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Abstract:	This Deliverable describes the different models that will be investigated in SP4 during the Ramp-Up Phase. The different approaches are outlined separately for each Task and Partner.

Keywords:	Model description, Theoretical Neuroscience, Computational modelling

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1. Introduction

1.1 The Human Brain Project (HBP)

The Human Brain Project (HBP) is a major international scientific research project, involving over 100 academic and corporate entities in more than 20 countries. Funded by the European Commission (EC), the ten-year, EUR 1 billion Project was launched in 2013 with the goal "to build a completely new ICT infrastructure for neuroscience, and for brain-related research in medicine and computing, catalysing a global collaborative effort to understand the human brain and its diseases and ultimately to emulate its computational capabilities."

The fields of neuroscience, medicine and information technology each have important roles to play in addressing this challenge, but the knowledge and data that each is generating have been very fragmented. The HBP is driving integration of these different contributions.

During the Ramp-Up Phase, the HBP will collect strategic data, develop theoretical frameworks, and perform technical work necessary for the development of six Information and Communication Technology (ICT) Platforms during the Operational Phase. The ICT Platforms, offering services to neuroscientists, clinical researchers and technology developers, comprise Neuroinformatics (a data repository, including brain atlases and analysing tools); Brain Simulation (building ICT models and multi-scale simulations of brains and brain components); Medical Informatics (bringing together information on brain diseases); Neuromorphic Computing (ICT that mimics the functioning of the brain); and Neurorobotics (allowing testing of brain models and simulations in virtual environments). A High Performance Computing Platform will support these Platforms.

1.2 HBP Subproject 4: Theoretical Neuroscience

SP4 works on the Mathematical and Theoretical Foundations of Brain Research. Its goals are to:

- Investigate mathematical techniques to link models used or developed in other modelling and simulation-oriented Subprojects.
- Investigate different scales that are observed in experimental data and that need to be present in the simulation Platforms.
- Develop plasticity rules for brain circuits that continually change during development and learning.
- Theoretically characterise different cognitive functions that are compiled in other Subprojects.

1.3 Purpose of this Document

This Deliverable provides a detailed account of the conceptual framework for first-draft models, algorithms and computing principles, and reports the progress made in validating them for general use.

1.4 Structure of this Document

The remainder of this document provides an SP-level overview, as well as descriptions of progress and issues within individual SP components, as defined in D4.6.1: Specification of Brain Models, Algorithms and Computing Principles to be Developed in the Ramp-Up Phase, Indicators of Progress and Target Values:

- WP4.1: Bridging Scales
- WP4.2: Synaptic Plasticity, Learning and Memory
- WP4.3: Large-Scale Models of Cognitive Processes
- WP4.4: Principles of Brain Computation
- WP4.6: Scientific Coordination

Please note that because this Deliverable describes computational models, we have omitted WP4.5: The European Institute of Theoretical Neuroscience (EITN). The EITN is the subject of a separate Deliverable (D4.5.1).

2. SP4 Overview

This Deliverable describes the different models that SP4 will investigate during the HBP Ramp-Up Phase, including the types of models that will be posted to the HBP database for use by other Partners. For most of these models, it is clear what will be investigated, why, and when the model will be posted. Other models still under development will be posted when they are ready; this is the case for cognitive models and simplified dendritic models for different cell types. For all SP4 models, a first description (accompanied by program codes if possible) will be posted in December 2014. We have also included the conceptual framework ('why') for model development, which is a more detailed version of the description given in the Description of Work.

3. WP4.1: Bridging Scales

3.1 T4.1.1: Derive simplified neuron and neural circuit models from biophysically morphologically detailed models (SP4_SKPI-01)

T4.1.1 (Task Leader: Idan Segev, HUJI (P21)) obtains experimental data via the VU-VUMC Partners of the HBP. In the first stage of WP4.1, we developed a complete and detailed cable model of 3D-reconstructed and physiologically measured cells. This required us to reconcile experimental data (input resistance, somatic voltage transients following brief current pulse, and EPSP shape from pair-recordings) with our model. The model includes dendritic spines (30,000 spines per cell), which are globally embedded in the respective cable model membrane.

With a detailed model of this unique preparation, we have started to develop novel methods for reducing the neuron model's complexity. The first stage was the analysis of the number of functional sections in the model (defined by dendritic regions where voltage attenuation is smaller by more than a factor of two). This computation started from the distal dendritic ends and progressed towards the soma. In the next stage, we reduced the detailed model to a simpler model that preserves the number of such functional subunits. The result is a simpler dendritic tree with some 30-40 compartments (compared to several hundred compartments in the detailed model). We are now in the first stage of examining how close the input-output response of the full model and the reduced model are to a set of standard synaptic inputs impinging on the dendritic tree.

We have initiated a second approach to model reduction, which involves first measuring the maximal transfer resistance ($R_{i,soma}$) in the detailed model (from the most distal apical branch, i), and building a single cylindrical cable whose most distal point preserves the measured $R_{i,soma}$ value. The next step is to map each original dendritic locus, j (in the detailed model) to the corresponding locus in the single cylinder model while preserving $R_{j,soma}$ for that locus. In the passive linear case, this mapping exactly preserves the impact of each synapse on the modelled soma (for the reduced versus the detailed model). Soon, we will also investigate the quality of this reduction when synapses are represented as a brief conductance change (rather than by linear current).

CNRS's Unit of Neuroscience Information and Complexity (UNIC) is investigating simplified models of neurons with dendrites using a simple ball-and-stick model (a soma connected by a dendrite consisting of a single cable). We include the local excitability of the dendrite (i.e., the capacity to generate dendritic spikes) and the response to *in vivo* synaptic bombardment. The goal is to theoretically identify the qualitative role of active dendrites, while preserving compatibility with the neuromorphic hardware prototype that will include dendrites.

The models investigated here thus consist of homogeneous chains of excitable systems bombarded by random spike trains. The first generic model we considered is a cellular automaton that qualitatively describes the behaviour of a homogeneous dendrite. Dendritic spikes are generated randomly along the dendrite, propagate in both directions, and cancel out when they collide. This model is both generic (it encompasses many dendrites propagating non-linearity) and mathematically tractable.

In the second type of model, which is compatible with neuromorphic computers, we will consider chains of AdEx spike generating mechanisms, as well as conductance-based exponential synapses. Each compartment contains the following mechanisms:

$$
\begin{aligned}
-C_{\mathrm{m}}\frac{\mathrm{d}V}{\mathrm{d}t} &= g_{\mathrm{l}}(V-E_{\mathrm{l}}) - g_{\mathrm{l}}\Delta_{\mathrm{t}}\mathrm{e}^{\left(\frac{V-V_{\mathrm{t}}}{\Delta_{\mathrm{t}}}\right)} + w \\
&\quad + g_{\mathrm{e}}(t)(V-E_{\mathrm{e}}) \\
&\quad + g_{\mathrm{i}}(t)(V-E_{\mathrm{i}}), \\
-\tau_{\mathrm{w}}\frac{\mathrm{d}w}{\mathrm{d}t} &= w - a(V-E_{\mathrm{l}}).
\end{aligned}
$$

where V is the membrane potential; Cm, gl, ge and gi are the membrane capacitance, the leak conductance and the conductance for excitatory and inhibitory synaptic inputs; and El, Ei and Ee, respectively, are their reversal potentials. The parameters Vt and Δt are the effective threshold potential and threshold slope factor. Finally, w is an adaptation variable with time constant τw.

We will validate the model in Task 4.4.1 (Principles of computation in single neurons and neural microcircuits). We will detail the properties of this system under *in vivo*-like conditions, and describe the type of computation it provides in addition to a single-compartment neuron.

