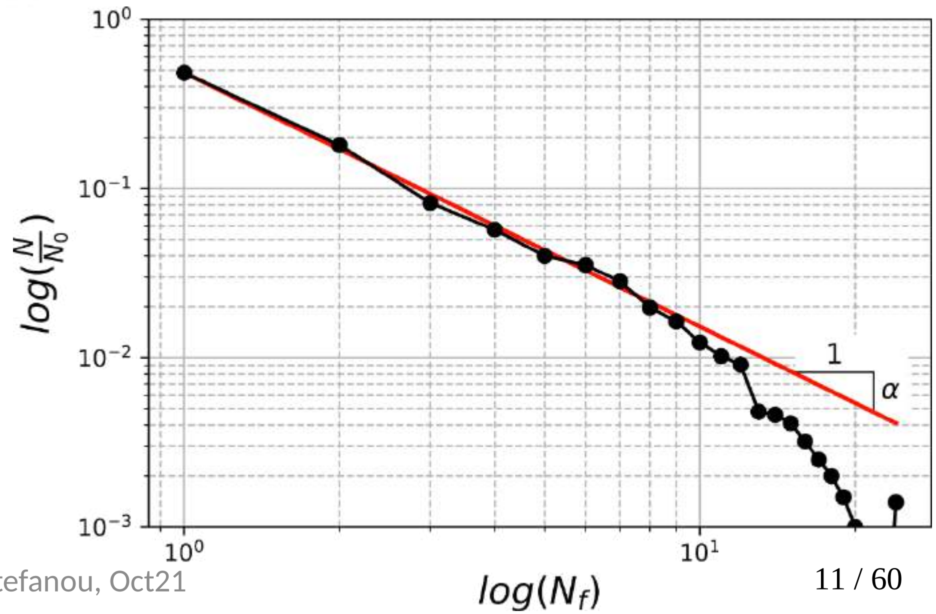
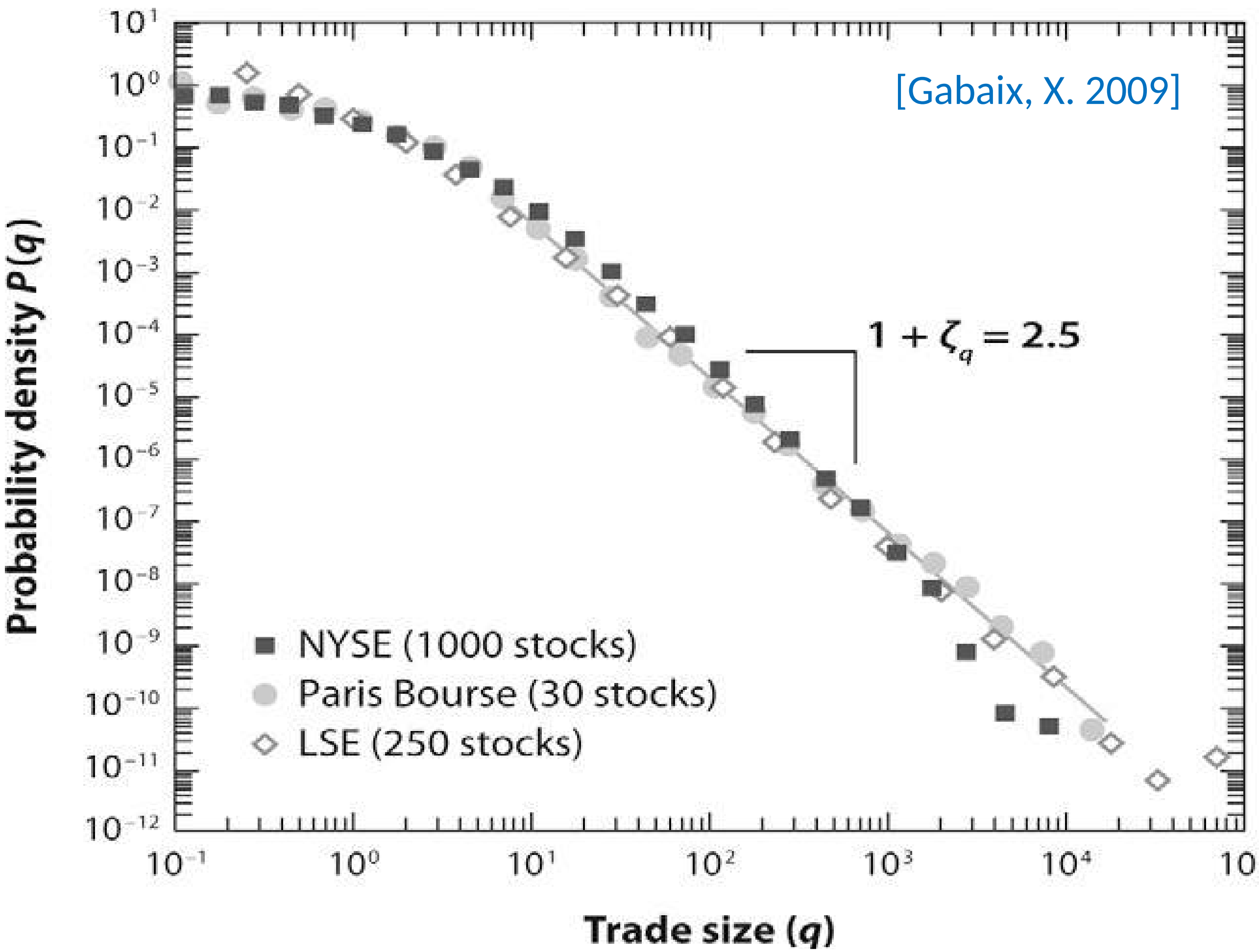
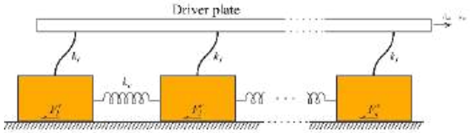
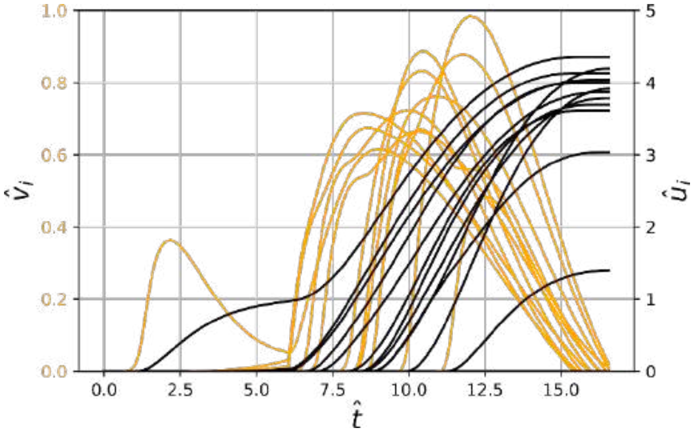


Stock markets?



