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<tr><th>authors</th><td>

Diesmann, Markus
Gerstner, Wulfram
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<tr><th>title</th><td>Phenomenological models of synaptic plasticity based on spike timing</td></tr>
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abstract	Synaptic plasticity is considered to be the biological substrate of learning and memory. In this document we review phenomenological models of short-term and long-term synaptic plasticity, in particular spike-timing dependent plasticity (STDP). The aim of the document is to provide a framework for classifying and evaluating different models of plasticity. We focus on phenomenological synaptic models that are compatible with integrate-and-fire type neuron models where each neuron is described by a small number of variables. This implies that synaptic update rules for short-term or long-term plasticity can only depend on spike timing and, potentially, on membrane potential, as well as on the value of the synaptic weight, or on low-pass filtered (temporally averaged) versions of the above variables. We examine the ability of the models to account for experimental data and to fulfill expectations derived from theoretical considerations. We further discuss their relations to teacher-based rules (supervised learning) and reward-based rules (reinforcement learning). All models discussed in this paper are suitable for large-scale network simulation
versions	

doc_2

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- R GÃ¼tig
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- RC Malenka
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- S Fusi
- S Fusi
- S Grossberg
- S Radpour
- S Rotter
- S Song
- S Song
- SM Dudek
- SR Kelso
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- U Frey
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- W Gerstner
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- W Senn
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- W Senn
- WB Levy
- WM Kistler
- Wulfram Gerstner
- Y Fregnac

title	Phenomenological models of synaptic plasticity based on spike timing
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