Prior to the start of the Project, Wulfram Gerstner's laboratory (EPFL-LCN) developed methods to extract simplified neuron models directly from experimental data. The idea is to formulate a stochastic spiking neuron model with escape noise, which can be optimised by maximising the likelihood. Simplified neuron models such as the generalised integrate-and-fire model (GIF), Spike Response Model (STM), or Generalised Linear Model (GLM) all fall into the class of models that can be optimised in this fashion. Initially, methods were limited to experimental paradigms of somatic current injection. Using a detailed model from the HBP as a starting point, we applied the methods to model reduction. We were able to measure the loss of spike train predictability induced by model simplification in a detailed, multi-compartment model. This means that the model reduction methods have now been validated. In the next year, we will apply the methods to extract a simple model for multi-site current injection into the detailed neuron model, which corresponds to the large-scale HBP simulations.

Also prior to the start of the Project, the model used a simplified threshold mechanism for spiking. We have now included a sophisticated firing mechanism that relies on coupling of the sub-threshold voltage and the threshold. This shifts the neuron model closer to a detailed biophysical model, while keeping attractive properties of convex parameter optimisation via the likelihood. A manuscript is in preparation.

3.2 T4.1.2: Modelling brain signals at different scales, from intracellular, local field potentials, and VSD up to EEG and MEG signals (SP4_SKPI-02)

(This Task began on 1 October 2014, and will not be reported here)

3.3 T4.1.3: Mechanistic models of cognition linked to the neural substrate by population density methods (SP4_SKPI-10)

ULEEDS (P110) is developing a simulator for networks of populations of neurons, based on population density techniques. Population density techniques describe the state of a neural population in terms of a density function. They are more general than neural mass

models, which should be contained as a special case. Recently, ULEEDS developed a method that is valid for every one-dimensional point model neuron, and that does not rely on the size of synaptic input contributions or continuity of the density function.

Prior to simulation, an array needs to be generated with numerical values specifying the behaviour of a typical neuron point model; otherwise, the simulation method should be independent of that model. This will allow novel applications of this technique. Although there is extensive theoretical literature on population density techniques, experimentalists and computational neuroscientists cannot use those techniques unless they have a substantial background in scientific computing. Our simulator, MIIND, will make these techniques accessible to the community. At the moment, we are finishing an alpha version with the following features:

a) Arbitrary 1D neuron point models that can be defined for a homogeneous population of neurons.

b) Arbitrarily large synaptic efficacies that can be modelled (the method is thus more general than Fokker-Planck methods, which are contained as a special case).

c) Large networks that can be instantiated (connections can be interpreted either as a distribution of synapses or a Gaussian white noise source).

d) An MPI-based simulation engine.

e) A C++ API.

Contact with the Brain Simulation Platform (SP6) has been established to discuss terms for integrating MIIND with the Platform.

We obtained preliminary results of simulations of a small circuit - part of basal ganglia. These results are compatible with earlier spike-based simulations, but incompatible with rate-based models. We expect to gain insight from the simulations regarding when a computationally less expensive rate-based model is appropriate, and when it is not. In the latter case, population density techniques are required.

Future developments are 1) an extension to 2D models, and 2) development of a user interface, either in the form of a mark-up language or a programming language.

4. WP4.2: Synaptic Plasticity, Learning and Memory

4.1 T4.2.1: Derive learning rules from biophysical synapse models (SP4_SKPI-03)

The aim of T4.2.1 is to formulate learning rules that are compatible with experimental data, and that are functionally useful.

No personnel have yet been hired for Walter Senn's group (UBERN, P62), as this group is only partially funded in the Ramp-Up Phase. However, the Senn group recently achieved important results in terms of biophysically realistic learning rules. We have shown that the separation of the dendritic tree into a somatic and dendritic compartment allows for a biological version of supervised learning. In this interpretation, 'teaching input' is supplied to the somatic compartment through conductance-based excitatory synapses that define a target potential. 'Student input' projecting to the dendritic tree tries to match this target potential by adapting its synaptic strengths.

The discrepancy between the somatic firing and the local dendritic potential is considered a prediction error that drives synaptic plasticity on the dendrite. Such prediction errors can arise in our model from stochastic fluctuations as well as from the teaching input that directly targets the soma. Depending on the nature of this somatic input, our plasticity rule sub-serves supervised or unsupervised learning. When a reward signal modulates the learning rate, reinforcement-learning results. The rule we have suggested therefore unifies the various learning paradigms in a single type of synaptic plasticity.

In the next year, we will hire a postdoc on the HBP grant. His or her task will be to show that the suggested learning rule is compatible with the experimentally observed spike-timing-dependent plasticity, which was shown to depend not only on the pre- and postsynaptic spike timings, but also on the local dendritic membrane potential. Specific experiments (funded by sources other than the HBP) will be realised to validate this model.

Wulfram Gerstner's laboratory (EPFL-LCN) has taken a closer look at existing diverse experimental data on synaptic plasticity. In this zoo of observed facts, theoreticians cannot be expected to extract one single learning rule that fits all cases. Rather, our approach is two-fold. First, we started to formulate a mathematical framework in which different observed plasticity phenomena can be classified. Different terms in the mathematical formulas can be interpreted as:

- Hebbian or anti-Hebbian plasticity
- Heterosynaptic plasticity
- Transmitter-induced plasticity

where 3) depends only on the activity of the presynaptic neuron, 2) depends only on the activity of the postsynaptic neuron, and 1) depends on the joined activity of the pre- and postsynaptic neuron (where activity includes rate, spike timing, voltage).

Second, within this framework we identified a learning rule using an appropriate combination of 1) – 3) that is functionally useful, so that a recurrent network of spiking neurons may form memories online and retrieve them while the plasticity rule remains active. This work has been submitted to a respected journal.

Work in Misha Tsodyks' group (WIS, PS78) suffered from a delay due to the late recruitment of a postdoc. We considered a phenomenological synaptic learning rule that

was derived from a combination of Hebbian plasticity and adiabatic plasticity. In the next year, we will apply this learning rule to consider the effects of continuous streams of input patterns on a neural network. We will derive the conditions for forming stable memory states in the network.

4.2 T4.2.2: Unsupervised learning rules and emergent connectivity (SP4_SKPI-04)

The goal of T4.2.2 is to explain the connectivity patterns in cortical microcircuits through unsupervised synaptic learning rules. Experimental data are available in the form of statistics on the number of actual synaptic connections between pairs of neurons, as well as on the frequency of motifs connecting several neurons. These data can be contrasted with the number of potential synaptic contacts, defined as locations where the axon and dendrite of two neurons are in close proximity (~2 microns). Typically, there are fewer actual than potential synapses, and actual synapses tend to come in groups, indicating a cooperation of synaptic contacts in synapse formation. This cooperation can be explained by spike timing-dependent plasticity (STDP) of synaptic contacts, as shown in our previous theoretical work. The analysis of the multi-synaptic connection of a neuron pair demonstrated that the distributions of actual synapse numbers could be reproduced by STDP rules under rather general conditions. However, the study did not propose a specific unsupervised learning rule. Here, we propose and simulate candidate local STDP rules for individual synaptic contacts, with the goal of reproducing the experimental distributions of the number of synaptic contacts in cortical microcircuits. The models will be related to previously suggested biophysical models that feature dependencies on the local calcium concentration. Network effects beyond connection pairs will be discussed.

4.3 T4.2.3: Structures of Spiking Learning Algorithms (SP4_SKPI-11)

Partner SURREY (P111) began on 01/04/2014 and hired a postdoc 30% FTE on 01/04/2014. This position was extended to 100% on 01/10/2014.