Tracking and global stabilization





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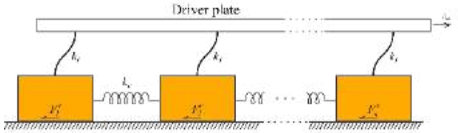
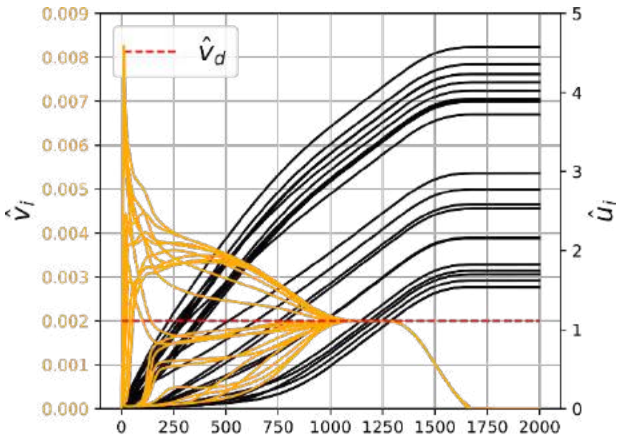
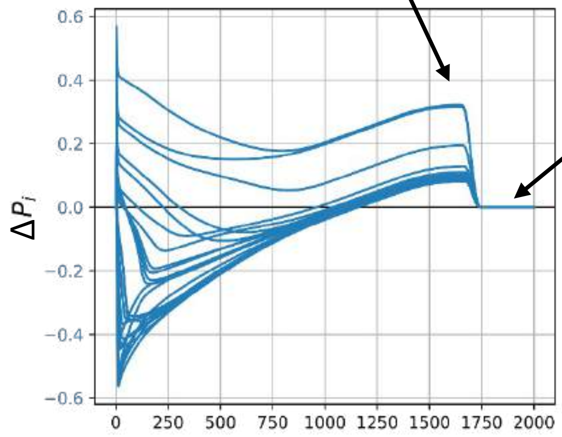


