An Integrated Modelling Framework for Neural Circuits with Multiple Neuromodulators

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Abstract

Neuromodulators are endogenous neurochemicals that regulate biophysical and biochemical processes, which control brain function and behaviour, and are often the targets of neuropharmacological drugs. Neuromodulator effects are generally complex partly due to the involvement of broad innervation, co-release of neuromodulators, complex intra- and extra-synaptic mechanism, existence of multiple receptor subtypes, and high interconnectivity within the brain. In this work, we propose an efficient yet sufficiently realistic computational neural modelling framework to study some of these complex behaviours. Specifically, we propose a novel dynamical neural circuit model that integrates the effective neuromodulator-induced currents based on various experimental data (e.g. electrophysiology, neuropharmacology and voltammetry). The model can incorporate multiple interacting brain regions including neuromodulator sources, simulate efficiently, and easily extendable to large-scale brain models e.g. for neuroimaging purposes. As an example, we model a network of mutually interacting neural populations in the lateral hypothalamus, dorsal raphe nucleus and locus coeruleus, which are major sources of neuromodulator orexin/hypocretin, serotonin and norepinephrine/noradrenaline, respectively, and which play significant roles in regulating many physiological functions. We demonstrate that such model can provide predictions of systemic drug effects of the popular antidepressants (e.g. reuptake inhibitors), neuromodulator antagonists, or their combinations. Finally, we developed user-friendly graphical interface software for model simulation and visualization for both fundamental sciences and pharmacological studies.

Keywords: Computational neural circuit models, neuromodulators, neuropharmacology, orexin/hypocretin, serotonin, norepinephrine/noradrenaline
1. Introduction

Neuronal activities, through the firing of action potentials, and synaptic transmissions can be modulated by endogenous neurochemicals called neuromodulators, acting through biophysical and biochemical processes (1, 2). These neuromodulators are released by a distinct population of neurons, and the neuromodulators act on specific receptors which are distributed throughout the brain (3). Major neuromodulators include serotonin, dopamine, norepinephrine (or noradrenaline), acetylcholine, orexin (or hypocretin), endorphins, and octopamine (3). As a consequence of neuromodulation, neural circuit function can be altered, which in turn can affect cognition, mood and behaviour (3). In neuropharmacological drug treatment of neurological and neuropsychiatric illnesses, the monoaminergic systems (especially that of serotonin, dopamine and norepinephrine) are often targeted (4). These are achieved, for example, by altering the affinity of the associated receptors that influences the release and reuptake mechanism of the monoaminergic systems (5, 6). As neuromodulators can also influence the biophysical properties of the neurons and synapses via multiple receptors with differential affinities, the complexity level in a neuronal circuit function can be substantial (7, 8). Experimental work often focuses on a specific brain region or system (e.g. certain receptor subtype) or employs a specific experimental methodology specific to the single level of biological organization (e.g. whole-cell recording at the neuronal level or voltammetric recording at specific brain region). Thus, it is difficult to reconcile their systemic implications.

Sufficiently realistic computational neural models can help to integrate various data types from different studies, and can also generate testable predictions. However, modelling the detailed biophysical effects of neuromodulators model can be complex and computationally costly (9-11). In particular, neuromodulation often involves intracellular signalling processes at the presynaptic and postsynaptic sites, and can subsequently
affect neuronal firing activities (12, 13). Hence, such computational models that incorporate these biological processes can be time-consuming to develop, and with the multiple model parameters and equations, computationally intensive to evaluate while posing a considerable challenge in scalability.

In this work, we propose a novel neural circuit modelling framework to circumvent such difficulties. To develop a scalable model, we make use of neural population averaged activity (mean-field like) or firing-rate type models that describe how the neural population activities depend on the averaged effective neuromodulator induced currents. The latter are determined by neuromodulators’ concentration levels and the corresponding receptors affinity. Compared to other more abstract population averaged firing-rate type models (14-17), our model parameters describing the input-output functions and temporal dynamics are informed and constrained by data integrated from a variety of experiments, which include electrophysiology, neuropharmacology, radioimmunoassay, voltammetry and microdialysis.

We discuss such modelling approach in the context of developing and simulating a neural circuit model interconnected among the dorsal raphe nucleus (DRN), locus coeruleus (LC) and lateral hypothalamus areas (LHA), which are major sources of the important neuromodulators serotonin (5-HT), norepinephrine (NE), and orexin, respectively. The motivations for selecting these brain systems to model are that they are important in regulating physiological functions especially in arousal, are known to interact mutually with each other, and are the targets of several drugs (13, 18-21). In particular, the neuropeptide Ox is known to play an important role in energy homeostasis, food intake and appetite regulation, neuroendocrine functions and sleep-wake regulation (22-24). The monoamine NE is suggested to be responsible for numerous functions including stress response, attention, emotion, motivation, decision-making, learning, memory, and regulation of sleep
(e.g. REM) (25-30), while the monoamine 5-HT can affect several physiological functions that includes eating behaviour, emotion, and sleep regulation (31-33). Abnormal 5-HT or NE levels are implicated in mood disorders and anxiety (18, 34).

**Figure 1.** Interactions among three brain regions, which are sources of neuromodulators. LHA: lateral hypothalamus; DRN: dorsal raphe nucleus; LC: locus coeruleus. Ox: orexin; 5-HT: serotonin. Arrows: effective excitatory connections between any two areas; circles: inhibitory connections. Different colours denote different brain areas. Small fonts denote receptor subtypes at the target sites (35-39).

The overlapping roles of these neuromodulators are not surprising, given their mutual interconnectivity, and any targeted neurons could themselves be sources of neuromodulators (Fig. 1). We have also purposefully selected the Ox system as a case study to demonstrate how we can model a neural system that may not be well characterised (as compared to NE).

A comprehensive, biologically faithful, yet efficient computational model at the neural circuit level would enable us to conveniently evaluate, account and predict, at a systems level, important measurable variables such as the concentration levels of the neuromodulators, the neural population firing rate activities, the effects of individual or combined drugs (e.g. reuptake inhibitors or antagonists), and their interdependencies.
The organization of the rest of the paper is as follows. We first describe the general modelling framework. Then, as an example, we demonstrate the steps in modelling three mutually interacting brain regions and discuss the simulation results including drug effects. Next, we describe our user-friendly software for simulating and visualizing the behaviour of such models. Finally, we summarise the results and discuss the implications of this study.

2. Results

2.1. An integrated modelling framework

To develop a biologically compatible neural circuit model would require knowledge of electrophysiological properties of the composing neurons in a specific brain region, and the nature of the interactions among themselves and with other neuronal groups. This can include neurons which themselves release neuromodulators. Modelling the release-and-reuptake/decay dynamics of the extracellular concentrations of the neuromodulators would require information inferred from in-vivo voltammetry or microdialysis studies at the targeted sites under neuronal stimulation. We would also need to know how the variation in neuromodulator concentration can in turn affect neural firing rate activities via neuromodulator induced currents, hence requiring knowledge of firing rate-neuromodulator concentration or firing rate-current relationships (Fig. 2). These neuromodulator induced currents typically involve relatively slow metabotropic G-protein-coupled receptor (GPCR) types, e.g. G-protein-coupled inwardly-rectifying potassium (GIRK) or transient receptor potential (TRP) type cation currents (37, 38), on targeted neurons, which alter the neuronal firing rate activities. As discussed, explicitly modelling such signalling pathway mechanisms can be complex and computationally intensive if
large-scale neural circuits are involved. To circumvent such challenges, we turn to phenomenological yet biologically faithful models to mimic the overall effects.