The goals of T4.2.3 are to:

- Provide a concise mathematical framework for the formulation of learning rules for spiking neural networks.
- Formulate new and generalise existing such learning rules.
- Link neural and synaptic scale rules of plasticity with systems-scale goal-oriented behaviour.

Our overall research strategy is to consolidate and extract the main underlying concepts of existing algorithms for spiking neural networks, to formalise these concepts in a new framework using the notation of functional derivatives, to generalise existing learning algorithms, and to develop new ones that overcome the shortcomings of the existing ones. Existing algorithms do not relate to each other, and use different terminologies and notations without connection. Some are strikingly similar conceptually and/or practically, but are unaware of each other. Currently, we systematically compare approaches for goal-oriented learning in networks of spiking neural networks, e.g., regarding 1) admissible neuronal and synaptic models, network structures, 2) goal-orientedness, and 3) scalability.

As stated in its research plan, SURREY is consolidating and extracting the main underlying concepts of existing learning. Initial results of this process show that despite the very

different motivations, heuristics, derivations and purposes of these so far unconnected algorithms, individual weight changes Dw can be calculated for most of them as follows:

$$\Delta w_i = c(t^f - \hat{t}^f)[\exp(-(t_i^f - \hat{t}^f)\frac{t_i^f - \hat{t}^f}{\tau_m}) - \exp(-(t_i^f - t^f)\frac{t_i^f - t^f}{\tau_s})]$$

where tpre is the presynaptic spike time, tf is the postsynaptic spike time, and t^f is the target spike time. Tau and tau-s are membrane and synaptic time constants. Importantly, parameters can be constants, or they can be dependent on other factors such as the membrane potential or the general state of the network. Parameters can also be reward-modulated.

Thus, we conclude that most algorithms suggested so far lead to the same form of weight changes. We are currently developing a reference implementation of a first generalisation of existing algorithms for NEST. This reference implementation is intended for comparative purposes.

5. WP4.3: Large-Scale Models of Cognitive Processes

5.1 T4.3.1: Models of perception-action (SP4_SKPI-05)

T4.3.1 (Task Leader: Gutstavo Deco, UPF (P65)) investigates the dynamics of interconnected neural populations with a focus on the relationship between the connectivity structure and activity patterns. On the one hand, effective connectivity (EC) describes how the populations excite or inhibit each other. EC encompasses structural connectivity (i.e., the existence of connections), and indicates the corresponding strengths, which depend on neurotransmitter types and receptor concentration. On the other hand, network activity is observed via functional connectivity (FC)—i.e., the fluctuations of populations' firing rates and their co-variations.

The developed theory is applied to a model of the whole cortex. The goal is to understand how the interplay between the local dynamics for each population node model, and the long-range intercortical coupling shapes FC for non-trivial and biological-like connectivity topologies.

Our approach is twofold. The first step is predicting the FC for known EC, which can be done based on connectomes that have been measured experimentally. The second step is to infer EC from empirical FC, as measured by fMRI or MEG. This approach aims to develop a model that is constrained by both structural and functional data (for EC and FC, respectively). The dynamical state of the model will then be used for evoked activity and to investigate how external stimuli are represented in the internal activity.

The models will be tested for their ability to reproduce spatio-temporal patterns of the recorded FC for individuals, as well as general trends across all subjects. The optimisation procedures will be verified using both surrogate and experimental data. All work will be carried out in collaboration with WP3.1, which will provide experimental data tailored to validate the models.

Technically, the framework can account for different models for the population-node dynamics, such as linear activation and Kuramoto's model. So far, the efforts have been on variants of the DMF model.

As an illustration, the minimum model describes each population with a synaptic variable S_i, which exponentially decays with time constant τ and receives a current U_i that lumps excitation/inhibition from itself and other populations: $\frac{dS_i}{dt} = \frac{-S_i}{\tau} + \Phi[U_i] + dB_i$ where Φ is the activation function that applies to the current $U_i = wS_i + \sum_{j \neq i} C_{ij} S_j + I_i$, dB_i is white noise and I_i the external input. The local connectivity is described by w and the EC connectivity by the matrix C_{ij}. FC is the second-order moments of the variables S_i, evaluated in the matrix with elements $Q_{ij} = \langle [S_i - \bar{S}_i][S_j - \bar{S}_j] \rangle$, where the bar indicates the mean $\bar{S}_i = \langle S_i \rangle$. The angular brackets denote the averaging over the noise in the network. The matrices $Q = (Q_{ij})$ and $C = (C_{ij})$ are related by the Lyapunov equation: $JQ + QJ^T + \Sigma = 0$, where Σ is the noise matrix. The Jacobian J depends on the connectivity and time constants: $J_{ij} = \frac{-1}{\tau} + C_{ij} \Phi'[U_i]$.

We develop algorithms to evaluate Q from C, and vice-versa. In particular, to infer C from Q, a direct calculation can be done for a linear Φ, but a gradient descent is necessary for the nonlinear case.

UCL is developing models of navigation and spatial decision-making. The goal is to theoretically and computationally identify the roles of the hippocampus and basal ganglia in navigation, by examining experimental results in rodents and humans that illuminate the distinct representations and learning rules present in each area.

To achieve this, we are simulating the activity in the relevant areas during navigation of the simulated agent using neural networks of firing rat-based neurons. Each unit of the network represents a small subpopulation of neurons that encodes information specific to the area to which it belongs: locations in hippocampus, value in ventral striatum, and perceptions and movements in neocortex. A firing rate model with synaptic inputs describes the behaviour of each neuronal pool. The set of equations governing the behaviour of a single neuronal pool is as follows:

$$\begin{cases} \tau_I \dfrac{dI_{syn}}{dt} = -I_{syn} + I_{ext} \\ \nu = \nu_{\max} \cdot \tanh^{+}[\gamma(I - I_{thr})] \end{cases}$$

where I_{syn} is the total synaptic current, and τ_I the corresponding time constant; I_{ext} is the external input current; ν is the firing rate; ν_{max} is the maximum firing rate; γ is the steepness of the response function and I_{thr} is the firing threshold below which no response is present; and $\tanh^{+}$ signifies that the response is 0 when the functions produces a negative value.

In our architecture, we have also implemented learning mechanisms between the different areas. While the hippocampus utilises a one-shot learning method to link the sensory information to place cells, plastic connections between sensory and striatal neurons are updated using a classical TD learning rule.

The equations that govern the synaptic modification are as follows:

$$\Delta w_{Sens-Str} = \beta \cdot [R + \gamma \cdot \nu_{Str}(t) - \nu_{Str}(t-1)]$$

where $w_{Sens-Str}$ is the weight between the sensory neurons and the neurons in the ventral striatum, β is the learning rate, R is the reward, γ is the discount factor.

During the experiments described above, we will simulate the known behaviour of the agent, including learning rates and effects of local inactivation and the known measures of neural activity.

INRIA is investigating a model of the sensitivity of V1 to visual orientation. The distribution of the preferred orientations defines an orientation preference map (the OP map), which has a near-lattice structure, and which is continuous except at particular points called pinwheels. We assume that the pinwheels are arranged in a doubly periodic lattice, and that the main features of cortical activity in V1 can be interpreted within this framework. This idealisation naturally introduces symmetries to the problem, which makes deeper analysis possible. As long as the pinwheels are nearly arranged on a periodic lattice, we can expect that the main conclusions of our analysis will still be valid for the 'real' lattice.

