Reproducible neural network simulations: model validation on the level of network activity data

This poster summarizes [5,6].

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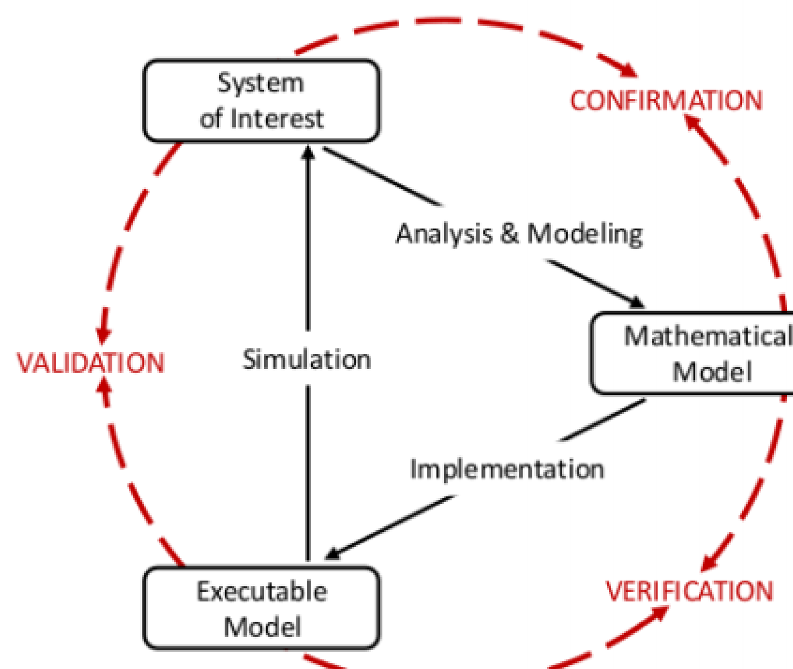
Concept

A model has the purpose to describe and predict its **system of interest**, which is a well defined entity selected for analysis. The model can be separated into two parts. The **mathematical model** is an abstract description formed by analysis and observation. The **executable model** is the implementation of the mathematical model which can perform simulations and thus generate testable predictions. [1][2]



Adapted from [1,2]

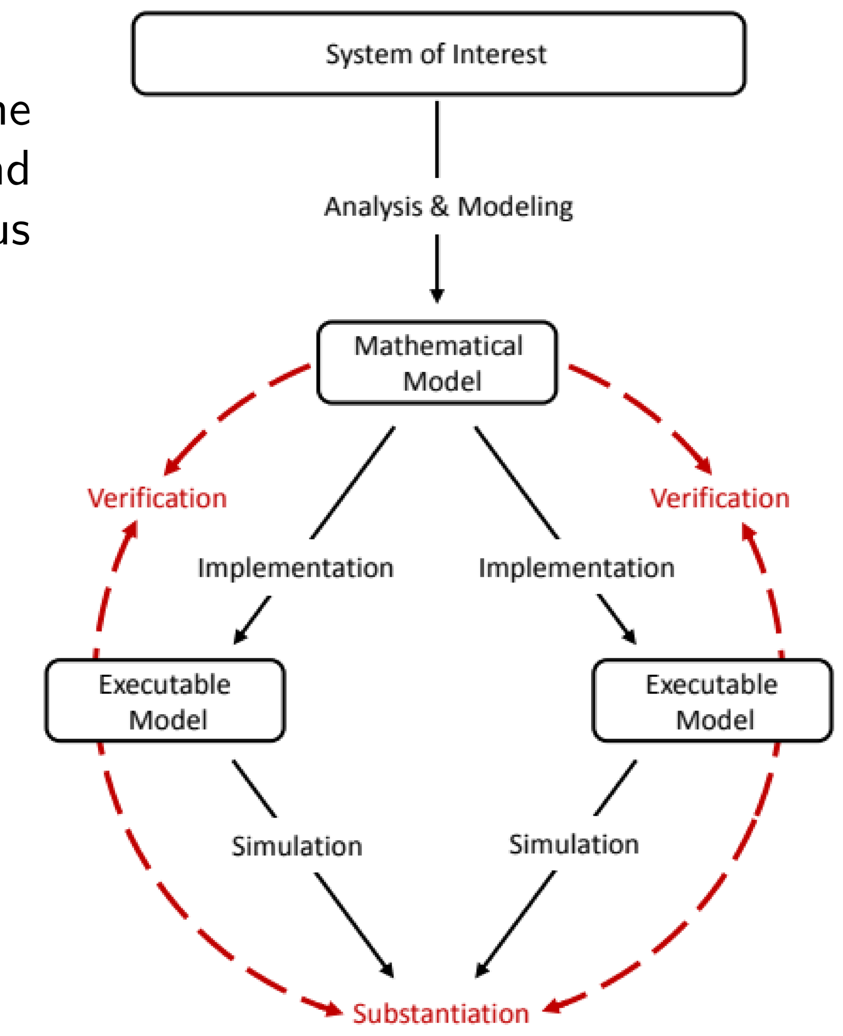
Confirmation: Assesses the plausibility of modeling choices and premises.