Figure 2. Incorporating afferent currents from neuromodulator concentration levels. 

\[ [y_1] \ldots [y_n] \] denote the different neuromodulator concentrations. \( i \) represents a particular targeted brain region. \( I_{j \rightarrow i} \) is the corresponding induced currents to region \( i \). \( I_{Total,i} \) is the total afferent current and \( f_i \) is the firing frequency in region \( i \). For example, \( [y_1] \) and \( [y_2] \) may be the concentration levels of serotonin \( [5-\text{HT}] \) and norepinephrine \( [\text{NE}] \), and \( i \) can be the lateral hypothalamus LHA. The big arrow denotes “closing the loop” in the modelling process.

To begin the modelling process, we first model the neural activity for each brain region using neural population averaged activity (40). Since the time-constant of the typical neural population firing-rate dynamics is \( \sim 10-100 \) msec, it is much faster than the dynamics due to neuromodulators, which is \( \sim \) sec to min (Table 1). Hence, we shall ignore the neural population dynamics and assume the system to be dominated by the slower neuromodulator induced dynamics (41). In general, different neuronal types can respond differently (in terms of firing rate activity) to the same current injection. In experiments, such relationship is demonstrated by the frequency-current \( (f-I) \) relationship. In a similar vein, we can describe the \( i \)-th neural population by the population firing rate-current \( (f-I) \) curve or input-output function (42).
where \( f_i \) is the population firing rate, \( F_i \) the input-output function, and \( I_{\text{Total},i} \) the total averaged afferent current. Under typical physiological ranges, it suffices to use a threshold-linear function (42).

\[
F_i(I_{\text{Total},i}) = K_i [I_i - I_{0,i} + I_{\text{Bias},i}]_+
\]

(2)

where \([x]_+ = x\) if \(x > 0\), and 0 otherwise. \( K_i \) is the constant gain or slope of the input-output function, \( I_{0,i} \) is the threshold current for non-zero firing, and \( I_{\text{Bias},i} \) is the current coming from other brain areas. Thus, after a specific threshold value of the averaged afferent current, the neural population will be activated, and there is a linear relationship between the neural firing rate and the overall afferent current. We shall later show that this function fits the experimental data for Ox, 5-HT and NE neurons.

In general, the afferent current \( I_i \) can consist of several different types of currents mediated by the different modulators and their receptor subtypes. Each of these currents will be determined by the corresponding neuromodulator concentration levels and the receptor affinities (Fig. 2). For example, suppose a neuromodulator \( y \) from region \( j \) induces a current \( I_{j \rightarrow i} \) on target region \( i \), then we can describe the dynamics of the current by,

\[
\tau_{j \rightarrow i} \frac{dI_{j \rightarrow i}}{dt} = -I_{j \rightarrow i} + G_{j \rightarrow i}([y])
\]

(3)

where \([y] \) is the neuromodulator concentration level, and \( \tau_{j \rightarrow i} \) is the effective time constant due to the applied neuromodulator which can be estimated from experiments. (If there are more than one receptor subtypes mediated by the same neuromodulator over the same brain regions, we can specify the above variables further, e.g. by defining \( \tau_{j \rightarrow i,R} \) and \( I_{j \rightarrow i,R} \) for a receptor subtype \( R \).) The value of \( \tau_{j \rightarrow i} \) can be deduced from the response dynamics of the induced current (or neural firing rates, if the induced current data is not available) upon infusion of specific neuromodulator at the targeted neurons. The input-output
function $G_{j\rightarrow i}$ can be described by the sigmoid like function commonly used in pharmacology (43):

$$G_{j\rightarrow i}(\{y\}) = p_{j\rightarrow i,LR} + \frac{p_{j\rightarrow i,UR}}{1+\exp\left(-\frac{\log(10) \times p_{j\rightarrow i,LS}}{p_{j\rightarrow i,UR}}\right)}$$ (4)

where $p_{j\rightarrow i,LR}$ and $p_{j\rightarrow i,UR}$ determine the range of the neuromodulatory effect on the currents, and $p_{j\rightarrow i,LS}$ and $p_{j\rightarrow i,LS}$ control the lateral shift and the slope of the neuromodulator response current function, respectively. The values of these parameters will be fitted to experimental data through firing rate-neuromodulator concentration or firing rate-current relationships. We used the standard nonlinear regression method, nlinfit from MATLAB (The MathWorks Inc., Natick, MA, 2000). This approach particularly allows us to circumvent the complexity of actually simulating the intracellular signal transduction at the post-synaptic neurons. This post-synaptic current depends upon the extracellular neuromodulator release which is in turn dependent on the (pre-synaptic) neural population firing rate of the source neurons. Thus, to close the loop in the model, we have to mathematically describe how the release-and-reuptake dynamics are affected by the neural firing rate of the neuromodulator source. We follow a mathematical form similar to that estimated from voltammetric measurements (44):

$$\frac{d\{y\}}{dt} = \{y\}_{p,j\rightarrow i} f_j - \frac{V_{\text{max}} \{y\}}{K_m + \{y\}}$$ (5)

where $\{y\}_{p,j\rightarrow i}$ is the per stimulus $\{y\}$ release (at the targeted area $i$ from source $j$). The rightmost term in Equation (5) represents the reuptake rate, and is approximated from the Michaelis-Menten equation. Here, $K_m$ and $V_{\text{max}}$ are the Michaelis-Menten constants, with $V_{\text{max}}$ defined as the maximum uptake rate and $K_m$ the substrate concentration where the uptake proceeds at half of the maximum rate. The value for both of these parameters can be obtained from experiments (44). In voltammetry experiments, $f_j$ is typically an artificially applied high current stimulus frequency to stimulate the release of $y$. However, following our previous work (45), we can redefine it as the neural firing frequency of the...
neuromodulator source. Hence the value of $[y]_{p,j-i}$ has to be adjusted from that in voltammetry experiments, and the exact value in the model can be obtained by constraining the overall basal activity levels of the system to be within the observed experimental ranges (see below).

For the case of Ox, there is a lack of available experimental data, particularly its release and reuptake dynamics. Hence we adopt the simplest mathematical form to describe the Ox dynamics (45), with only 2 parameters:

$$\frac{d[Ox]}{dt} = \alpha f_{LHA} - \eta [Ox]$$

(6)

where $\alpha$ is the rise-factor and $\eta$ a constant decay rate, and both considered to be free parameters. The value of $\alpha$ is selected so that the release of [Ox-A/B] at DRN or [Ox-A] at LC is close to the observed basal value (see Table 1).