There is also experimental evidence that the spatial distribution of connections emanating from one neuron in V1 differs according to whether the connections are local (within one hyper column) or long-range (between different hyper columns). Local connections are

considered to be isotropic. In the absence of long-range connections, the network (or field) of local connections would be Euclidian invariant—that is, invariant under rigid displacements and reflections in the plane. This is a property that is transmitted to the model equations. On the other hand, long-range connections are subject to the constraint of respecting the symmetries of the OP map, thereby reducing the full Euclidean group symmetries to a crystallographic subgroup associated with the lattice of pinwheels. Moreover, experimental observations suggest that the strength of long-range connections is significantly weaker than that of local connections, which allow us to treat the long-range connections as a perturbation of the local ones.

We investigated the bifurcation structure of this model in detail, and it produced the different patterns that are seen experimentally.

5.2 T4.3.2: Models of working memory and the effects of attention (SP4_SKPI-06)

We built an attractor neural network with synaptic facilitation performing working memory tasks. In particular, we considered an issue of multiple items that have to be kept in a particular order. We made good progress on calculating how to retrieve several items by applying properly paced readout signals. In another project, we considered an attractor neural network performing a free recall task. We found that such a network with oscillating inhibition and weak stochasticity accounts for some of the classical observations of free recall. In the next year, we will continue this research by computing the maximal number of items that can be recalled.

5.3 T4.3.3: Models of biologically realistic network states; wakefulness and sleep (SP4_SKPI-07)

(This Task began on 1 October 2014, and will not be reported here)

5.4 T4.3.4: Computational model of astrocyte-neuron interaction for future large-scale simulations (SP4_SKPI-12)

T4.3.4 (Task Leader: Marja-Leena Linne, TUT (P99)) extensively analysed experimental literature and existing models of astrocyte-neuron interactions during the first six months. Based on this work, state-of-the-art model components are currently being selected to develop the so-called generic model for regulation of neuronal synapses by astrocytes.

The first generic reference model that T4.3.4 is considering is based on relatively phenomenological descriptions of the astrocyte-neuron interactions. This model contains the following components:

- The leaky-integrate-and-fire model for neuronal excitability
- The deterministic dynamic model for synaptic information transfer
- The Li-Rinzel model for Ca2+ dynamics in astrocytes (including three ionic fluxes, J_{pump}, J_{leak}, and $J_{channel}$)
- The gatekeeper model for modulation of presynaptic neuron by astrocyte (mimicking the hypothesised role of glutamate)
- The slow inward current model of astrocytic modulation of postsynaptic neuron (mimicking the effects of extra synaptic NMDA receptor mediated neuronal currents)

The second model we will develop will replace the above-mentioned component 4) with state-of-the-art biophysical descriptions of presynaptic Ca^{2+} dynamics and vesicle release. This will make it possible to study the implications of (stochastic) glutamate release and associated presynaptic signalling on information transfer in cortical synapses. We expect to select the model components within the next three months and implement the models using Matlab during next six months, according to the plan we presented in the competitive call application.

We will validate models using the following strategy:

1) We will validate the new biophysical model against experimental data from literature
2) We will compare the new model to a generic phenomenological reference model of cortical synapses
3) Toward the end of the Project, we will validate our model against the complex vessel-astrocyte-neuron model implemented in SP6.

We expect to gain insight into astrocyte's capacity to modulate cortical synaptic information transmission and neuronal spiking. This work can be used as a basis for extracting simplified algorithms of astrocyte modulation for large-scale neural dynamics.

6. WP4.4: Principles of Brain Computation

6.1 T4.4.1: Principles of computation in single neurons and neural microcircuits (SP4_SKPI-08)

T4.4.1 (Task Leader: Wolfgang Maass, TUGRAZ (P54)) focused on identifying generic computational modules of cortical microcircuits, the functionality of which is analysed through both theory and simulations, and compared with biological data. The primary computational modules, which are currently studied in Graz, are ensembles of pyramidal cells that interact with ensembles of inhibitory neurons, i.e., variations of so-called Winner-Take-All (WTA) circuits. The primary model was recently published[1]. TUGRAZ focuses on a more biologically realistic version of the WTA model, in which a sparse subset of pyramidal cells can fire simultaneously. Such softer inhibition is more consistent with experimental data, which show that single neurons cannot in general recruit lateral inhibition. We call such modules with 'softer' lateral inhibition sWTA-circuits, (where the 's' stands for 'sparse' firing). We have shown that STDP induces in such sWTA circuits an important computational function: different neurons become feature detectors for different components of their high-dimensional inputs (even if these components are never presented in isolation), rather than for episodes of the full high-dimensional spike input. For example, they learn through STDP to solve the 'superposition-of-bars' problem by Földiak, a well-known benchmark task for unsupervised emergence of feature extraction. Subsequent work will examine whether similar computational capabilities emerge through STDP in corresponding sub-networks of the column model from EPFL.

UNIC is investigating simplified models of neurons with dendrites (see description of the model in T4.1.1). In T4.4.1, we investigate what type of computation is provided by a model neuron with dendrites, compared to a single-compartment neuron. To explore this problem, we conceived models of the stochastic synaptic activity of neurons under *in vivo* conditions. The synaptic input is modelled by conductance-based exponential excitatory and inhibitory synapses, driven by stochastic point processes (Poisson statistics). This system is adjusted to intracellular measurements of cortical neurons *in vivo,* and to particular conductance measurements that directly constrain this type of activity (especially the 'high conductance states', which strongly impact neuronal dendrites). The model of *in vivo*-like synaptic activity is described by:

$$\frac{dg_e(t)}{dt} = -\frac{1}{\tau_e}[g_e(t) - g_{e0}] + \sqrt{D_e}\,\chi_1(t)$$

$$\frac{dg_i(t)}{dt} = -\frac{1}{\tau_i}[g_i(t) - g_{i0}] + \sqrt{D_i}\,\chi_2(t)$$

where the synaptic conductance ge and gi vary around an average conductance ge0 and gi0 with a time constant te and ti, and following the action of two independent noise sources X1 and X2 with noise strength De and Di.

This model will be provided as PyNN codes for maximum compatibility with other SPs, particularly SP9. This code will be made available in HBP databases, as well on public databases at the time of publication.

Model validation will consist of carefully matching all measurable properties of the model, such as the mean membrane potential (Vm); its standard deviation – or more generally the Vm distribution; and the conductance statistics (mean, variance) as compared to

experimental measurements. Our goal is to have a model that closely mimics *in vivo* conditions, and that is entirely compatible with neuromorphic hardware circuits that include dendrites.

6.2 T4.4.2: Novel computing systems-inspired by biology (SP4_SKPI-09)

T4.4.2 (Task Leader: Joni Dambre, UGENT (P66)) is addressing generic ways to directly exploit the dynamics of physical systems for computation. This research builds upon the reservoir computing approach (e.g., liquid state computing, echo state networks) applied to different types of non-spiking physical systems (photonic, mechanical, memristive, etc.) However, within the framework of the HBP, the aim is to transfer principles of learning through local adaptation (i.e., plasticity) from the brain to other implementation substrates.

In the present study, we extend our previous work on simple feedback controllers for compliant tensegrity robots. The main message of that article was that the control of highly compliant robots can be simplified by exploiting the inherent computational resources of such dynamical systems. UGENT has evaluated the use of reward-modulated Hebbian plasticity with delayed rewards for training the feedback loops in this approach. The learning rules fit into the class of reward-modulated Hebbian plasticity rules. We specifically target this type of learning rule, because of the limited number of assumptions needed about the substrate to which it is applied. Our algorithm, which is analogous to existing work in the context of neural networks, adds exploration noise to the actuator signals. By correlating the effects of the noise and the resulting change in reward, the learning rule attempts to improve the average reward.

Our main conclusion is that, despite the simple nature of the learning rules, reward-modulated Hebbian plasticity can be applied to a large variety of substrates. It is not linked to a specific reward function and can handle delayed reward delivery. A paper about this work is in preparation. A detailed description of the approach used, as well as example scripts to illustrate their application in a robotics context, will be made available in HBP databases.