Verification: Ensures that the implementation is a correct representation of the mathematical model, concerning the code and the calculations.

Validation: Establishes confidence in the model by testing whether its prediction accuracy is within an acceptable agreement to the system of interest.

Substantiation: Defined here as the evaluation and quantifying the level of agreement between two executable models.

In practice the substantiation performs equivalent tests as a validation and differs only in its interpretation.



Validation approach: We validate by evaluating the simulation outcome on the **level of the network activity**, as opposed to the complementary approach of validating on a **single-cell level.**

Model & Implementations

Mathematical Model

polychronization network model: (*Izhikevich* [3])
800 exc. / 200 inh. spiking neurons
random connectivity, out-degree 100, random input,
integer delays, trained with STDP, measured without STDP

Implementation — Implementation

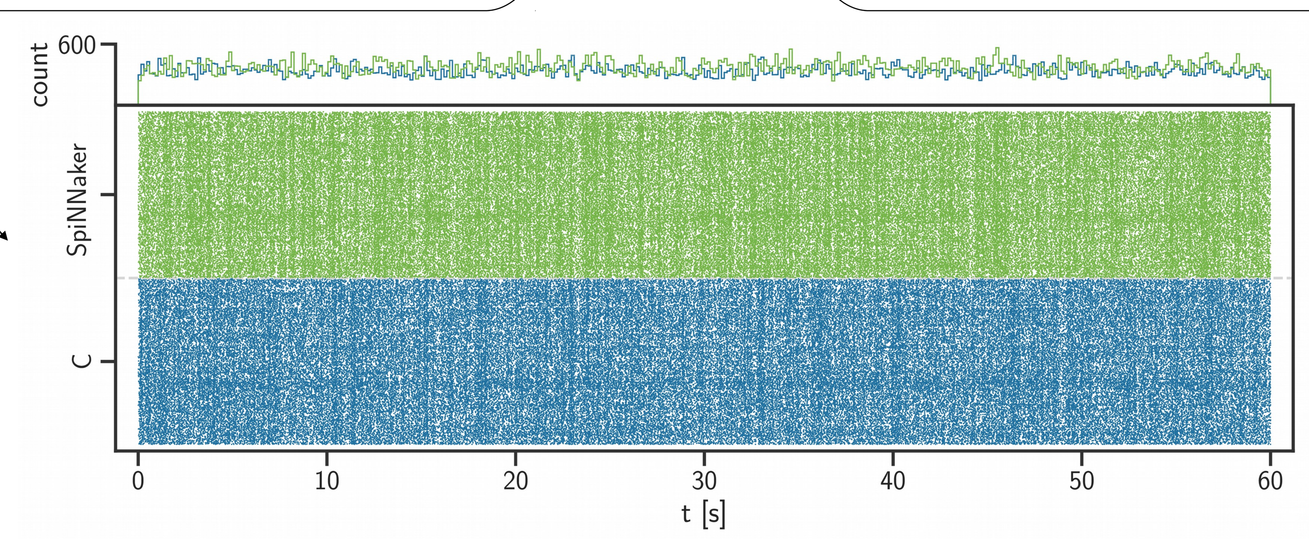
Executable Model

custom C code:
original publication [3], refactored,
adapted to make it transferable to SpiNNaker,
1ms time steps

Executable Model

SpiNNaker neuromorphic system: [4]
brain-inspired digital computer architecture,
uses fixed point representation of variables [5]
3 iterative stages of the implementation (I,II,III)

Simulation — Simulation



→ compare statistical measures:
firing rates (FR),
local coefficient of variation (LV),
correlation coefficients (CC),
inter-spike intervals (ISI),
rate correlations (RC), ...