A summary of the general model construction process is summarised in Fig. 2. Such a modelling approach can allow multiple brain regions to be constructed, simulated, and analysed. (See Methods for a simpler approach when only two brain regions are considered). Overall, we have proposed an efficient and scalable approach by incorporating neuromodulator properties and dynamics into traditional firing-rate type models. We shall next apply this approach to develop a neural circuit model involving multiple interacting neuromodulators.

### 2.2. An example with three interacting neuromodulators

We shall now demonstrate, as an example, the steps towards developing a neural circuit model of 3 interacting neuromodulator systems (lateral hypothalamus, dorsal raphe nucleus and locus coeruleus) through 3 corresponding neuromodulators (Ox, 5-HT and NE), based on available experimental data and Equations (1)-(6). These brain regions
were chosen mainly because: (i) they consist of different neuromodulator systems that can directly influence each other; (ii) they were targets of existing drugs, and (iii) we can demonstrate how one could model with incomplete information. It is important to bear in mind that different datasets from various experiments are used for model construction and validation.

First, the frequency-current \((f-I)\) curves for neurons from the 3 brain regions are determined according to the available electrophysiological data \((f-I\) curves and typical baseline firing rate ranges). Using the threshold-linear function (Equation 2), the fitted parameter values for the LC’s NE neuronal \(f-I\) curve are \(k_{LC} = 0.058 \text{ Hz}/\text{pA}, I_{0,LC} = 0.028 \text{ pA}\) and \(I_{\text{Bias},LC} = 37.41 \text{ pA}\) (46); that for DRN’s 5-HT neuron are \(k_{DRN} = 0.033 \text{ Hz}/\text{pA}, I_{0,DRN} = 0.13 \text{ pA}\) and \(I_{\text{Bias,DRN}} = 24.82 \text{ pA}\) (11, 47, 48); and that for LHA’s Ox neuron are \(k_{LHA} = 0.2 \text{ Hz}/\text{pA}, I_{0,LHA} = 0 \text{ pA}\) and \(I_{\text{Bias,LHA}} = 11.5 \text{ pA}\) (49).

Next, parameters of the induced currents and associated \(G\) functions are fitted to the experimental data through the concentration–response relationships for the change in firing-rate induced by the neuromodulator. For example, the total afferent current induced by neuromodulators on DRN’s neurons can be rewritten as a sum: \(I_{DRN} = I_{LHA \rightarrow DRN} + I_{LC \rightarrow DRN}\). The terms on the right are the currents due to Ox-A/B from LHA and NE from LC (for simplicity, we ignore the current due to autoreceptors and interneurons within each brain region, see (17, 50)). The dynamics for each induced current are dependent on the concentration of the neuromodulator. The Ox induced current on DRN neurons (when NE induced current on DRN is clamped) can be described by

\[
\tau_{LHA \rightarrow DRN} \frac{dI_{LHA \rightarrow DRN}}{dt} = -I_{LHA \rightarrow DRN} + G_{LHA \rightarrow DRN}(\lbrack Ox\rbrack) \tag{7}
\]

where \(\tau_{LHA \rightarrow DRN}\) is the effective time constant due to the injected Ox deduced from experiments. The \(G_{LHA \rightarrow DRN}\) function (from Equation 4, with units of currents) parameters
are fitted to experimental data (51), such that $p_{LR} = 0 \, \text{pA}$, $p_{UR} = 65 \, \text{pA}$, $p_{LS} = -2.08 \, \text{nm}$, $p_s = 0.452 \, \text{nm}$, and $\tau_{LHA\rightarrow DRN} = 60 \, \text{s}$. With these values, we obtain the best fit for the overall firing rate-concentration function (Fig. 3A), having the induced currents becoming an implicit function.

Similarly, we can obtain the parameter values for the other currents: $I_{LC\rightarrow DRN}$, $I_{LHA\rightarrow LC}$ and $I_{DRN\rightarrow LC}$. The fitted parameter values for $I_{LC\rightarrow DRN}$ are $p_{LR} = 0 \, \text{pA}$, $p_{UR} = 57 \, \text{pA}$, $p_{LS} = -3.7 \, \text{nm}$, $p_s = 0.193 \, \text{nm}$, and $\tau_{LC\rightarrow DRN} = 20 \, \text{s}$ (Fig. 3B)(52). Parameter values for the incoming current from LHA to LC neurons $I_{LHA\rightarrow LC}$ are found to be $p_{LR} = 3.8 \, \text{pA}$, $p_{UR} = 54 \, \text{pA}$, $p_{LS} = -2.3 \, \text{nm}$, $p_s = 0.341 \, \text{nm}$, and $\tau_{LHA\rightarrow LC} = 20 \, \text{s}$ (36) (Fig. 3C). For $I_{DRN\rightarrow LC}$: $p_{LR} = 0 \, \text{pA}$, $p_{UR} = 40 \, \text{pA}$, $p_{LS} = 4.214 \, \text{nm}$, $p_s = 0.347 \, \text{nm}$, and $\tau_{DRN\rightarrow LC} = 20 \, \text{s}$ (Fig. 3D). With these parameter values, we were able to obtain reasonable fits with respect to experiments for the various input-output functions.
We now proceed to model the effects of 5-HT on LC’s NE neurons. However there is a lack of experimental data on the direct effects of 5-HT on LC’s NE neurons (experiments typically focused on how different 5-HT₂ receptor agonists affect the firing rate of LC neurons (53)). Thus to estimate the 5-HT dependent input-output function of firing frequency, we approximate the input-output function from other experimental data by restricting the basal activities to $[5 - HT] \sim 0.11 \, fM$ and $f_{LC} \sim 2.15 \, Hz$ (see Table I). We considered the same sigmoidal shape (as defined in Eq. 4) for all the neuromodulator dependent firing-rate function which is defined as follows:

$$H_{j \rightarrow i}([y]) = q_{j \rightarrow i,LR} + \frac{q_{j \rightarrow i,LR}}{1 + \exp\left(-\frac{\log_{10}(1^\gamma + q_{j \rightarrow i,LS})}{q_{j \rightarrow i,LS}}\right)}$$

Figure 3. Fitted input-output functions. (A-B) Effects of concentrations [Ox-A/B] and [5-HT] on DRN neurons. (C-D) [5-HT] and [NE] on LHA neurons. (E-F) [Ox-A] and [5-HT] on LC neurons. Estimated function (pink) is based on $f$-$I$ curves and current input-output functions.
where \( q_{j \rightarrow i,LR} \) and \( q_{j \rightarrow i,UR} \) determine the range of the neuromodulatory effect on the firing-rate, and \( q_{j \rightarrow i,LS} \) and \( q_{j \rightarrow i,LS} \) control the lateral shift and the slope of the neuromodulator concentration dependent firing-rate function \( H_{j \rightarrow i} \), respectively. Considering these baseline values, the estimated parameter values are \( q_{LR} = 2.15 \text{ Hz}, \ q_{UR} = -2.15 \text{ Hz}, \ q_{LS} = 4.273 \text{ nM} \) and \( q_{S} = 0.3 \text{ nM} \) (54).