Work at TUGRAZ for this Task is focused on constructing a network of spiking neurons with noise that can solve hard computational tasks[2]. This research builds on new construction and analysis methods that have recently been made available for the neuromorphic engineering community. Our results give rise to new models for networks of spiking neurons with noise that have powerful problem-solving capabilities. These models are constructed such that network states with low energy correspond to good solutions of given hard problems. Their construction is based on a new Modularity Theorem, which tells us how the energy function of the network is modulated through the addition of particular generic network motifs. In this way, one can construct networks of spiking neurons that produce rapid approximate solutions to difficult (in fact, NP-hard) problems from the domain of planning and optimisation (e.g., the Travelling Salesman Problem, or TSP), and also from the domain of logical inference and verification (e.g., the Satisfiability Problem, or 3-SAT). Surprisingly, one can demonstrate that some of the resulting models can solve difficult problems faster than non-spiking networks can.

6.3 T4.4.3: Closed Loop Analysis of Population Coding (SP4_SKPI-13)

The first purpose of this Task is to design closed-loop experiments in which the stimulus delivered to the retina is modified in real time as a function of the previous responses of the recorded network. For this, we first needed to solve several technical issues. First, we designed a program that detects spikes over the 252 electrodes of the multi-electrode array, and sends them via a UDP protocol to another computer that generates the stimulus. Second, we developed a program to update the stimulus during the time course of the experiment according to the recorded activity. Now that these technical issues are solved, we have to design an optimisation algorithm that will choose which stimulus to present from the previous network responses.

We are now designing an algorithm to test the separation capacity of the retinal network. Here, the idea is to find pairs of stimuli that are only slightly different, but that will evoke distinguishable responses in the retina. Starting from an initial stimulus trajectory, we are creating random perturbations that generate new trajectories, which in turn are used as a stimulus online. An algorithm selects the perturbations, and this algorithm will implement an optimisation procedure based on a Metropolis algorithm—a variant of Monte Carlo. This algorithm will propose perturbations to the reference stimulus so as to maximise the change in the retinal response, while keeping the distance from the reference stimulus below a pre-defined constant. Briefly, perturbations are picked randomly, added to the current trajectory, and tested as a stimulus. The trajectory space is explored in the following way: starting from an initial point, a perturbation is generated and used as a stimulus. This perturbation is accepted if the distance between the response to this stimulus and the response to the initial trajectory (i.e., the reference stimulus) is bigger than for the previous perturbations. Otherwise, this perturbation is rejected with a probability that increases when the effect of this perturbation on the response decreases. Then the loop starts again in order to maximise the impact of the perturbation on the response.

We are currently developing and testing this Monte-Carlo algorithm using a simple model of the retina to test the viability of the strategy. This retina model is composed of a spatio-temporal filter of the stimulus, followed by static non-linearity. The parameters of this model have been fitted on previous data using the same type of stimulus, and this retina model generates spikes according to a Poisson process.

Once we have found a valid strategy for searching the optimal perturbations, we will use the same algorithm on a real retina using our online recording rig.

7. WP4.6 Scientific Coordination

Please refer to Deliverable 4.5.1, European Institute for Theoretical Neuroscience, for a full listing of SP4 events held in M1-M12.

Annex A: Milestones

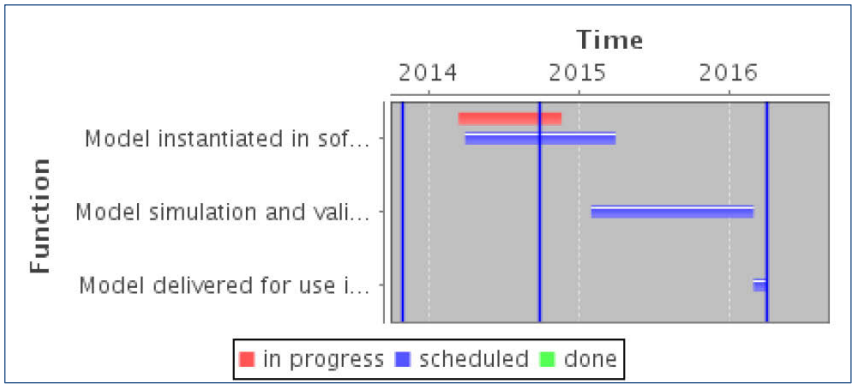
No.	Milestone Name	WP	Month Due	Month Achieved	See Page
M66	Requirements identified.	4.1	6		
M70	Requirements identified.	4.2	6		
M74	Requirements identified.	4.3	6		
M78	Requirements identified.	4.4	6		
M82	EITN workshop programme for first thirty months defined.	4.5	6	12	
M83	European Institute for Theoretical Neuroscience in operation.	4.5	12	6	

Annex B: Scientific Key Performance Indicators (SKPIs)

7.1 WP4.1 "Bridging Scales"

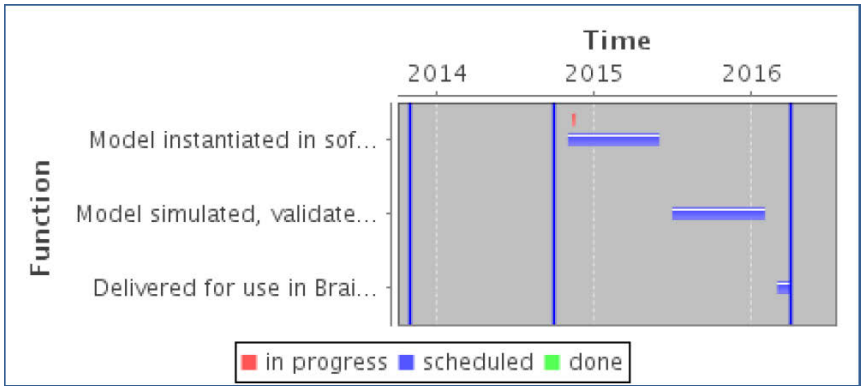
7.1.1 T4.1.1 "Derive simplified neuron and neural circuit models from biophysically morphologically detailed models"

- SP4_SKPI-01: Derive simplified neuron and neural circuit models from biophysically morphologically detailed model
- Responsible: idan@lobster.ls.huji.ac.il
- Model instantiated in software. Planned: 2014/03/31 - 2015/03/31
- Model simulation and validation. Planned: 2015/01/31 - 2016/02/29
- Model delivered for use in Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



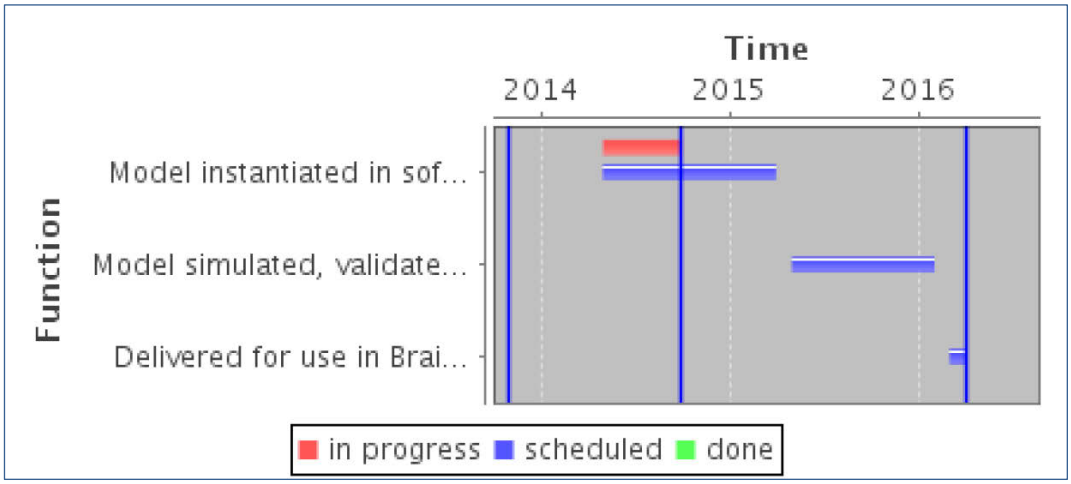
T4.1.2 "Modelling brain signals at different scales from intracellular local field potentials and VSD up to EEG and MEG signals"