Python Validation Framework

developed at github.com/INM-6/NetworkUnit

We developed the module **NetworkUnit** as a formalized Validation test framework based on *Elephant* [7] and *SciUnit* [8] for validation and substantiation in experiment and simulation.

```
import networkunit as newt
import sciunit
```

```
class polychonization_model(sciunit.Model, newt.capabilities.ProducesSpiketrains):
    def load():  # loads simulation outcome
        # ...

class C_model(polychronization_model):
    file_path = './simulation_data/C/'

class SpiNNaker_model(polychronization_model):
    file_path = './simulation_data/SpiNNaker/'

C = C_model()
S = SpiNNaker_model()
```

```
class rate_test(sciunit.TestM2M, newt.tests.firing_rate_test):
    score_type = newt.scores.effect_size  # equips the test with a score

FR_test = rate_test()
```

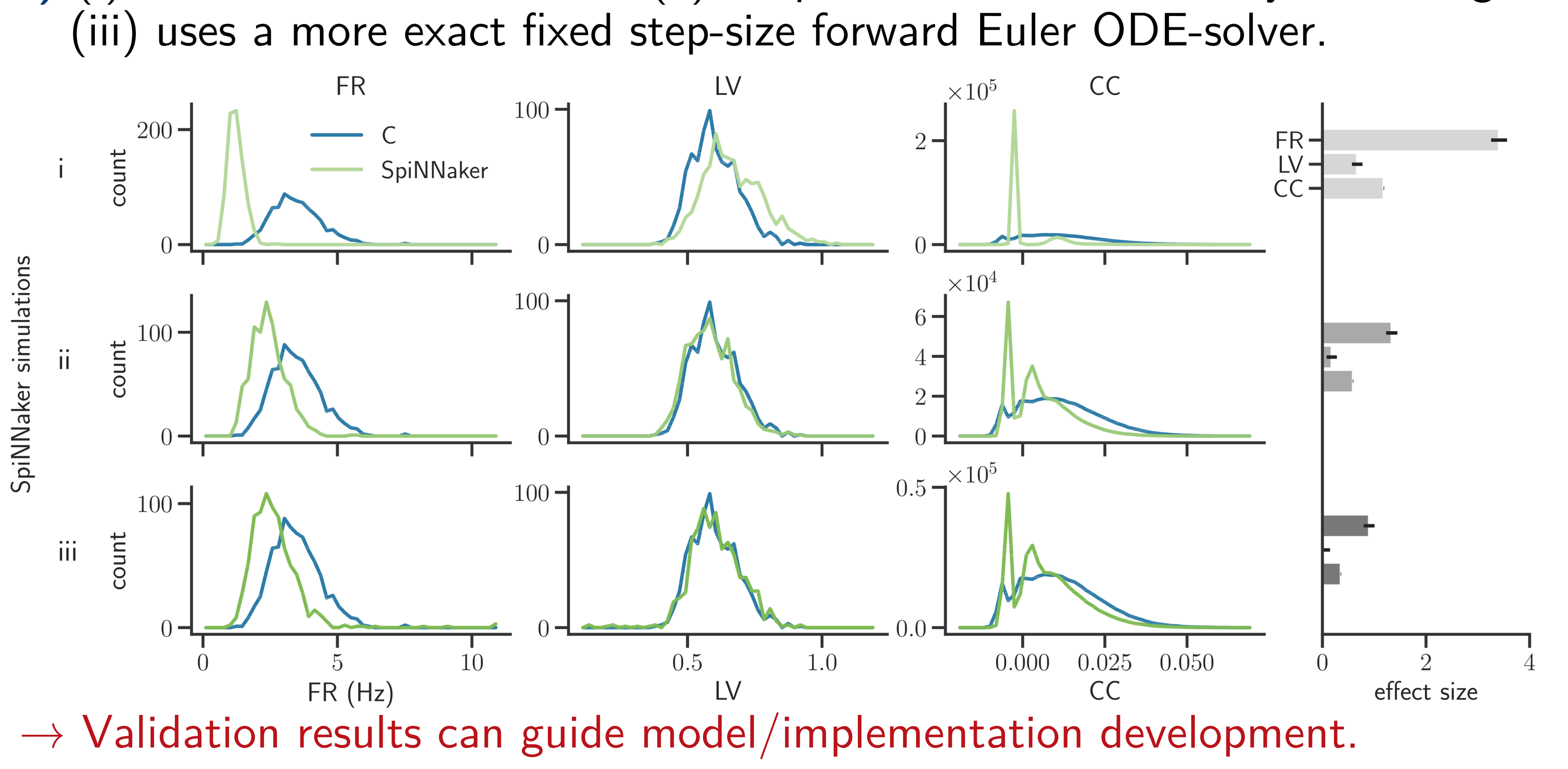
```
FR_test.judge([C,S])  # performs the validation test
```

```
Effect Size
        datasize: 800    800
        Effect Size = 0.394      CI = (0.295, 0.493)
```