Similar to the 5-HT modulating effect on LC, the 5-HT response direct firing frequency curve was not available for LHA neurons. Thus, we approximate the input-output function from other experimental data (38, 55) and restricting the basal activities to \([5-\text{HT}] \sim 1.6 \text{ nM} \) and \( f_{LHA} \sim 2.3 \text{ Hz} \). Then the estimated parameter values are \( q_{LR} = 2.3 \text{ Hz} \), \( q_{UR} = -2.3 \text{ Hz} \), \( q_{LS} = 0.9 \text{ nM} \), \( q_{S} = 0.1 \text{ nM} \) (37). Then we approximated the parameters for \( I_{\text{DRN-LHA}} \) to be: \( p_{LR} = 0 \text{ pA}, p_{UR} = 36 \text{ pA}, p_{LS} = -1.55 \text{ nM} \), and \( p_{S} = 0.4 \text{ nM} \). With these values, we observe that there is no Ox neuronal firing even for \( 10 \mu \text{M} \) of [5-HT] (Fig. 3E). This is due to the strong inhibition caused by the induced inward GIRK current (~32 pA), which eventually saturates (at ~35 pA) for higher [5-HT] levels.

As the model has a hard threshold in the \( f-I \) curve, there is a sharp change within the 10 ~ 100 nM of [5-HT]. Thus, we could not obtain a perfect fit for the functions \( G_{\text{DRN-LHA}}([5 - \text{HT}]) \) and hence the \( f_{LHA} - [5 - \text{HT}] \) curve. Similarly, the fitted parameters for the NE induced GIRK currents on LHA, \( I_{\text{LC-LHA}} \), are \( p_{LR} = 0 \text{ pA}, p_{UR} = 120 \text{ pA}, p_{LS} = -5.39 \text{ nM}, p_{S} = 0.4 \text{ nM} \) and \( \tau_{\text{LC-LHA}} = 1 \text{ s} \) (56). We encounter a similar issue for higher [NE] level, i.e. no perfect fit for \( G_{\text{LC-LHA}} ([5 - \text{HT}]) \) (Fig. 3F).

Compared to the effect of 5-HT on the target areas, estimating the parameter values (q’s) for the effect of NE/Ox on the target areas was relatively straight forward. As experimental data related to neuromodulator dependent firing-rate input-output function was available.

We approximated the q values for the Ox effect of DRN as \( q_{LR} = 0.8 \text{ Hz}, q_{UR} = 2.2 \text{ Hz}, \ q_{LS} = 4.273 \text{ nM} \) and \( q_{S} = 0.3 \text{ nM} \) (54).
\[ q_{LS} = -2.072 \, nM, \quad q_S = 0.4463 \, nM \] (36). q values for the Ox effect of LC are \[ q_{LR} = 2.35 \, Hz, \quad q_{UR} = 3.15 \, Hz, \quad q_{LS} = -2.3066 \, nM, \quad q_S = 0.3468 \, nM \] (36). Similarly q values for the NE effect of LHA are estimated as \[ q_{LR} = 2.3 \, Hz, \quad q_{UR} = -2.3 \, Hz, \quad q_{LS} = -4.235 \, nM, \quad q_S = 0.302 \, nM \] (56). For NE effect on DRN are \[ q_{LR} = 0.8 \, Hz, \quad q_{UR} = 0.193 \, Hz, \quad q_{LS} = -3.711 \, nM, \quad q_S = 0.208 \, nM \] (39).

After determining the input-output functions and dynamics for all the currents, the final step is to integrate all three brain regions and their interactions. In general, the activities for the combined system will be different from the individual isolated systems. Thus, the baseline activities of the coupled system will be different from that observed from the individual systems. However, the remaining set of parameters, the neuromodulator release per-stimulus frequencies, i.e. the \([y]_p\)'s can be adjusted to resolve this. We found that for values of \([5-HT]_{p,LHA}, [5-HT]_{p,LC}, [NE]_{p,DRN}, \text{ and } [NE]_{p,LHA}\) at 12.14 nM, 0.852 fM, 27.272 nM and 0.0642 nM, respectively, and Ox rise-factor and decay rate (\(\alpha\) and \(\eta\)) for DRN are 1.405 and 0.85 1/s while for LC are 0.2314 nM and 0.85 1/s, the overall basal firing rates and concentration levels are reasonably within the experimental ranges (Table I). Note that the baseline activities are obtained after sufficiently long simulation to attain their (stable) steady states (see Fig. 4 for a sample trial).

After successfully constructing the LHA-DRN-LC circuit model, we shall demonstrate simulating neuropharmacological drug effects in the system. In particular, we shall focus on Ox-1 receptor antagonist (SB-334867-A), SSRIs and/or SNRIs on the LHA-DRN-LC circuit.
Figure 4. Single trial activity dynamics under baseline condition. (A) Firing-rate of DRN neural population. (B, C) Concentration level of 5-HT in the LHA and LC areas.

2.3. Drug effect simulations

Pharmacologically, antagonists can be classified into two categories, competitive and irreversible antagonists (57). Pre-treatment or application of competitive antagonist can shift the baseline dose response curve horizontally. This shift towards the higher doses (of neurotransmitter) increases the effective dose (ED\textsubscript{50}) value of the dose-response curve (where 50% of the maximal response of the dose is being observed). Conversely, application of an irreversible antagonist can cause shifts in the maximum range of the antagonist effect and does not affect the ED\textsubscript{50} value (58).

Ox-1 receptor antagonists have been suggested to encourage sleep, as well as treatment and prevention of many psychiatric disorders (59). In particular, the Ox-1 receptor antagonist, SB-334867-A, acts as a competitive antagonist which rightward shifts the Ox-A response curve in 5-HT and NE neurons in DRN and LC (36, 60). Thus, we can easily incorporate the effect of SB-334867-A, by simply laterally shifting the function $G_{LHA\rightarrow DRN/LC}([Ox-A])$.

Selective serotonin/norepinephrine reuptake inhibitors (SSRIs/NRIs) are some of the commonly known pharmacological agents that are used for the treatment of various psychiatric disorders. The basic (acute) actions of these drugs are similar: primarily to
increase the extracellular concentration level of their respective neuromodulator
concentration by inhibiting the uptake process and reduce the synaptic clearance in the
extracellular space (61). There have been numerous studies conducted to understand the
effects of uptake inhibitors on [5-HT] uptake (61, 62). In particular, John et al. (62) shows
that monoamine uptake inhibitors can affect the values of the Michaelis-Menten constants
$K_m$ and $V_{max}$ in the limbic part of the brain. For example, a 10 $\mu$M of fluoxetine, a SSRI
(when applied to the substantia nigra area) increased the value of $K_m$ by about a factor of
5 but did not alter the value of $V_{max}$ significantly (61). Thus, to incorporate the influence of
SSRIs/NRIs in our model, we can mimic the different doses of SSRIs by varying the
different values of $K_m$. For simplicity, our model will ignore chronic or other long-term
secondary actions such as receptor density changes.