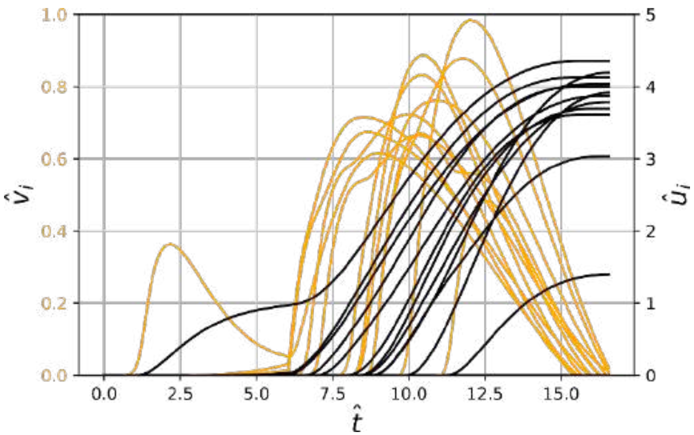


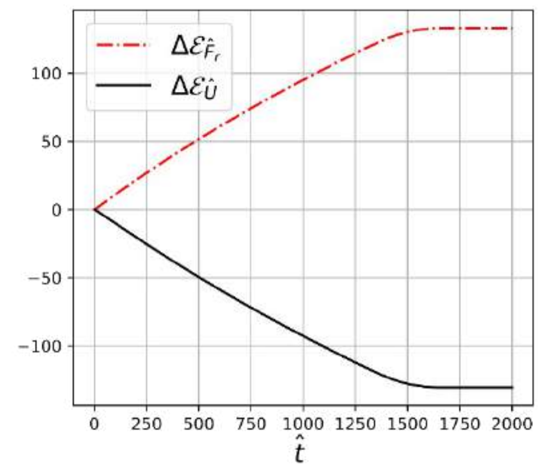
Deactivation of the controller



Stable equilibrium

Control



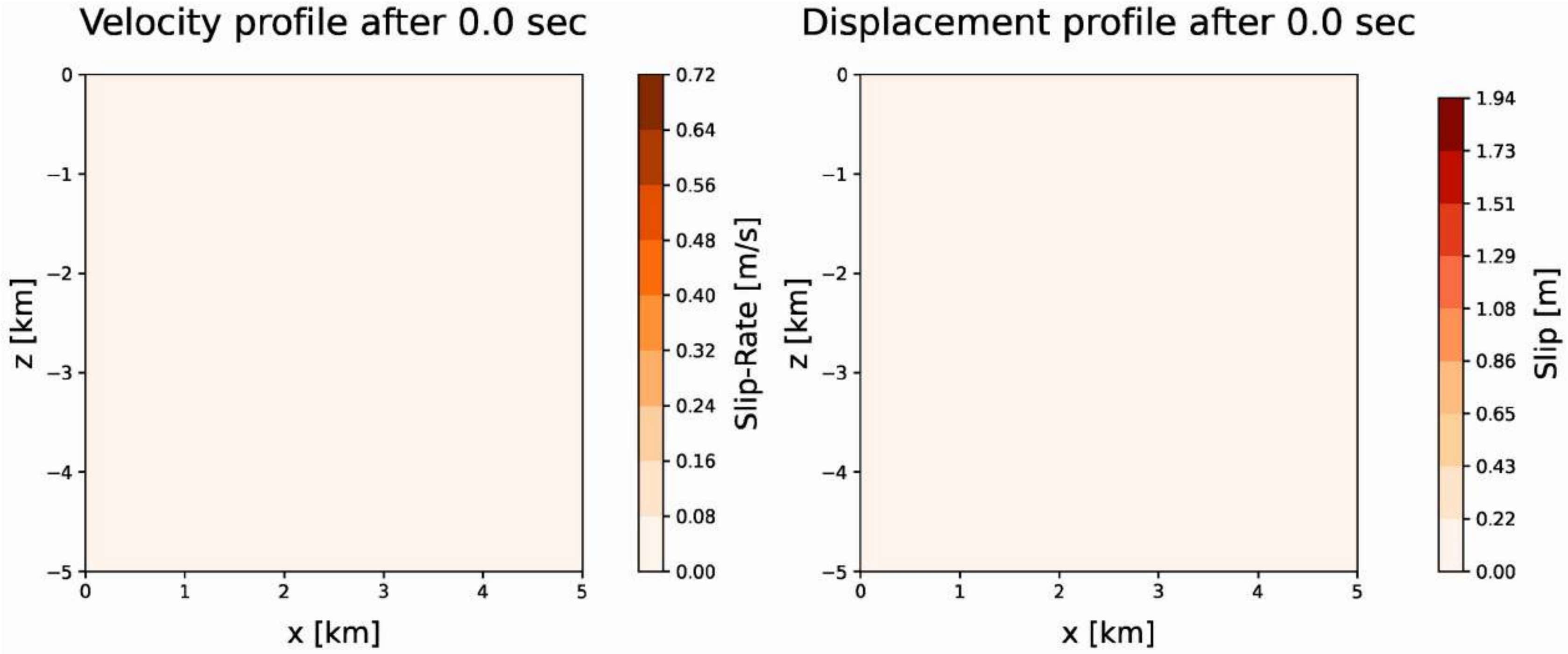


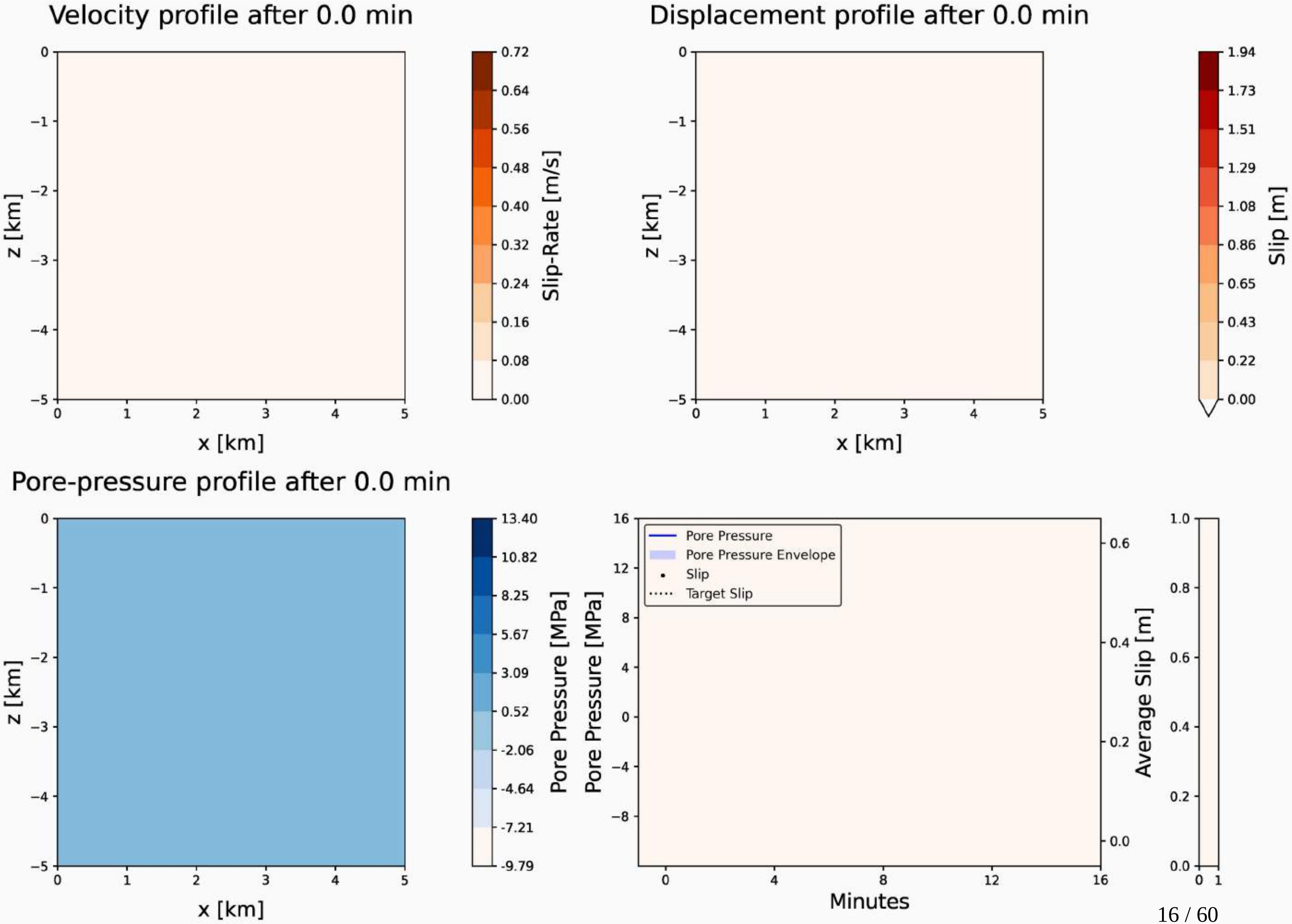
Strike-slip fault with Rate & State friction

a, b, d_c distributed over the fault area according to a log-normal distribution

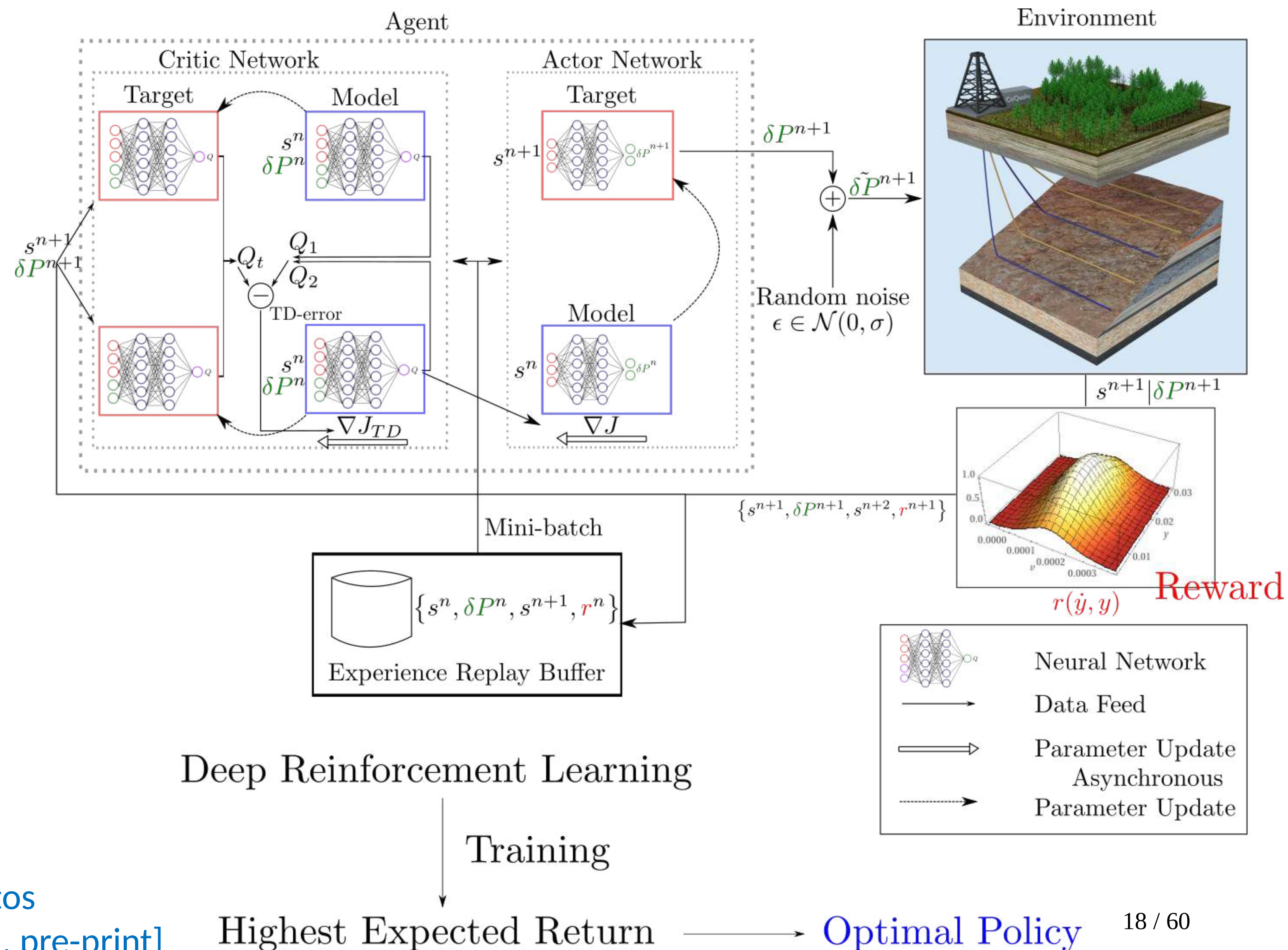
[Stefanou & Tzortzopoulos, submitted]