Substantiation by Iterative Validation Test Cycles (I, II, III)

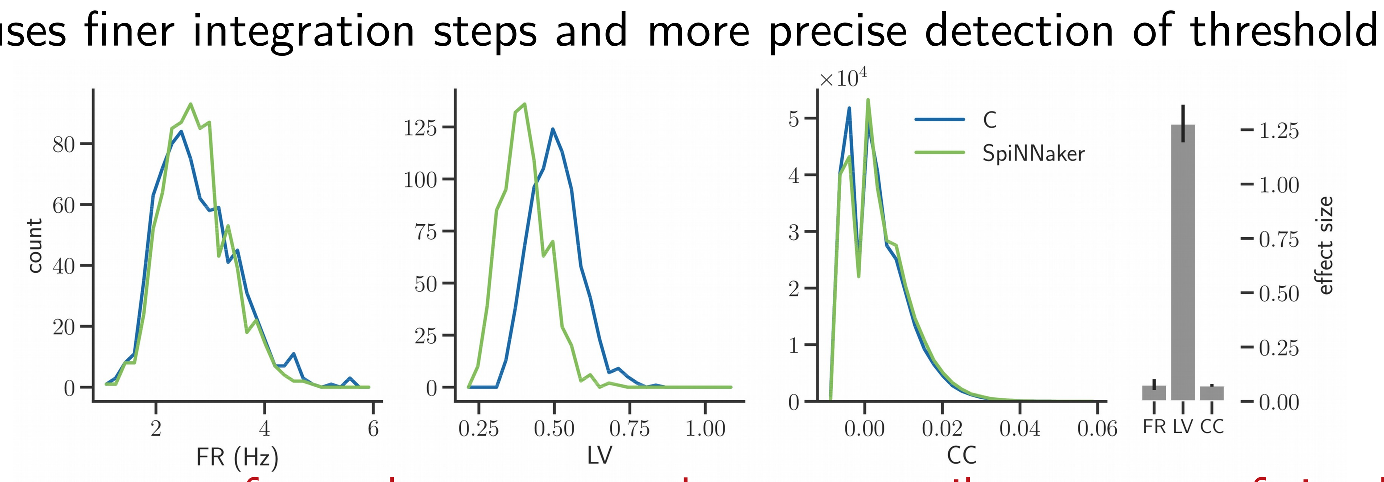
data, simulation code, and analysis code published at web.gin.g-node.org/INM-6/network_validation

I) (i) uses an ESR ODE-solver, (ii) adapts Izhikevich's neural dynamics algorithm, (iii) uses a more exact fixed step-size forward Euler ODE-solver.