As we increase the value of $K_m$ (mimic SSRI), [5 – HT] linearly increases in both the
targeted areas LHA and LC (Figs. 5A and H, solid blue). This increase in [5-HT] level
causes a significant decrease in $f_{LHA}$ (Fig. 5C, solid blue), which is consistent with
experimental findings (37). This in turn causes a decrease in [Ox-A/B] levels in the DRN
and LC areas (Figs. 5D and G, solid blue). Interestingly, because of the network effect,
there is a subsequent decrease in $f_{DRN}$ (Fig. 5F, solid blue), consistent with (63) even
when we did not incorporate any inhibitory 5-HT autoreceptors (64, 65). However, 5-HT’s
effect on LC’s NE neurons is minimal, consistent with (66), and therefore $f_{LC}$ does not alter
the [NE] levels in the DRN and LHA significantly (Fig. 5I, solid blue). These effects
remained to be validated in the intact brain.
Figure 5. Effects of substrate concentration factor $K_m_{[5-HT]}$ and $K_m_{[NE]}$, and $[Ox−A]$ antagonist SB-334867-A on the firing rates and concentration levels in the circuit.

Each panel varies both $K_m_{[5-HT]}$ and $K_m_{[NE]}$ values to simulate the effects of drugs and their combinations. $K_m_{[NE]} = 400\ \text{nM}$ (control basal value).

Next, we simulate the combined effects of SSRIs and NRIs, by increasing the value of $K_m_{[NE]}$ to 3 and 5 times its control value (400 nM) while varying $K_m_{[5-HT]}$ as previously. The model shows that for higher values of $K_m_{[NE]}$ more [5-HT] and [NE] are released in the targeted areas in the LHA and LC as compared to controls (Figs. 5A and H, dashed red and dotted-dashed pink). This suggests that other than $K_m_{[5-HT]}$, [NE] release in DRN also helps stimulate the release of [5-HT] in these targeted areas, consistent with (67).

This rise in the [5-HT] level significantly affects $f_{LHA}$, $[Ox−A/B]_{DRN}$, $[Ox−A]_{LC}$, $[NE]_{DRN}$ and $[NE]_{LHA}$ while there is little impact on $f_{LC}$ (Figs. 5B-E, G and I).
Finally, to assess the combined effect of SSRIs, NRIs and SB-334867-A, we set $K_{m,[NE]}$ to be 5 times the control value and mimic the influence of 10 $\mu M$ SB-334867-A on DRN and LC (by changing the $p_{LR}$ value from 3.8 to 2 $pA$, $p_{UR}$ from 54 to 51 $pA$, shift factor $p_{LS}$ from $-2.3$ to $-4.192$ $nM$, and slope factor $p_S$ from $0.341$ to $0.592$ in LC). For DRN, $p_{LS}$ is changed from $-2.08$ $nM$ to $-2.97$ $nM$ and $p_S$ from $0.452$ to $0.367$. We find that this triple-drug combination can cause a further decrease in the $f_{DRN}$ and $f_{LC}$, and a substantial reduction in $[NE]_{DRN}$ levels (Figs. 5E-F and I, solid green), while the rest are not significantly affected by the addition of SB-334867-A (Figs. 5A-D, G-H, solid green).

2.4. Software for model simulation and visualization

Using MATLAB, we have designed and developed a software, called “NModC” (Neuromodulator circuit), with friendly graphical user interface (GUI) for simulation, analysis and visualization of the types of models described. The software is easy to use, and can easily be generalized to additional brain regions, other neural sub-populations, and neuromodulator types. The user can visualize the activities of multiple brain regions dynamically and simultaneously. These brain regions are embedded in a rotatable 3-D glass brain using standard Montreal Neurological Institute (MNI) coordinates (Fig. 6A). The user can also further specify brain regions of interest to find the dynamical variables’ time courses and mutual relationships (Fig. 6B) for more detailed analysis. The model parameters can be easily altered to visualize the variation in the steady-state values of the transients of neuromodulator concentration level and firing-rates, and can also compare the firing-rates of the two brain regions (Fig. 6C). Further details are described in the Methods section and the software is available at https://github.com/vyoussofzadeh/NModC.
Figure 6. Screenshot of the NModC software. A user friendly GUI of neuromodulator neural circuit model that can simulate, analyse, visualize and edit. (A) Users can run the model to visualize the results within a rotatable 3-D glass brain after pressing the ‘Start’ button. The user can stop the simulation using the ‘Stop’ button. Simulation time parameters can be controlled using ‘Time’ and ‘Sim scale’, and the GUI can be closed using ‘Close’ buttons. (B) Model variables’ time courses and their mutual relationships can be observed using the ‘Outputs’ button. (C) Model variables’ exact values can be found and model parameters edited upon pressing the ‘Parameters’ button. ‘Default’ returns to
default model parameters and ‘Simulate’ re-run the model after editing the parameter values.

3. Discussion

In this work, we have proposed a new computational modelling framework for incorporating essential biological features of neuromodulation in neural circuits. This provides a computational platform to link from low-level neurobiology to large-scale brain activities.

Our framework is based on the population averaged firing-rate type of model which have model parameters constrained by neurobiology. This is to be compared to other firing rate type models without such constraints (14-16). The model integrates pharmacological and electrophysiological data from separate experimental studies to constrain the input-output neuronal functions, and also the timescale and profile of the effective neuromodulator induced currents. Another key difference in our modelling approach is the consideration of the release-and-reuptake/decay dynamics of the extracellular neuromodulator concentration level which can be inferred from voltammetry. By doing this, we circumvented modelling the complex intracellular biochemical processes, but instead, directly modelled the concentration dependent effect on neural firing rate activity based on pharmacological-electrophysiological data.

In particular, to allow our approach to be generalizable to multiple interacting brain regions, we introduced neuromodulator induced currents to bridge the gaps between neuromodulator concentration levels and targeted neural firing rate activities – afferent influences from different brain regions can be accounted by their summed currents. The timescale and response curve of the neuromodulator concentration dependent currents
were constrained by data from combined pharmacological and electrophysiological experiments.

We demonstrated our modelling approach with the example of a neural circuit that involves three mutually interacting brain regions (LHA, DRN and LC), which are also sources of three different neuromodulators: orexin, serotonin and norepinephrine respectively. The transient and steady-state dynamics of the experimentally measurable variables (neural firing rates and neuromodulators’ extracellular concentration levels) could be easily simulated. In particular, our model supported the co-existence of the observed (steady-state) baseline firing rates and neuromodulator levels found in separate experiments.