Without control (open loop)



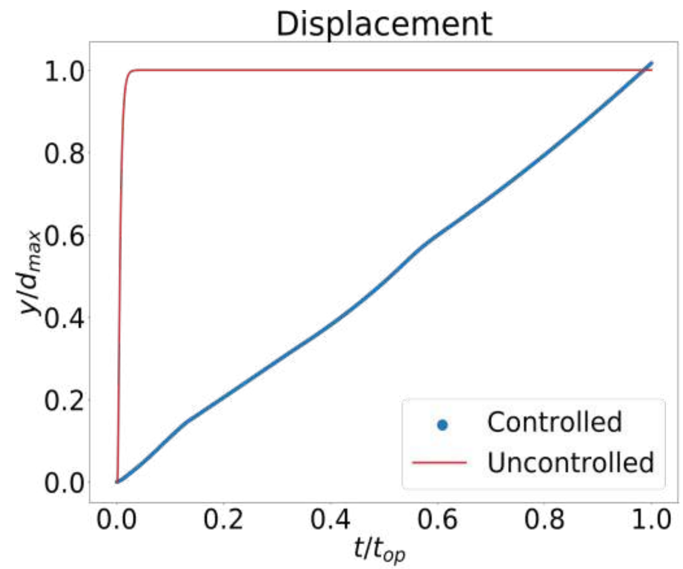

Velocity profile after 0.0 min
Displacement profile after 0.0 min
Pore-pressure profile after 0.0 min
Slip-Rate [m/s]
Slip [m]
Pore Pressure [MPa]
Pore Pressure [MPa]
Average Slip [m]
z [km]
x [km]
Minutes
Pore Pressure
Pore Pressure Envelope
Slip
Target Slip

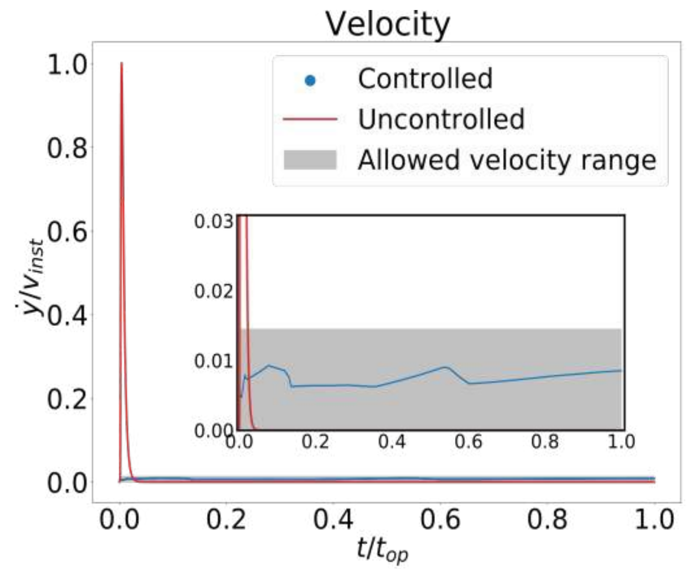
Earthquake control with Reinforcement Learning

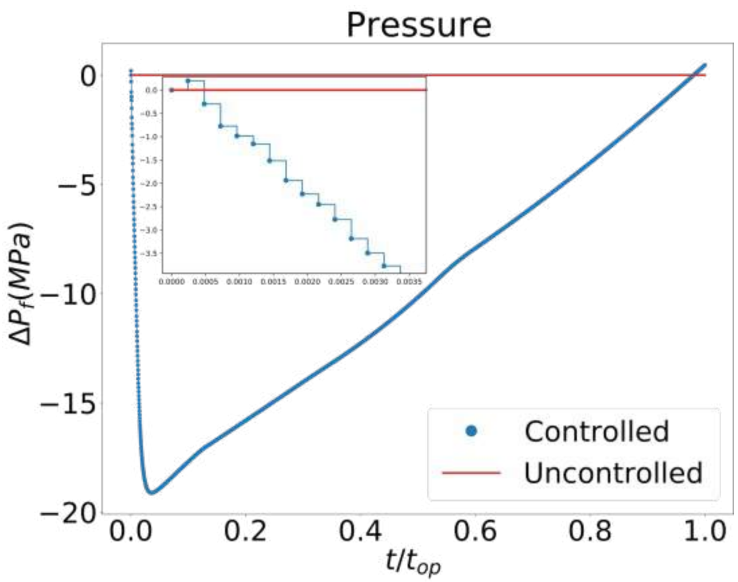


[Papachristos & Stefanou, pre-print]