- SP4_SKPI-02 Modelling brain signals at different scales, from intracellular, local field potentials, VSD up to EEG and MEG signals
- Responsible: destexhe@unic.cnrs-gif.fr
- Model instantiated in software. Planned: 2014/10/31 - 2015/05/31
- Model simulated, validated. Planned: 2015/06/30 - 2016/01/31
- Delivered for use in Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.1.2 T4.1.3 "Mechanistic Models of Cognition Linked to the Neural Substrate by Population Density Method"

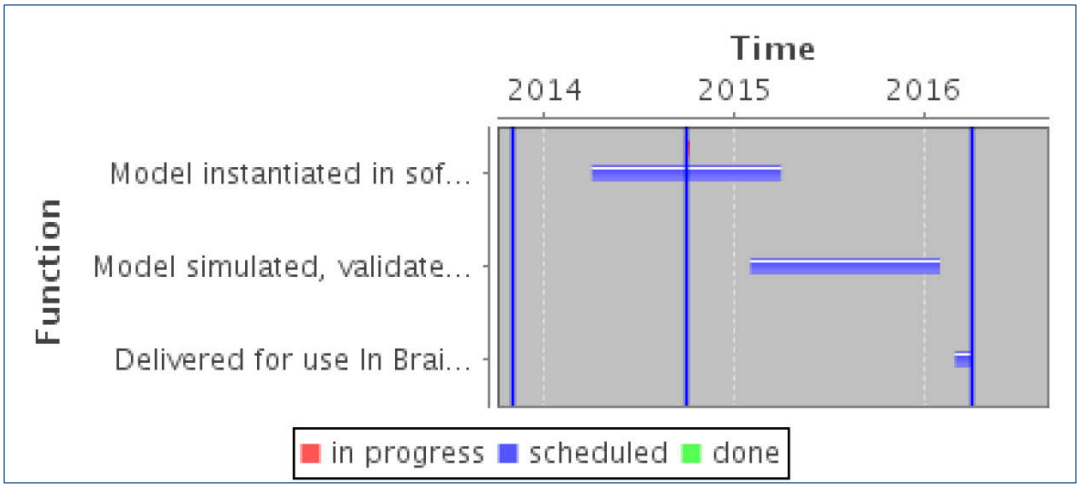
- SP4_SKPI-10 Mechanistic Models of Cognition Linked to the Neural Substrate by Population Density Methods
- Responsible: m.dekamps@leeds.ac.uk
- Model instantiated in software. Planned: 2014/04/30 - 2015/03/31
- Model simulated, validated. Planned: 2015/04/30 - 2016/01/31
- Delivered for use in Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.2 WP4.2 "Synaptic plasticity, learning and memory"

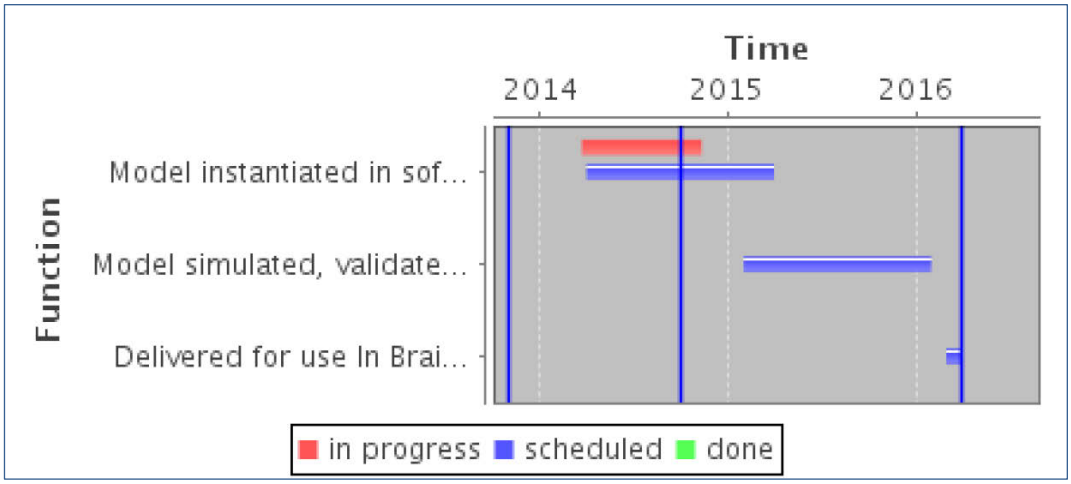
7.2.1 T4.2.1 "Derive learning rules from biophysical synapse models"

- SP4_SKPI-03 Derive learning rules from biophysical synapse models
- Responsible: misha@weizmann.ac.il
- Model instantiated in software. Planned: 2014/04/01 - 2015/03/31
- Model simulated, validated. Planned: 2015/01/31 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



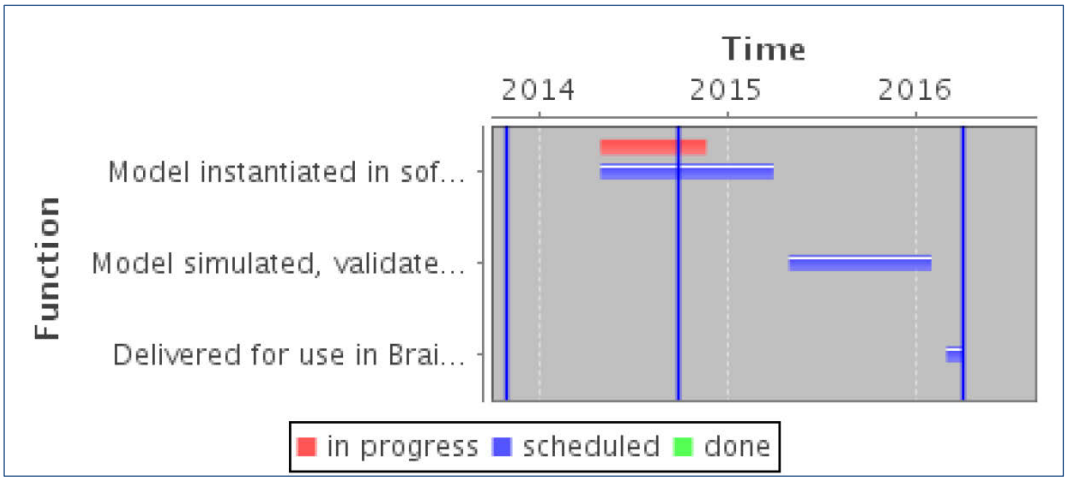
7.2.2 T4.2.2 "Unsupervised learning rules and emergent connectivity"

- SP4_SKPI-04 Unsupervised learning rules and emergent connectivity
- Responsible: wulfram.gerstner@epfl.ch
- Model instantiated in software. Planned: 2014/03/31 - 2015/03/31
- Model simulated, validated. Planned: 2015/01/31 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.2.3 T4.2.3 "Structures of spiking learning algorithms"