An important application of our model was the prediction of the effects of neuropharmacological drugs on neural circuits. We simulated the effects of SSRIs, NRIs and Ox-1 receptor antagonist on the LHA-DRN-LC model. We first showed that SSRIs could have a wide effect on the neural circuit, except the LC-NE system. Interestingly, SSRI could inhibit the DRN (decrease in \( f_{\text{DRN}} \)), the source of 5-HT, even though we did not implement its inhibitory autoreceptors. This effect was essentially due to the direct effects on serotonin heteroreceptors on the LHA and LC, which in turn inhibited the DRN. Similar circuit-based effects could be explained for the addition of NRIs and/or Ox-1 receptor antagonists.

The constructed LHA-DRN-LC circuit model turned out to be dominated by a unidirectional influence between any pair of interacting brain areas (Fig. 5). Hence, these result in monotonic relationships (either increased or decreased) as the model parameters (e.g. \( K_m \)) were varied. However, this need not generally be the case. For example, a more balanced (especially excitatory-inhibitory) coupled network could easily lead to emergent circuit oscillations or even non-monotonic effects (8, 68). In the latter case, it might then
be possible to search for the optimal drug dosage. In fact, we had shown evidence of such nonlinear emergent behaviour when the model incorporated autoreceptors and non-principal (e.g. inhibitory GABAergic) interneurons (to mediate indirect connections) (17). Moreover, the excitatory-inhibitory balance of the network can also be influenced by the co-release of the neurotransmitters (e.g. glutamate) (69, 70). In this case, our framework can still accommodate this by introducing additional dynamical equations to describe the effects of glutamate or GABA (for the same pre-synaptic firing rate).

Our work has also shown that administration of multiple drugs (serotonin/norepinephrine reuptake inhibitors and Ox-A antagonist) simultaneously can be simulated in neural circuits to search for the optimal mixture of drugs. However, the results remain to be validated as there is a lack of such work done in experiments. Hence, this will form model predictions that can help experimentalists in designing future studies. For example, multi-electrode array (MEA) in-vivo recordings can be designed to study the wide-ranging effects of drugs on different brain areas. It would also be interesting to use the model to minimize the side effects of drugs, which is an important issue in neuropharmacology.

Our modelling framework is scalable to incorporate multiple brain regions and hence can be used to study large-scale brain effects. This includes studying the changes in REM/non-REM stages or sleep-wake cycle (15, 16), cortical dynamics (8), and cognitive-emotional processing (8, 68). This would require extending our current GUI software by including cortical brain structure and their connectivity with the neuromodulator sources. Thus these models could potentially reveal insights into the relationships among various brain and behavioural disorders (depression, addiction, antidepressants, and sleep disorders). Importantly, neuroimaging data, especially from positron emission tomography and functional magnetic resonance imaging (fMRI), could potentially be incorporated into our modelling framework, bridging across multiple scales and modalities, similar in spirit to the
popular dynamic causal modelling approach (71). Interestingly, recent whole brain
molecular imaging (functional MRI) of serotonin transporter to characterise 5-HT dynamics
in humans before and after (e.g. SSRI) drug administration is now possible (72), opening
up another possible application of our modelling framework.

In summary, we have proposed a promising new computational modelling framework that
can integrate various experimental neurobiological data into a computationally efficient
large-scale neural circuit model for simulating, testing and predicting the effects of multiple
endogenous neuromodulators and neuropharmacological drugs.

4. Methods

A simpler modelling approach for modelling two brain regions. Note that if one is only
interested in the mutual interactions of two brain regions, then one may ignore the induced
current implementation step (Fig. 2, second column), and directly model the influence of
\([y]\) on the firing rates \(f_i\) (45), i.e.

\[
\tau_{j\rightarrow i} \frac{df_i}{dt} = -f_i + K_i([y])
\]  

(9)

where \(\tau_{j\rightarrow i}\) is the effective time constant due to the injected neuromodulator \(y\) on the \(i\)-th
neural population. \(K_i([y])\) can follow a similar form as the \(G\) function in Eqn. (4).

Model parameter and baseline values. A summary of the LHA-DRN-LC model
parameter values and baseline activities are shown in the table below.