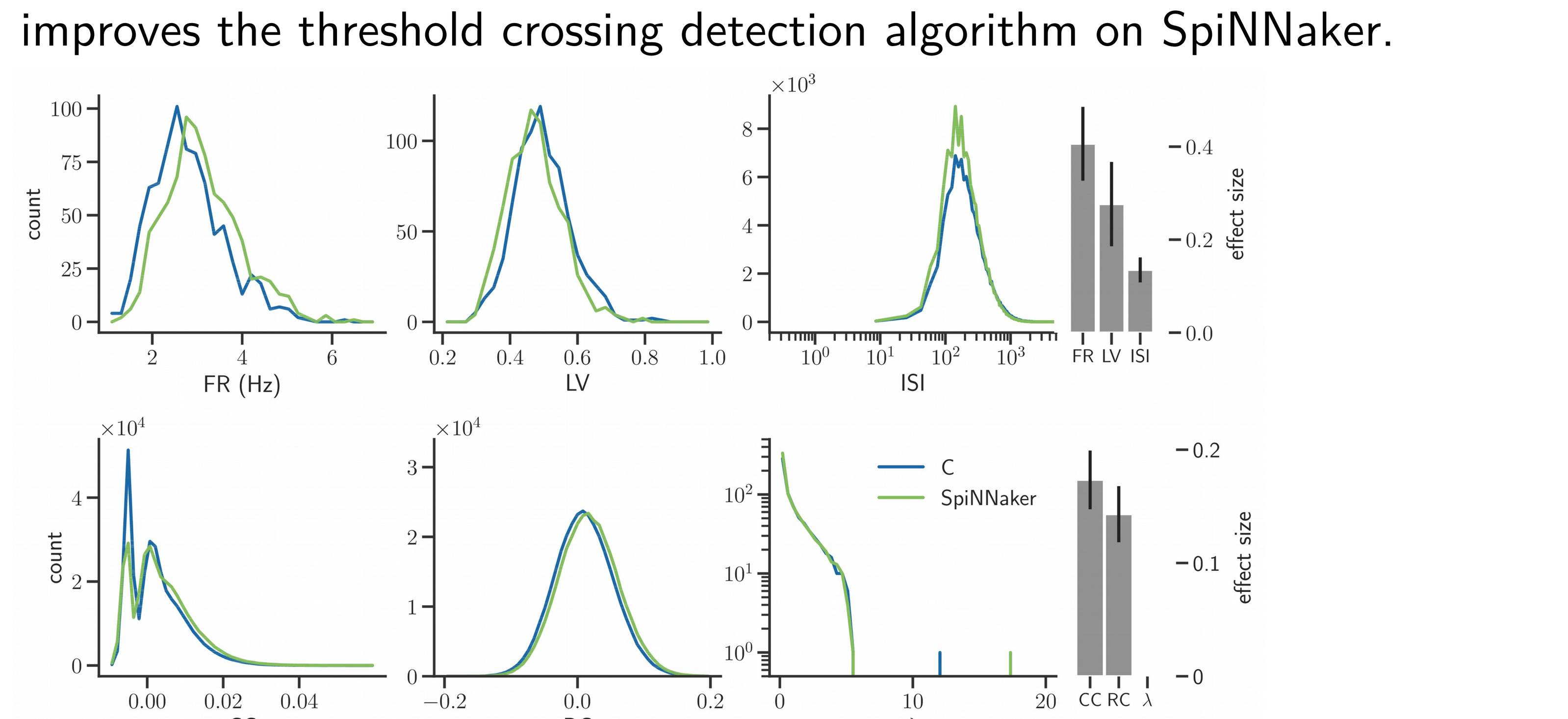
→ Validation results can guide model/implementation development.

II) uses finer integration steps and more precise detection of threshold crossing.

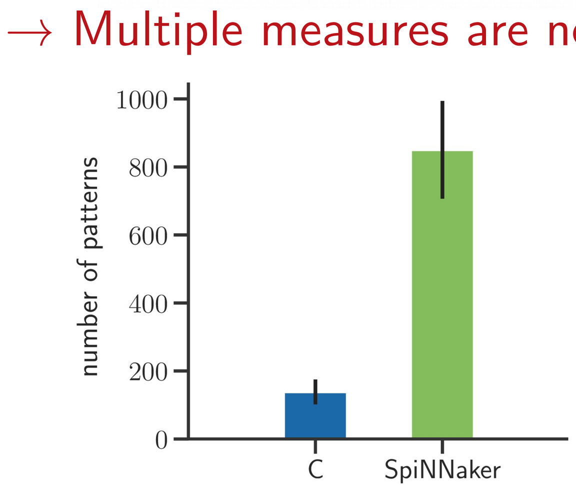


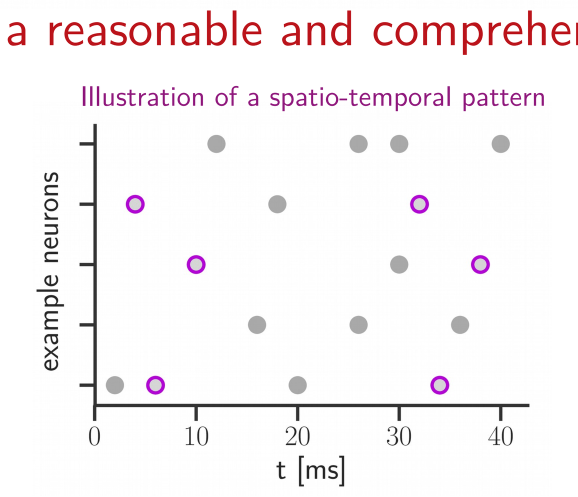
→ Agreement of complex measures does not entail agreement of simpler measures.

III) improves the threshold crossing detection algorithm on SpiNNaker.



→ Multiple measures are needed for a reasonable and comprehensive validation.





→ The evaluation of the level of agreement depends on the intended application. Here, despite good agreement of other measures, complex measures such as the pattern density (detected with SPADE [9]) is not yet consistent.

References

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[7] Electrophysiology Analysis Toolkit (python-elephant.org)
[8] SciUnit (scidash.github.io)
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