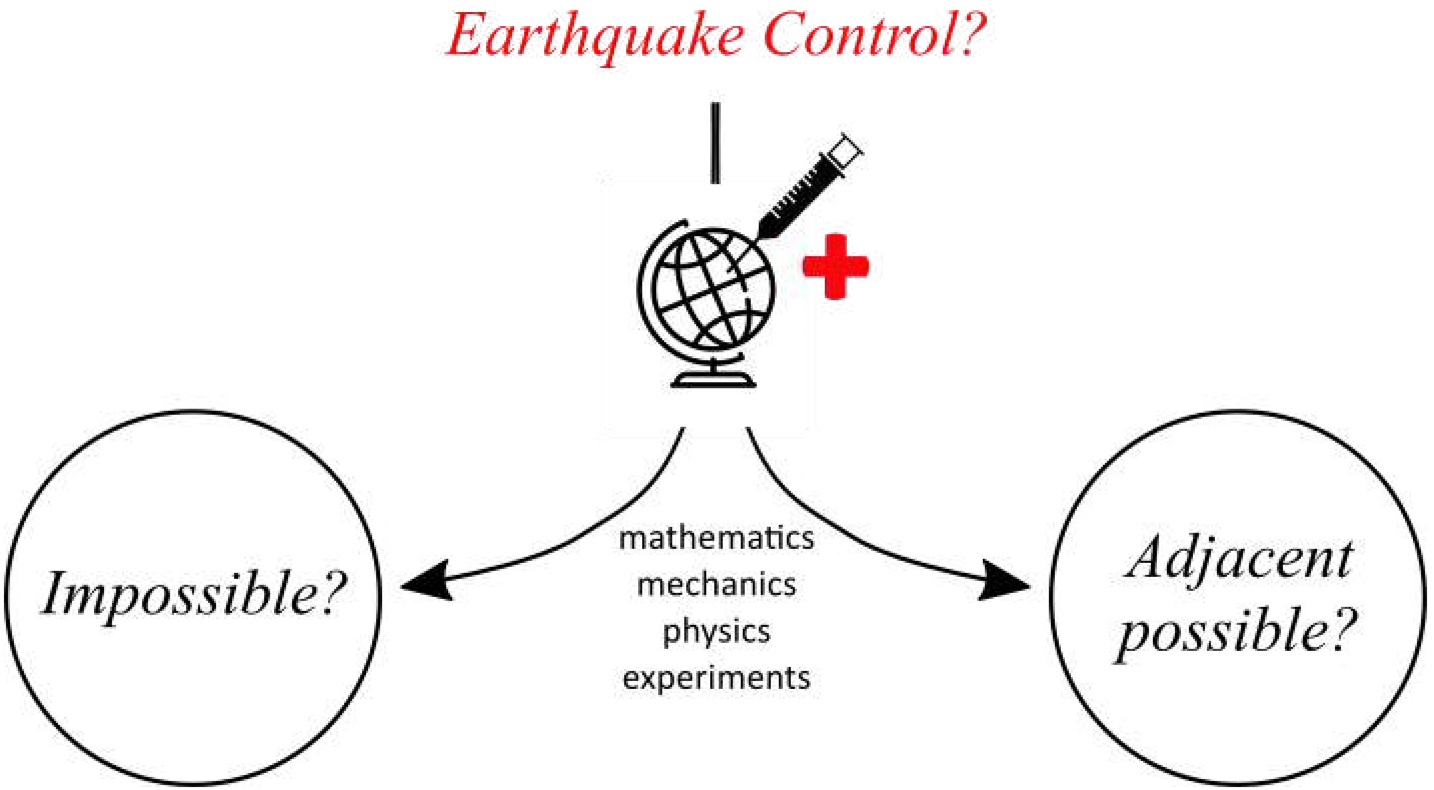
DRL, discrete time dynamics & results







Conclusions



Thank you!

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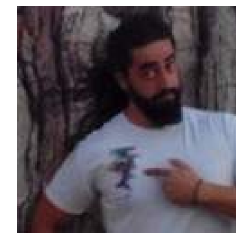
Alexandros Stathas

Filippo Masi



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Pravin Badarayani

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TEDx Talk: https://youtu.be/9JXdv-3e2bc

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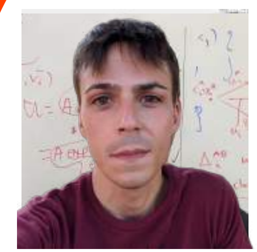
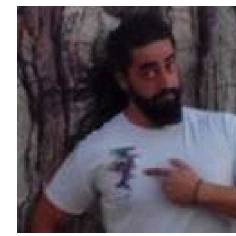


Filippo Masi



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THE UNIVERSITY OF SYDNEY

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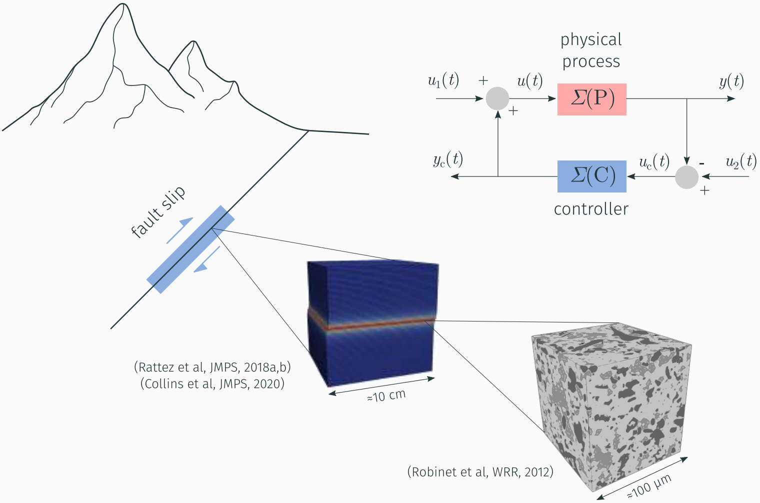
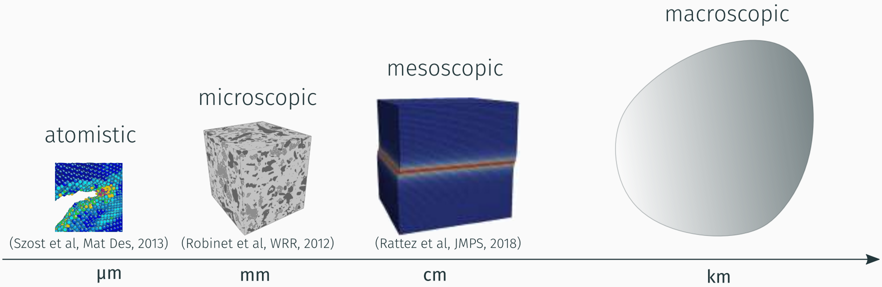
BRIDGING THE SCALES

Systems involving complex materials — multiple inherent scales



BRIDGING THE SCALES — MULTISCALE MODELING



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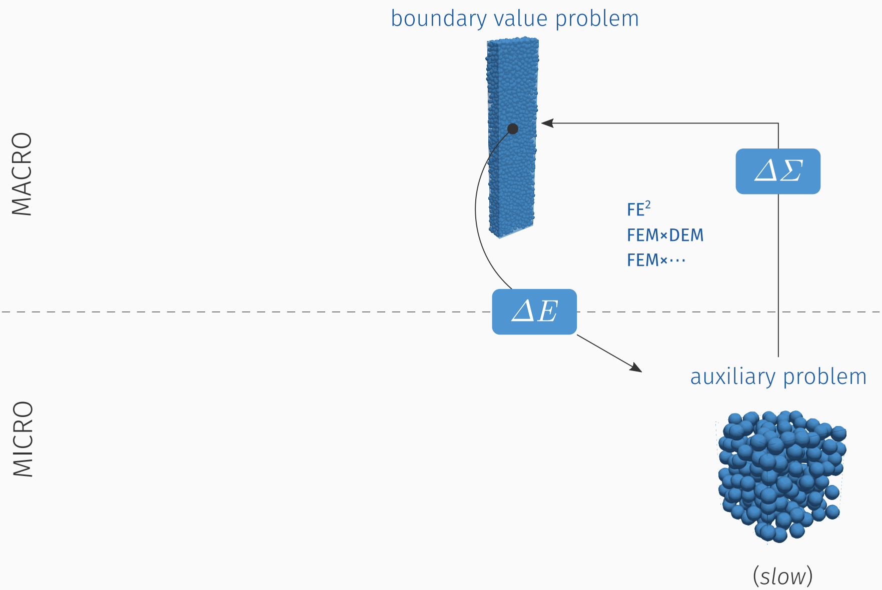
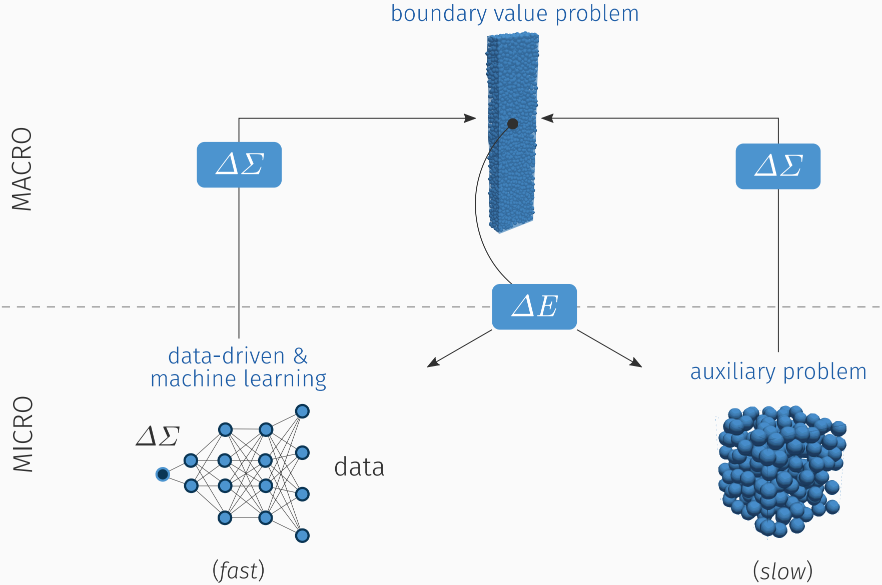
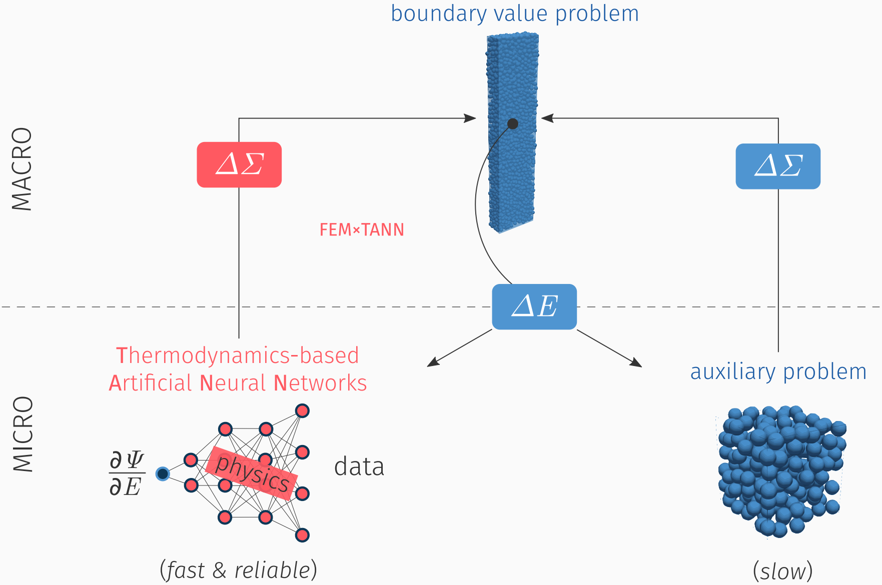