Table 1. Basal firing rate, neurotransmitter levels, dynamical time constants, and other
model parameters for the LHA-DRN-LC circuits.
Asterisk: (73), Assuming $V_{\text{max}}$, and per stimulus release at dorsal lateral geniculate (DLG) and LC will be same, #: (44), + : Parameter values are tuned to obtain the basal values close to those in experiments.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Reference, remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{\text{DRN}}$</td>
<td>Basal firing rate of 5-HT neurons in DRN</td>
<td>0.8 Hz</td>
<td>(74), in vitro</td>
</tr>
<tr>
<td>$f_{\text{LC}}$</td>
<td>Basal firing rate of NE neurons in LC</td>
<td>2.15 Hz</td>
<td>(54), in vitro</td>
</tr>
<tr>
<td>$f_{\text{LHA}}$</td>
<td>Basal firing rate of Ox neurons in LHA</td>
<td>2.3 Hz</td>
<td>(38), in vitro</td>
</tr>
<tr>
<td>$K_{\text{LHA}}$</td>
<td>Gain of the input-output function for LHA neurons</td>
<td>0.2 Hz/pA</td>
<td>(49)</td>
</tr>
<tr>
<td>$K_{\text{DRN}}$</td>
<td>Gain of the input-output function for DRN neurons</td>
<td>0.033 Hz/pA</td>
<td>(11, 47, 48)</td>
</tr>
<tr>
<td>$K_{\text{LC}}$</td>
<td>Gain of the input-output function for LC neurons</td>
<td>0.058 Hz/pA</td>
<td>(46)</td>
</tr>
<tr>
<td>$I_{\text{LHA}}$</td>
<td>Threshold current for non-zero firing of LHA neurons</td>
<td>0 pA</td>
<td>(49)</td>
</tr>
<tr>
<td>$I_{\text{LC}}$</td>
<td>Threshold current for non-zero firing of DRN neurons</td>
<td>24.82 pA</td>
<td>(11, 47, 48)</td>
</tr>
<tr>
<td>$I_{\text{LHA}}$, $I_{\text{DRN}}$, $I_{\text{LC}}$</td>
<td>Afferent current to LHA neurons</td>
<td>11.5 pA</td>
<td>(49)</td>
</tr>
<tr>
<td>$I_{\text{LHA}}$, $I_{\text{DRN}}$, $I_{\text{LC}}$</td>
<td>Afferent current to DRN neurons</td>
<td>24.82 pA</td>
<td>(11, 47, 48)</td>
</tr>
<tr>
<td>$I_{\text{LHA}}$, $I_{\text{DRN}}$, $I_{\text{LC}}$</td>
<td>Afferent current to LC neurons</td>
<td>37.41 pA</td>
<td>(46)</td>
</tr>
<tr>
<td>$[5\text{-HT}]<em>{\text{LHA}}$, $[5\text{-HT}]</em>{\text{DRN}}$, $[5\text{-HT}]_{\text{LC}}$</td>
<td>Basal [5-HT] level in Ox neurons</td>
<td>1.6 nM</td>
<td>(55)</td>
</tr>
<tr>
<td>$[\text{NE}]_{\text{LHA}}$</td>
<td>Basal [NE] level in 5-HT neurons</td>
<td>500 pg/mg</td>
<td>(76), assuming baseline 5-HT levels at dorsal and rostral raphe are same.</td>
</tr>
<tr>
<td>$[\text{NE}]_{\text{LHA}}$</td>
<td>Basal [NE] level in Ox neurons</td>
<td>0.83 nM</td>
<td>(77), assuming baseline NE levels at hypothalamus and LHA are the same.</td>
</tr>
<tr>
<td>$[\text{Ox}]_{\text{DRN}}$</td>
<td>Basal [Ox] level in 5-HT neurons</td>
<td>0.2314 nM</td>
<td>(78), assuming baseline Ox level at pons and DRN are the same.</td>
</tr>
<tr>
<td>$[\text{Ox}]_{\text{LHA}}$</td>
<td>Basal [Ox] level in Drn neurons</td>
<td>2 pg/mg</td>
<td>(78)</td>
</tr>
<tr>
<td>$[\text{Ox}]_{\text{LC}}$</td>
<td>Basal [Ox] level in Ne neurons</td>
<td>0.56 nM</td>
<td>(78)</td>
</tr>
<tr>
<td>$\tau_{\text{[5-HT]}\rightarrow\text{LHA}}$, $\tau_{\text{[5-HT]}\rightarrow\text{LC}}$, $\tau_{\text{[5-HT]}\rightarrow\text{DRN}}$</td>
<td>Time constant of the effect of [5-HT] on Ox neurons</td>
<td>2 s</td>
<td>(37)</td>
</tr>
<tr>
<td>$\tau_{\text{[5-HT]}\rightarrow\text{LC}}$</td>
<td>Time constant of the effect of [5-HT] on Ne neurons</td>
<td>20 s</td>
<td>(39)</td>
</tr>
<tr>
<td>$\tau_{\text{[5-HT]}\rightarrow\text{LHA}}$</td>
<td>Time constant of the effect of [5-HT] on Ne neurons</td>
<td>60 s</td>
<td>(51)</td>
</tr>
<tr>
<td>$\tau_{\text{[NE]}\rightarrow\text{LHA}}$, $\tau_{\text{[NE]}\rightarrow\text{DRN}}$, $\tau_{\text{[NE]}\rightarrow\text{LC}}$</td>
<td>Time constant of the effect of [NE] on Ox neurons</td>
<td>20 s</td>
<td>(80)</td>
</tr>
<tr>
<td>$\tau_{\text{[NE]}\rightarrow\text{LHA}}$, $\tau_{\text{[NE]}\rightarrow\text{DRN}}$, $\tau_{\text{[NE]}\rightarrow\text{LC}}$</td>
<td>Time constant of the effect of [NE] on Ne neurons</td>
<td>1 s</td>
<td>(56)</td>
</tr>
<tr>
<td>$V_{\text{max}}(\text{[NE]}\rightarrow\text{LHA})$, $V_{\text{max}}(\text{[NE]}\rightarrow\text{DRN})$, $V_{\text{max}}(\text{[NE]}\rightarrow\text{LC})$</td>
<td>Maximum uptake rate for the [NE] release in LC neurons</td>
<td>74 nM/s</td>
<td>*</td>
</tr>
<tr>
<td>$K_{\text{max}}(\text{[NE]}\rightarrow\text{LHA})$, $K_{\text{max}}(\text{[NE]}\rightarrow\text{DRN})$, $K_{\text{max}}(\text{[NE]}\rightarrow\text{LC})$</td>
<td>Maximum uptake rate for the [NE] release in Ne neurons</td>
<td>400 nM</td>
<td>*</td>
</tr>
<tr>
<td>$V_{\text{max}}(\text{[NE]}\rightarrow\text{DRN})$, $V_{\text{max}}(\text{[NE]}\rightarrow\text{LHA})$, $V_{\text{max}}(\text{[NE]}\rightarrow\text{LHA})$</td>
<td>Maximum uptake rate for the [NE] release in DRN neurons</td>
<td>400 nM</td>
<td>*</td>
</tr>
<tr>
<td>$K_{\text{max}}(\text{[NE]}\rightarrow\text{DRN})$, $K_{\text{max}}(\text{[NE]}\rightarrow\text{LHA})$, $K_{\text{max}}(\text{[NE]}\rightarrow\text{LHA})$</td>
<td>Maximum uptake rate for the [NE] release in LHA neurons</td>
<td>74 nM/s</td>
<td>*</td>
</tr>
<tr>
<td>$V_{\text{max}}(\text{[5-HT]}\rightarrow\text{LHA})$, $V_{\text{max}}(\text{[5-HT]}\rightarrow\text{DRN})$, $V_{\text{max}}(\text{[5-HT]}\rightarrow\text{LC})$</td>
<td>Maximum uptake rate for the [5-HT] release in DRN neurons</td>
<td>1800 nM/s</td>
<td>#</td>
</tr>
<tr>
<td>$K_{\text{max}}(\text{[5-HT]}\rightarrow\text{DRN})$, $K_{\text{max}}(\text{[5-HT]}\rightarrow\text{LHA})$, $K_{\text{max}}(\text{[5-HT]}\rightarrow\text{LHA})$</td>
<td>Maximum uptake rate for the [5-HT] release in LHA neurons</td>
<td>170 nM</td>
<td>#</td>
</tr>
<tr>
<td>$V_{\text{max}}(\text{[5-HT]}\rightarrow\text{LHA})$, $V_{\text{max}}(\text{[5-HT]}\rightarrow\text{LC})$, $V_{\text{max}}(\text{[5-HT]}\rightarrow\text{LC})$</td>
<td>Maximum uptake rate for the [5-HT] release in LC neurons</td>
<td>1800 nM/s</td>
<td>#</td>
</tr>
<tr>
<td>$K_{\text{max}}(\text{[5-HT]}\rightarrow\text{LC})$, $K_{\text{max}}(\text{[5-HT]}\rightarrow\text{LHA})$, $K_{\text{max}}(\text{[5-HT]}\rightarrow\text{LHA})$</td>
<td>Maximum uptake rate for the [5-HT] release in LC neurons</td>
<td>170 nM</td>
<td>#</td>
</tr>
<tr>
<td>$\delta_{\text{Ox}}$, $\delta_{\text{NE}}$, $\delta_{\text{LHA}}$, $\delta_{\text{DRN}}$, $\delta_{\text{LC}}$</td>
<td>Rise factor for [Ox] release in LC neurons</td>
<td>0.2314 nM</td>
<td>+</td>
</tr>
<tr>
<td>$\xi_{[\text{Ox}] \rightarrow \text{LC}}$</td>
<td>Decay rate for $[\text{Ox}]$ release in LC neurons</td>
<td>0.85 s</td>
<td>+</td>
</tr>
<tr>
<td>$\eta_{[\text{Ox}] \rightarrow \text{DRN}}$</td>
<td>Rise factor for $[\text{Ox}]$ release in DRN neurons</td>
<td>1.405 nM</td>
<td>+</td>
</tr>
<tr>
<td>$\xi_{[\text{Ox}] \rightarrow \text{DRN}}$</td>
<td>Decay rate for $[\text{Ox}]$ release in DRN neurons</td>
<td>0.85 s</td>
<td>+</td>
</tr>
<tr>
<td>$[5\text{-HT}]_\text{per, LHA}$</td>
<td>Per-stimulus [5-HT] release in LHA neurons</td>
<td>12.14 nM</td>
<td>+</td>
</tr>
<tr>
<td>$[5\text{-HT}]_\text{per, LC}$</td>
<td>Per-stimulus [5-HT] release in LC neurons</td>
<td>0.852 fM</td>
<td>+</td>
</tr>
<tr>
<td>$[\text{NE}]_\text{per, DRN}$</td>
<td>Per-stimulus [NE] release in DRN neurons</td>
<td>27.272 nM</td>
<td>+</td>
</tr>
<tr>
<td>$[\text{NE}]_\text{per, LHA}$</td>
<td>Per-stimulus [NE] release in LHA neurons</td>
<td>0.0642 nM</td>
<td>+</td>
</tr>
</tbody>
</table>

