project proposal:

Effect of homeostatic regulation on dynamics of recurrent neuronal networks

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EITN fall school, Paris, 20.09.2023

JÜLICH Forschungszentrum

Outline

Background

Questions and hypotheses

Proposed work plan

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- both in nature and in Computational Neuroscience, neuronal network dynamics can become unstable, leading either
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- typical countermeasures
  - Computational Neuroscience: laborious parameter tuning and/or unrealistic assumptions
  - (healthy) brains: **homeostatic regulation**

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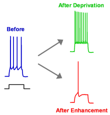
Known forms of homeostasis in biological neuronal networks

- intrinsic plasticity (hours–days): regulation of cell-intrinsic excitability (e.g., thresholds; “slow adaptation”) (Naudé et al. 2012)

Intrinsic plasticity



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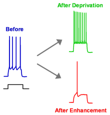

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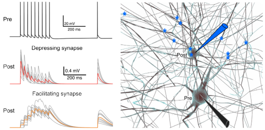

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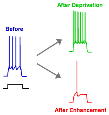

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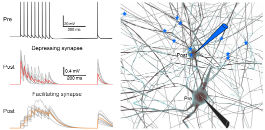

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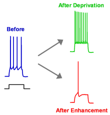

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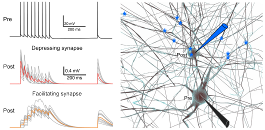

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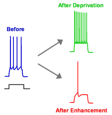

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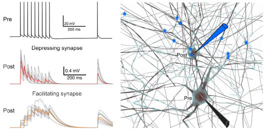

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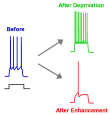

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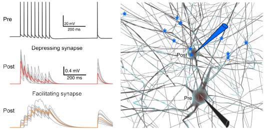

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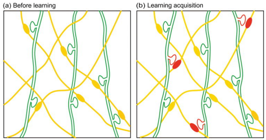

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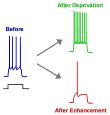

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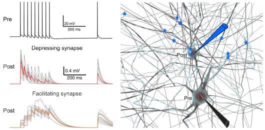

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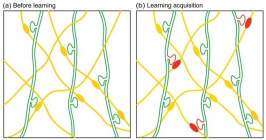

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2) How does the presence of such mechanisms alter network dynamics, such as the dynamics in response to perturbations?

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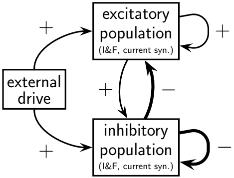

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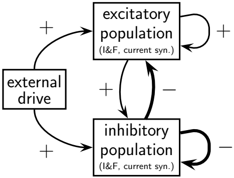

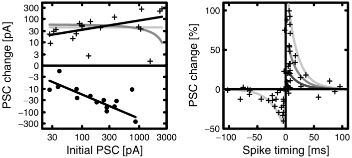

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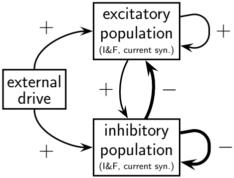

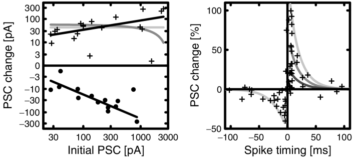

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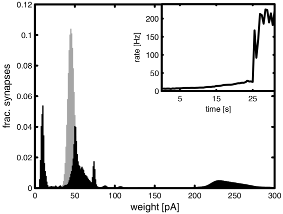

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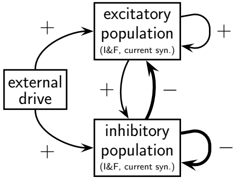

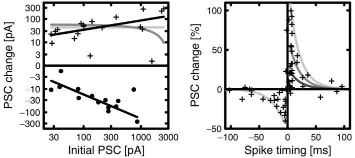

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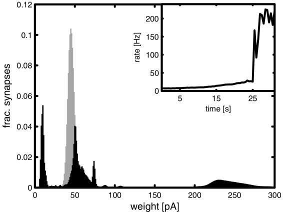

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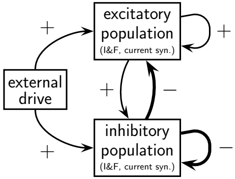

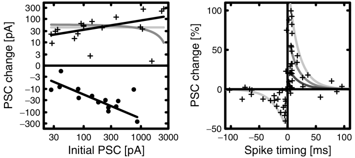

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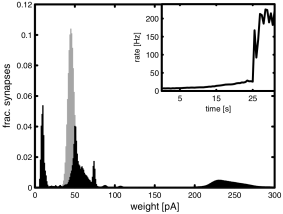

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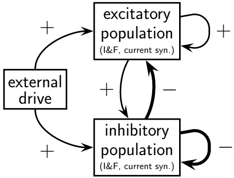
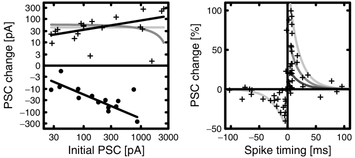
6. investigate how the implemented form of homeostasis affects network dynamics in the absence or presence of external perturbations (such as average firing rates, level of correlations in firing activity, power spectra of population activity, sensitivity to perturbations)

(Bachmann et al. 2020)





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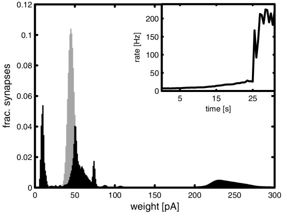

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