BRIDGING THE SCALES — DATA-DRIVEN MODELING



BRIDGING THE SCALES — TANN

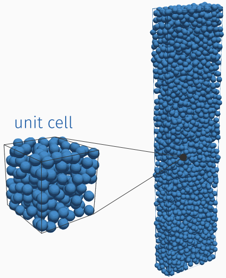


THERMODYNAMICS

Clausius-Duhem inequality (local)

$$d = s : \dot{f} - \dot{\psi} - \eta\dot{\theta} \geq 0$$

- d mechanical dissipation rate
- s 1^{st} Piola-Kirchhoff stress
- f deformation gradient
- ψ free-energy
- η entropy
- θ absolute temperature



Clausius-Duhem inequality (volume average)

$$D = S : \dot{F} - \dot{\Psi} - H^{\dagger}\dot{\Theta} \geq 0$$

with $Y = \langle\, y \,\rangle = \frac{1}{|\mathcal{V}|} \int_{\mathcal{V}} y \, dx$ and $\langle \eta\dot{\theta} \rangle = H^{\dagger}\dot{\Theta}$

THERMODYNAMICS

$$\text{STATE SPACE}(t) = \{\chi(t), Z(t)\}$$

state variables: observable $\chi = \{\Theta, F\}$ and internal $Z = \{?\}$

state functions: $\Psi\,(\chi, Z) \quad S\,(\chi, Z) \quad H^{\dagger}\,(\chi, Z) \quad D(\chi, Z, \dot{Z})$

time differentiation: $\dot{\Psi} = \frac{\partial \Psi}{\partial \Theta}\,\dot{\Theta} + \frac{\partial \Psi}{\partial F} : \dot{F} + \sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k$

THERMODYNAMIC RESTRICTIONS:

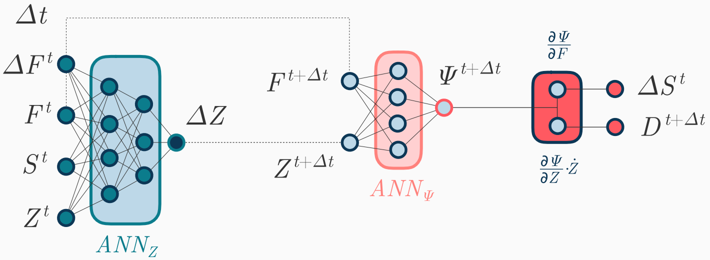
stress: $S = \frac{\partial \Psi}{\partial F}$

dissipation rate: $D = -\sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k \geq 0$

entropy: $H^{\dagger} = -\frac{\partial \Psi}{\partial \Theta}$

THERMODYNAMICS-BASED ARTIFICIAL NEURAL NETWORKS

state at $t + \Delta t =$ TANN$\{$ state at $t, \Delta F^t \}$



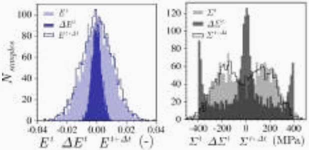
$$\mathcal{L}(o) = \frac{1}{N} \sum_{i=1}^{N} \ell(o_i)$$

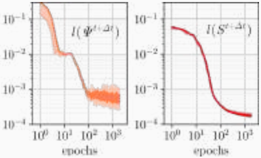
$$\ell(o_i) = ||\bar{o}_i - o_i||_1$$

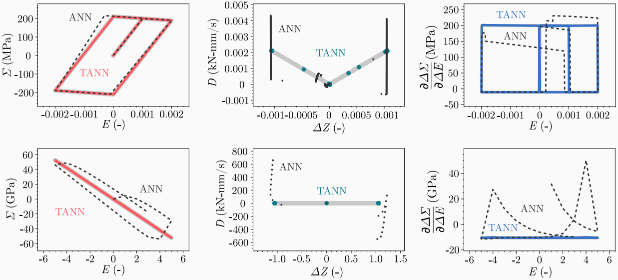
$$\ell = \lambda^{\dot{Z}} \ell(\dot{Z}) + \lambda^{\Psi} \ell(\Psi) + \lambda^{\Delta S} \ell(\Delta S) + \lambda^{D} \ell(D)$$

(Masi et al. J Mech Phys Solids 147, 2021; Masi et al. SPIGL, Springer, 2020)

HYPER- AND HYPO-PLASTICITY





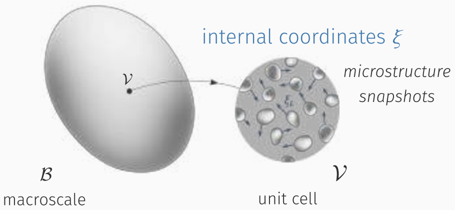


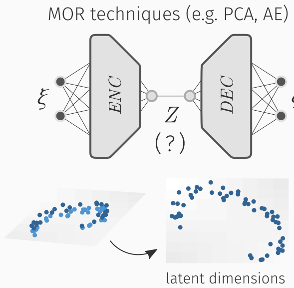
(Masi et al. J Mech Phys Solids 147, 2021; Masi et al. SPIGL, Springer, 2020)