**Numerical simulations.** The neural circuit model simulation for the interaction of the three brain areas is computed by using the forward Euler numerical integration method which is applied to the set of the first-order differential equations. A time step of 1 millisecond was used. Smaller time steps were tested without affecting the results. These simulations can also be extended to other (e.g. 2nd order or 4th order Runge-Kutta) numerical schemes. Simulations were run till stable steady states are obtained.

**GUI software.** To begin the software, the user presses the ‘Start’ button on the starting window of the GUI. This will result in the model outputs of the interacting brain regions (Fig. 6A). The outputs appear in the form of normalized neural (firing rate) at the specified brain regions, e.g. red colour represents relatively higher activity while blue colour represents lower activity. The range of the colour map is based on the absolute range of [0, 255] Hz. These colours of activity can change over time, reflecting their dynamics. The regions are embedded in locations based on the Montreal Neurological Institute (MNI) coordinates in a glass brain. 3-D rotation of the brain is also allowed in the software. Although the structure of the glass brain is currently based on a normal human MRI data, it can be easily replaced by an animal (e.g. rodent) glass brain using the appropriate brain atlas.

Once the model is converged after simulation, upon clicking on the “Outputs” button in the starting window, the dynamical variables for the selected regions will appear in a new window (Fig. 6B). The variables are the (absolute) neural firing rates and neuromodulator concentrations of the selected brain regions. Both the individual variable’s temporal
dynamics and mutual relationships between the variables can be plotted. Upon clicking
the ‘Parameters’ button in the starting window, a new window appear in which the model
parameter values and the initial numerical values of the variables are shown. The model
parameter values can be edited within this window. Once this is done, the user can re-
simulate the new model by pressing the ‘Simulate’ button within the same window. This
generates the transients of baseline firing rates and concentration levels and shows the
relationship among them (e.g. firing-rates). For default values, all the transient activities
eventually attain their stable steady-states. These steady-state values of the system
parameters varies as we change the model parameters. For example, to mimic the
complex drug effects of SSRI’s, \( K_m \) is varied and corresponding changes in the steady-
state values are analysed separately (see Section 2.3). If a mistake is made, the user can
always retrieve back the initial values of the parameters by clicking on the ‘Default’ button.

Author Contributions:
performed the computational simulations, and V.Y. and V.V. designed and developed the
computational software. A.J., V.Y., T.M.M., G.P. and K.W.-L wrote the manuscript.

Funding:
The research leading to these results was initially supported under the CNRT project by the
Northern Ireland Department for Employment and Learning through its “Strengthening the All-
Island Research Base” initiative, and later supported by the Centre of Excellence in Intelligent
Systems Project, ISRC, University of Ulster. G.P. and K.W.-L. were supported by the Northern
Ireland Functional Brain Mapping Project (1303/101154803), funded by InvestNI and the
University of Ulster, and V.Y. by the University of Ulster Vice-Chancellor’s Research
Scholarship. K.W.-L. was additionally supported by The Royal Society, BBSRC
Acknowledgements:
We thank the reviewers for their constructive comments which helped improve the manuscript.

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**Figure legends**

Figure 1. Interactions among three brain regions, which are sources of neuromodulators. LHA: lateral hypothalamus; DRN: dorsal raphe nucleus; LC: locus coeruleus. Ox: orexin; 5-HT: serotonin. Arrows: effective excitatory connections between any two areas; circles: inhibitory connections. Different colours denote different brain areas. Small fonts denote receptor subtypes at the target sites (35-39).

Figure 2. Incorporating afferent currents from neuromodulator concentration levels. $[y_1] ... [y_n]$ denote the different neuromodulator concentrations. $i$ represents a particular targeted brain region. $I_{j\rightarrow i}$ is the corresponding induced currents to region $i$. $I_{Total,i}$ is the total afferent current and $f_i$ is the firing frequency in region $i$. For example, $[y_1]$ and $[y_2]$ may be the concentration levels of serotonin [5 – HT] and norepinephrine [NE], and $i$ can be the lateral hypothalamus LHA. The big arrow denotes “closing the loop” in the modelling process.
Figure 3. Fitted input-output functions. (A-B) Effects of concentrations [Ox-A/B] and [NE] on DRN neurons. (C-D) [Ox-A] and [5-HT] on LC neurons. (E-F) [5-HT] and [NE] on LHA neurons. Estimated function (pink) is based on f-I curves and current input-output functions.

Figure 4. Single trial activity dynamics under baseline condition. (A) Firing-rate of DRN neural population. (B, C) Concentration level of 5-HT in the LHA and LC areas.

Figure 5. Effects of substrate concentration factor $K_{m, [5-HT]}$ and $K_{m, [NE]}$, and [Ox – A] antagonist SB-334867-A on the firing rates and concentration levels in the circuit. Each panel varies both $K_{m, [5-HT]}$ and $K_{m, [NE]}$ values to simulate the effects of drugs and their combinations. $K_{m, [NE]} = 400 \, nM$ (control basal value).

Figure 6. Screenshot of the NModC software. A user friendly GUI of neuromodulator neural circuit model that can simulate, analyse, visualize and edit. (A) Users can run the model to visualize the results within a rotatable 3-D glass brain after pressing the ‘Start’ button. The user can stop the simulation using the ‘Stop’ button. Simulation time parameters can be controlled using ‘Time’ and ‘Sim scale’, and the GUI can be closed using ‘Close’ buttons. (B) Model variables’ time courses and their mutual relationships can be observed using the ‘Outputs’ button. (C) Model variables’ exact values can be found and model parameters edited upon pressing the ‘Parameters’ button. ‘Default’ returns to default model parameters and ‘Simulate’ re-run the model after editing the parameter values.
Table legends

Table 1. Basal firing rate, neurotransmitter levels, dynamical time constants, and other model parameters for the LHA-DRN-LC circuits.