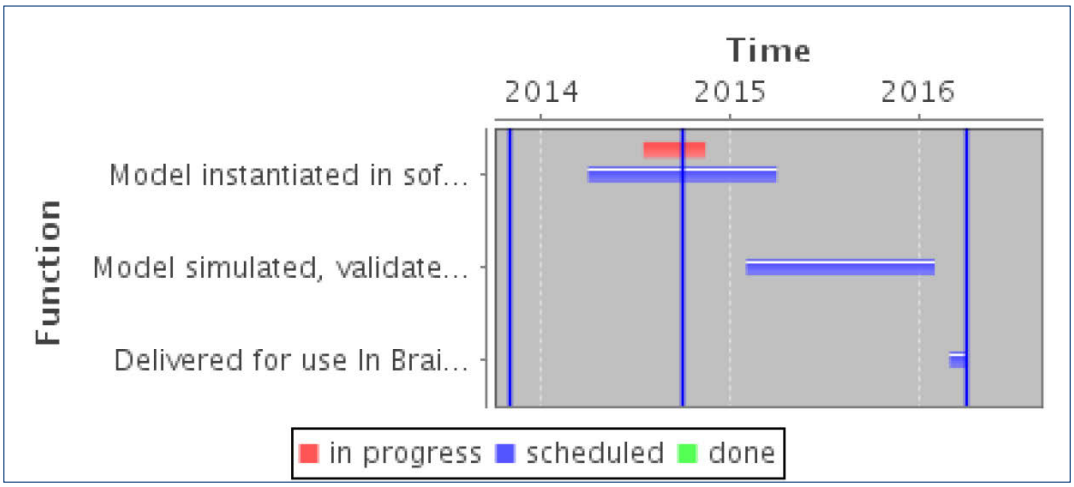
- SP4_SKPI-11 Structures of spiking learning algorithms
- Responsible: a.gruning@surrey.ac.uk
- Model instantiated in software. Planned: 2014/04/30 - 2015/03/31
- Model simulated, validated. Planned: 2015/04/30 - 2016/01/31
- Delivered for use in Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.3 WP4.3 “Large-scale models of human cognitive function”

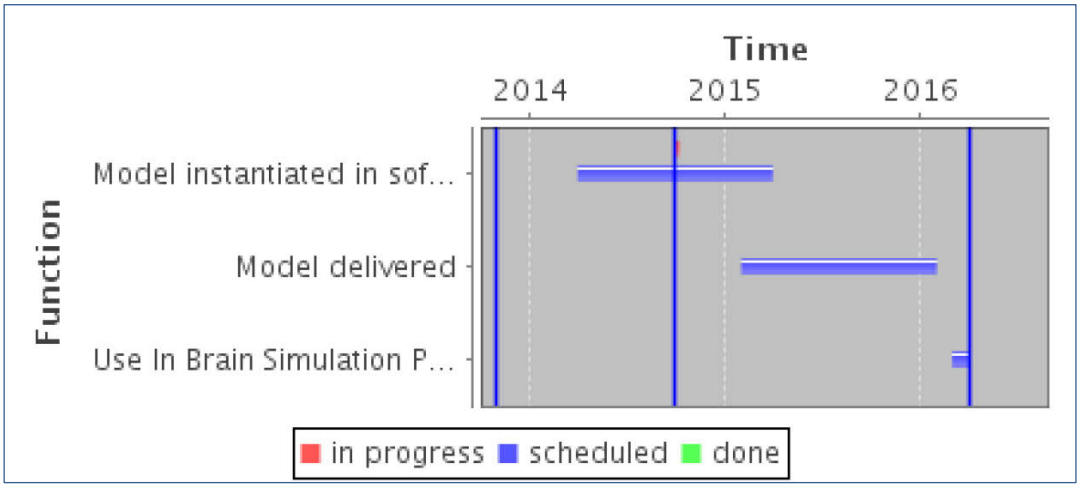
7.3.1 T4.3.1 “Models of perception-action”

- SP4_SKPI-05 Models for perception-action
- Responsible: gustavo.deco@upf.edu
- Model instantiated in software. Planned: 2014/03/31 - 2015/03/31
- Model simulated, validated. Planned: 2015/01/31 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



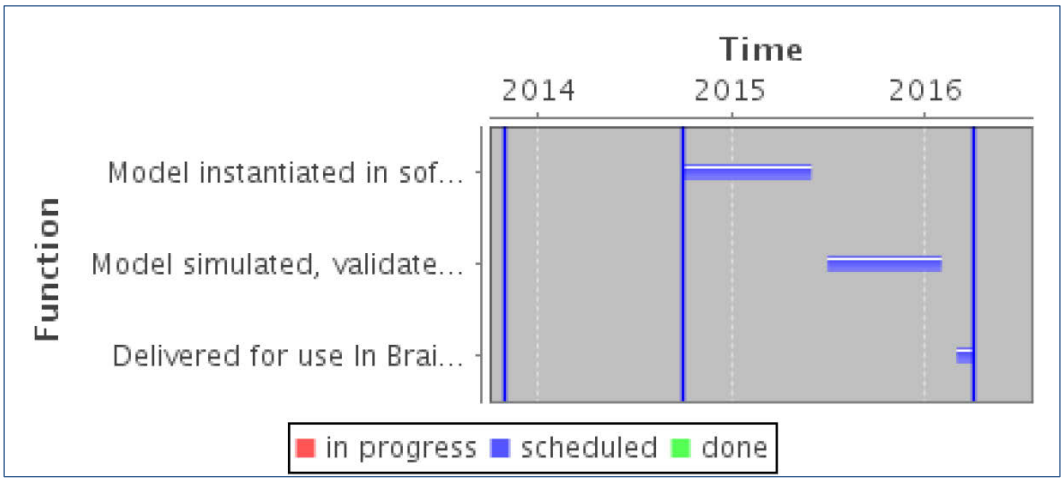
7.3.2 T4.3.2 “Models of working memory and the effects of attention”

- SP4_SKPI-06 Models of working memory and the effects of attention
- Responsible: misha@weizmann.ac.il
- Model instantiated in software. Planned: 2014/03/31 - 2015/03/31
- Model delivered. Planned: 2015/01/31 - 2016/01/31
- Use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



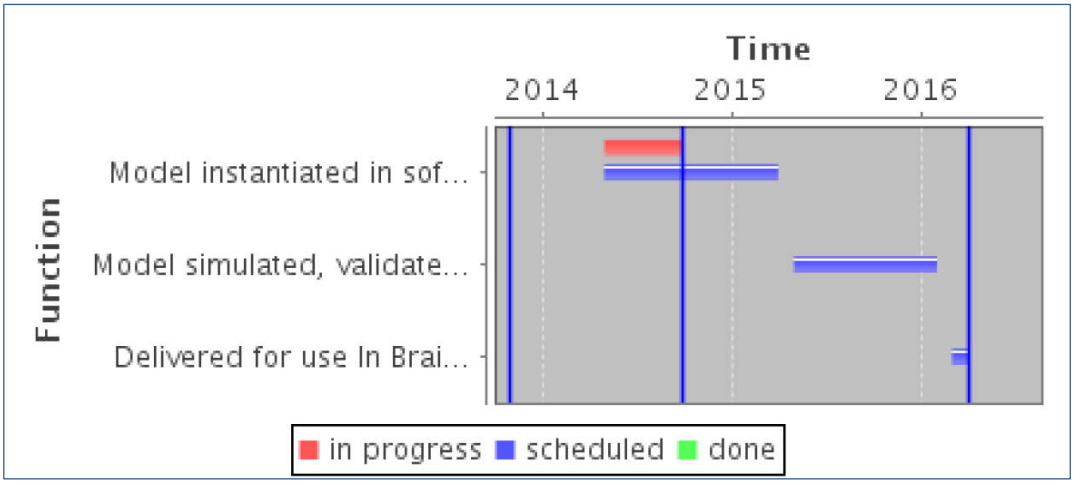
7.3.3 T4.3.3 Models of biologically realistic network states, wakefulness & sleep