STATE VARIABLES?

internal coordinates

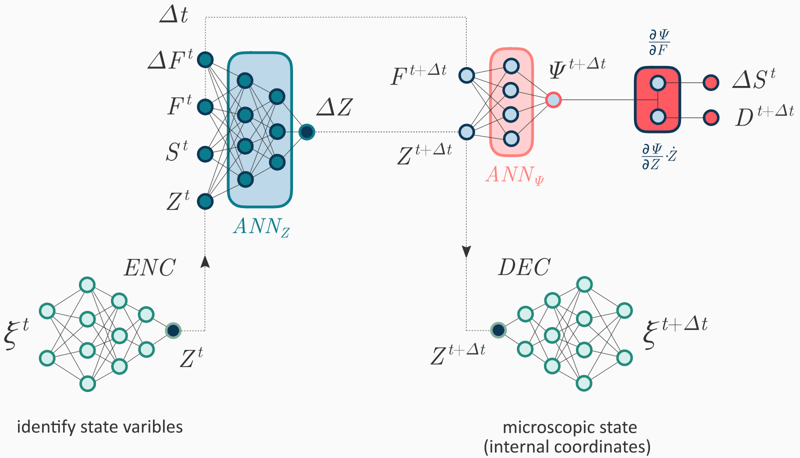
microscopic state space: displacement, velocity, momentum fields, etc.





(Masi et al. arXiv preprint arXiv:2108.13137, 2021)

THERMODYNAMICS-BASED ARTIFICIAL NEURAL NETWORKS



$$\ell = \lambda^{\xi} \left[\ell(\xi_*^t) + \ell(\xi_*^{t+\Delta t})\right] + \lambda^{\nabla_{ED}^t} \ell(\nabla_{ED}^t) + \lambda^{\Psi} \ell(\Psi) + \lambda^{\Delta S} \ell(\Delta S) + \lambda^{D} \ell(D)$$

(Masi et al. arXiv preprint arXiv:2108.13137, 2021)

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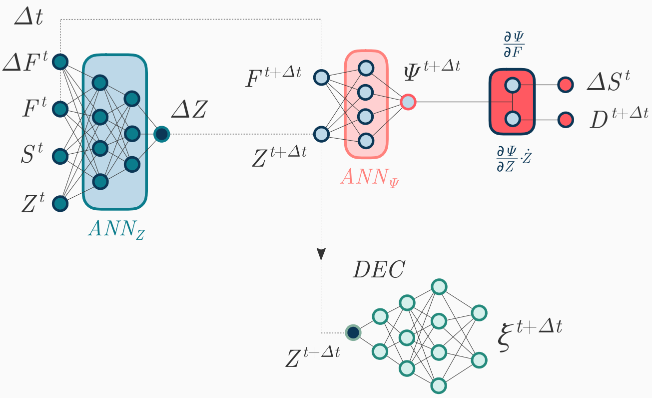


microscopic state
(internal coordinates)

$$\ell = \lambda^{\dot{Z}} \ell(\dot{Z}) + \lambda^{\Psi} \ell(\Psi) + \lambda^{\Delta S} \ell(\Delta S) + \lambda^{D} \ell(D)$$

(Masi et al. arXiv preprint arXiv:2108.13137, 2021)

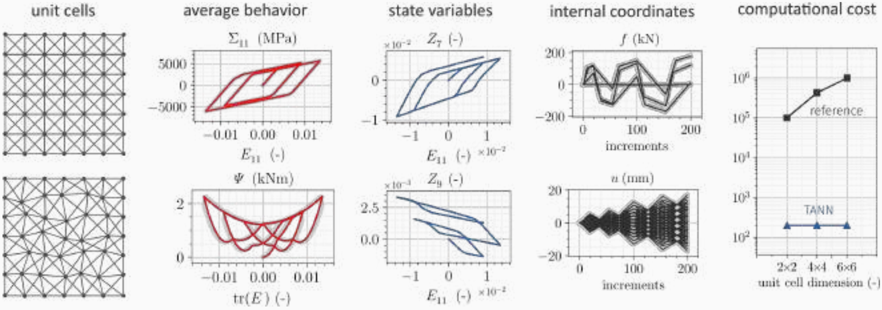
BENCHMARKS FOR LATTICE STRUCTURES

Inelastic lattice cells

$$\Sigma = \langle \sigma \rangle = \frac{1}{|\mathcal{V}|} \sum_k^{N^p_{nodes}} t_k \otimes y^p_{\Delta k}$$

$$E = \langle \varepsilon \rangle = \frac{1}{|\mathcal{V}|} \int_{\partial \mathcal{V}} u \otimes x \, ds$$

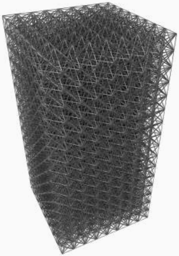
- training on micromechanical datasets generated from random loading paths



ACCURACY $\geq$ 99% — ACCELERATION $\approx 10^3$

THE FEM×TANN APPROACH

large-scale problem



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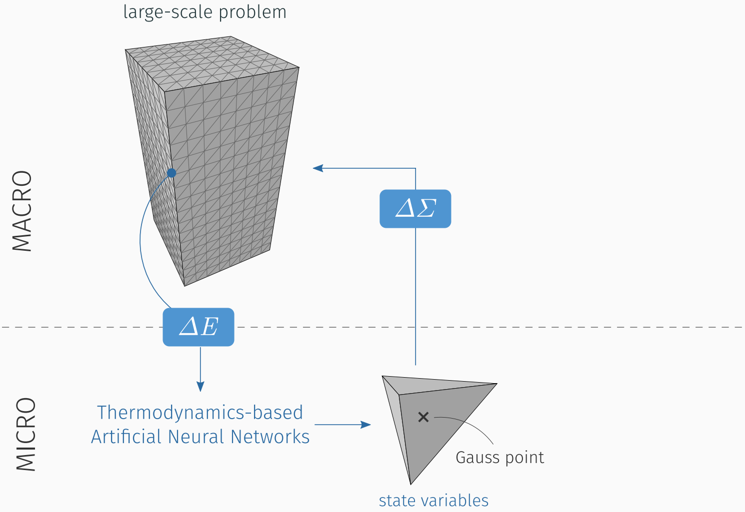