- SP4_SKPI-07 Models of biologically realistic network states; wakefulness & sleep
- Responsible: destexhe@unic.cnrs-gif.fr
- Model instantiated in software. Planned: 2014/10/01 - 2015/05/31
- Model simulated, validated. Planned: 2015/06/30 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.3.4 T4.3.4 "Computational model of astrocyte-neuron interaction for future large-scale simulations"

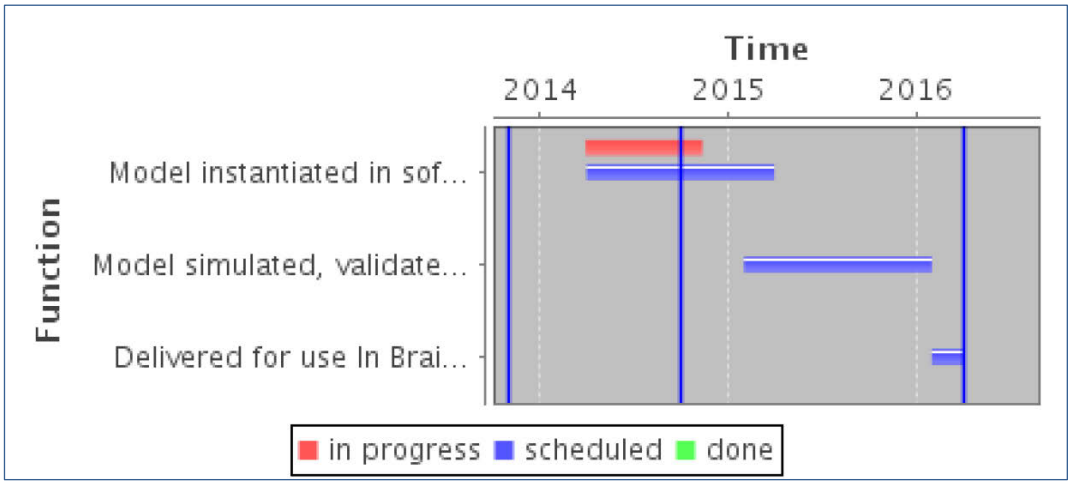
- SP4_SKPI-12 Computational model of astrocyte-neuron interaction for future large-scale simulations
- Responsible: marja-leena.linne@tut.fi
- Model instantiated in software. Planned: 2014/04/30 - 2015/03/31
- Model simulated, validated. Planned: 2015/04/30 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.4 WP4.4 “Principles of brain computation”

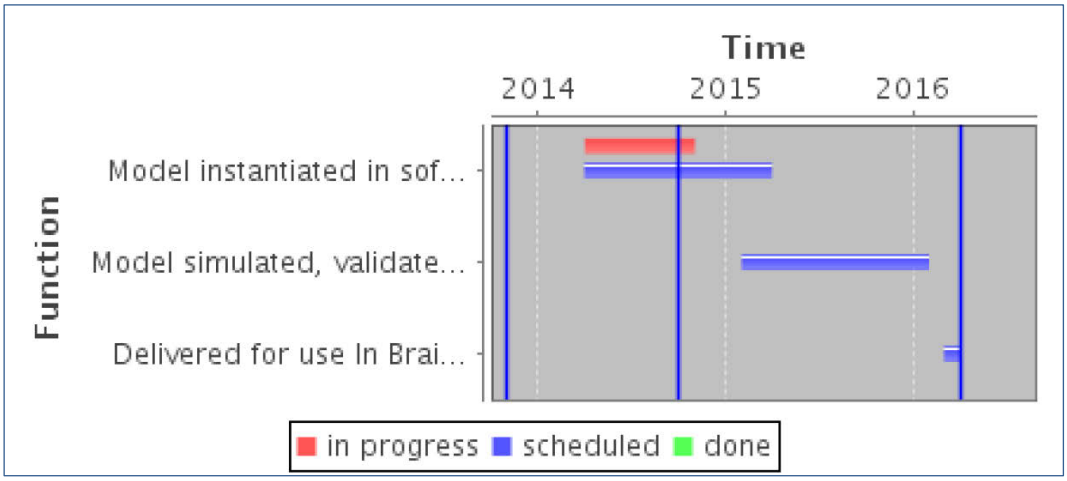
7.4.1 T4.4.1 “Principles of computation in single neurons and neural microcircuits”

- SP4_SKPI-08 Principles of computation in single neurons and neural microcircuits
- Responsible: maass@igi.tugraz.at
- Model instantiated in software. Planned: 2014/03/31 - 2015/03/31
- Model simulated, validated. Planned: 2015/01/31 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/01/31 - 2016/03/31



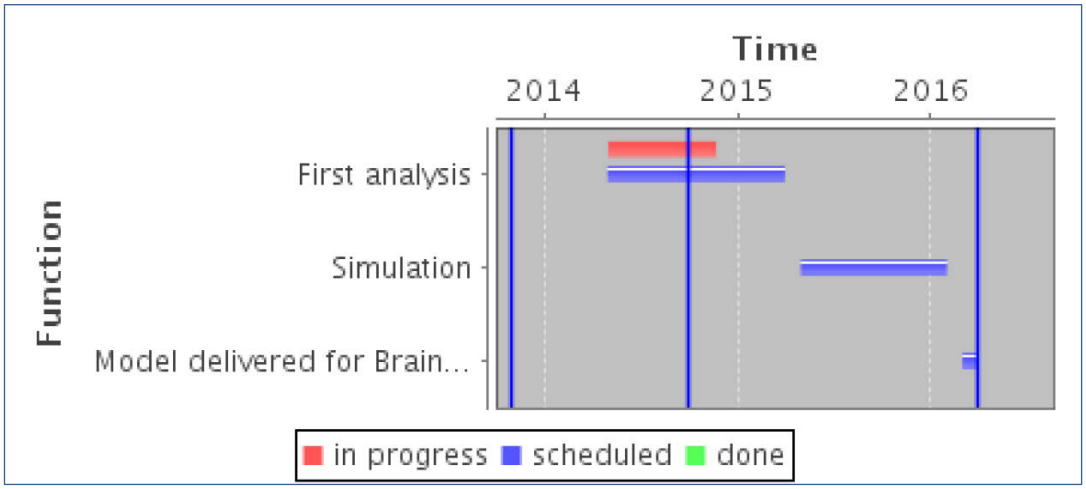
7.4.2 T4.4.2 “Novel computing systems inspired by biology”

- SP4_SKPI-09 Novel computing systems inspired by biology
- Responsible: benjamin.schrauwen@ugent.be
- Model instantiated in software. Planned: 2014/03/31 - 2015/03/31
- Model simulated, validated. Planned: 2015/01/31 - 2016/01/31
- Delivered for use In Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



7.4.3 T4.4.3 "Closed loop analysis of Population coding"

- SP4_SKPI-13 Closed loop analysis of Population coding
- Responsible: olivier.marre@gmail.com
- First analysis. Planned: 2014/04/30 - 2015/03/31
- Simulation. Planned: 2015/04/30 - 2016/01/31
- Model delivered for Brain Simulation Platform. Planned: 2016/02/29 - 2016/03/31



Annex C: References

[1] D. Kappel, B. Nessler, and W. Maass. STDP installs in winner-take-all circuits an online approximation to hidden Markov model learning. PLoS computational biology, 2014

[2] W. Maass. Noise as a resource for computation and learning in networks of spiking neurons. Proceedings of the IEEE, 2014