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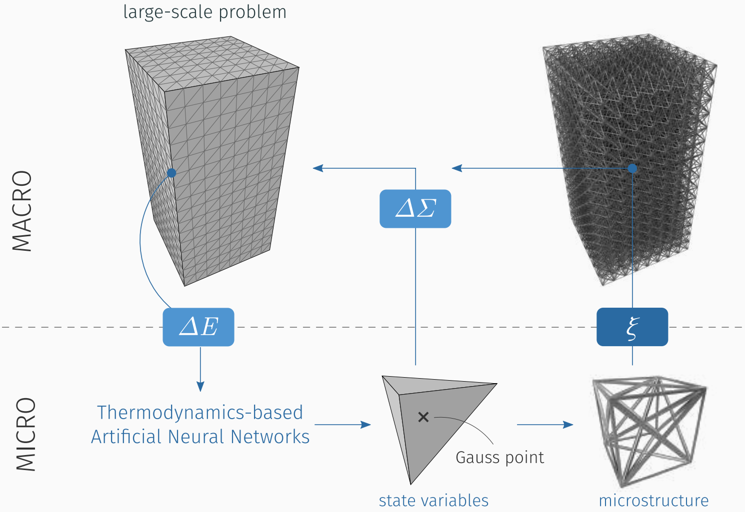
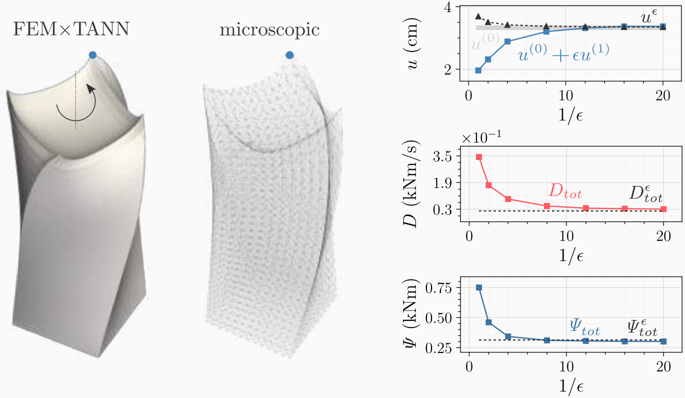
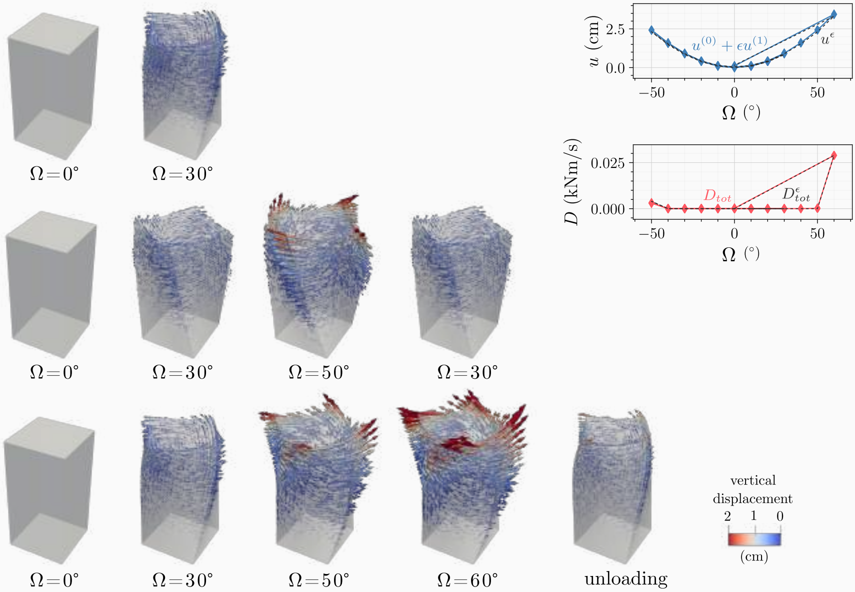


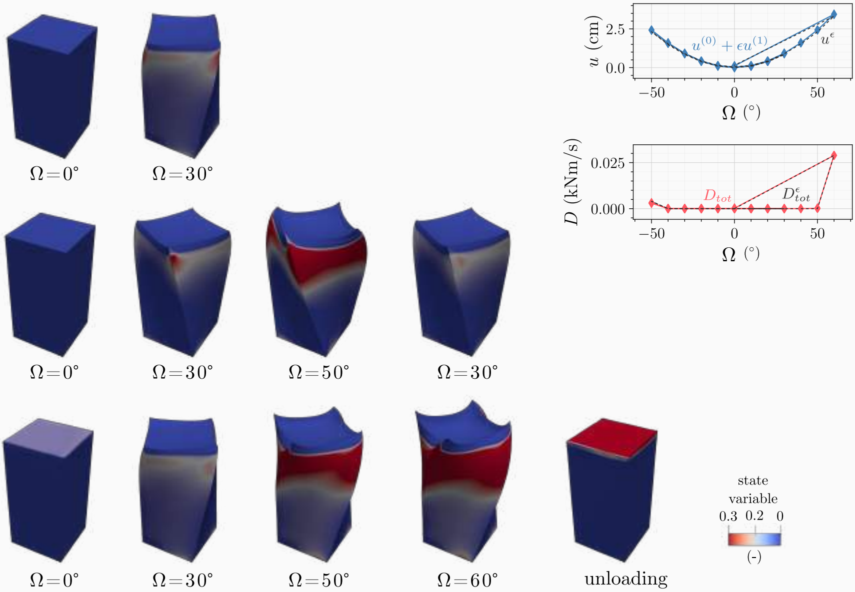
APPLICATION TO LARGE-SCALE PROBLEMS



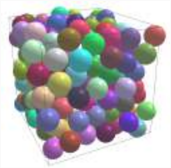
APPLICATION TO LARGE-SCALE PROBLEMS

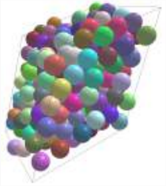


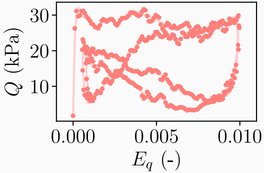
APPLICATION TO LARGE-SCALE PROBLEMS



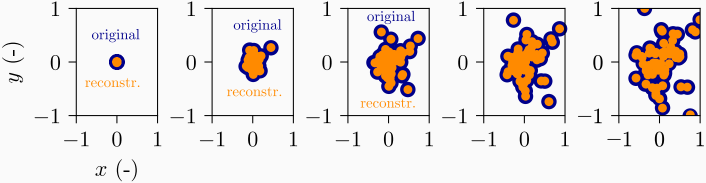
APPLICATION TO GRANULAR MEDIA







encoding the microscopic state space



CONCLUSIONS

Earthquake control?

mathematics
mechanics
physics
experiments

CoQuake.com

TANN
digital twins
++ complex materials

Impossible

Adjacent possible?

www.coquake.eu

www.blastructures.eu

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Acknowledgments

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Related articles

- Masi and Stefanou (2021) Thermodynamics-based Artificial Neural Networks for multiscale modeling of materials with inelastic microstructure, *submitted to* Comput Methods Appl Mech Eng. url: arxiv.org/abs/2108.13137
- Masi et al (2021) Material Modeling via Thermodynamics-based Artificial Neural Networks. Geometric Structures of Statistical Physics, Information Geometry, and Learning. Springer Proc. in Mathematics & Statistics. doi: 10.1007/978-3-030-77957-3_16
- Masi et al (2021) Thermodynamics-based Artificial Neural Networks for constitutive modeling, J Mech Phys Solids. doi: 10.1016/j.jmps.2020.104277

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- Masi et al (2021) Material Modeling via Thermodynamics-based Artificial Neural Networks. Geometric Structures of Statistical Physics, Information Geometry, and Learning. Springer Proc. in Mathematics & Statistics. doi: 10.1007/978-3-030-77957-3_16
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Thank you!

THE UNIVERSITY OF SYDNEY

Can we tame earthquakes?

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