A neurophysiological-metabolic model for burst suppression

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A neurophysiological–metabolic model for burst suppression

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Burst suppression is an electroencephalogram (EEG) pattern in which high-voltage activity alternates with isoelectric quiescence. It is characteristic of an inactivated brain and is commonly observed at deep levels of general anesthesia, hypothermia, and in pathological conditions such as coma and early infantile encephalopathy. We propose a unifying mechanism for burst suppression that accounts for all of these conditions. By constructing a biophysical computational model, we show how the prevailing features of burst suppression may arise through the interaction between neuronal dynamics and brain metabolism. In each condition, the model suggests that a decrease in cerebral metabolic rate, coupled with the stabilizing properties of ATP-gated potassium channels, leads to the characteristic epochs of suppression. Consequently, the model makes a number of specific predictions of experimental and clinical relevance.

Burst suppression—an electroencephalogram (EEG) pattern in which high voltage activity (burst) and flatline (suppression) periods alternate systematically but quasiperiodically (almost periodic but with variations in inter- and intra-burst duration) (1)—is a state of profound brain inactivation. It is frequently observed in deep general anesthesia (2). It is also observed in a range of pathological conditions including hypothermia (3–5), hypoxic–ischemic trauma/coma (6), and the so-called Ohtahara syndrome (7, 8), a type of early infantile encephalopathy. These etiologies indicate that the burst suppression pattern represents a low-order dynamic mechanism that persists in the absence of higher-level brain activity. Indeed, the fact that many different conditions produce similar brain activity suggests that there may be a common pathway to the state of brain inactivation and may indicate fundamental properties of the brain’s arousal circuits (2).

The basic features of the burst suppression phenomenon have been established through a variety of EEG studies that are reviewed in ref. 9. The two most notable of these features are the spatial homogeneity of bursts and the quasi-periodic nature of the suppression. Later research has been directed at describing the phenomenon in vivo and in the specific context of general anesthesia. In particular, the early work of Steriade et al. (10) helped establish the neural correlates of burst suppression, including the differential participation of cortical and subcortical cell types. More recent studies (11, 12) have suggested that burst suppression is associated with enhanced excitability in cortical networks. These studies implicate extracellular calcium as a correlate for the switches between burst and suppression.

Despite the findings of these studies, a unifying mechanism for burst suppression—one that explains its prevailing features and also accounts for its range of etiologies—has not been proposed. Indeed, the existing characterizations of burst suppression in pathological situations are highly limited. Computational models offer a means of synthesizing the available data with known physiology to propose potential mechanisms and predictions that may guide future experiments. Such is the objective of this paper. Previous attempts at modeling burst suppression have been largely phenomenological (13), using arguments from chaos theory to explain certain properties of the burst suppression waveform. These models do not clarify the underlying biophysical dynamics.

In contrast, we construct a biophysical model that is constrained by neurophysiology and the commonality between the aforementioned etiologies—specifically, a reduction in brain metabolism. The unique feature of our model is a nuanced interaction between neuronal dynamics and changes in cerebral metabolic rate of oxygen (CMRO). The model produces the distinctive characteristics of burst suppression, providing unique insights and predictions regarding low-order brain dynamics in states of reduced activity. Specifically, it suggests that burst suppression represents a basal neurometabolic regime that ensures basic cell function during states of lowered metabolism. We discuss clinical and experimental implications of these findings.

Prevailing Features of Burst Suppression

To constrain the model, we first consider three prevailing features of burst suppression, summarized in refs. 6 and 9, for which there is clinical and experimental evidence. The first feature of note is the synchrony of burst onset; (i.e., bursts begin and end nearly simultaneously across the entire scalp). Such a spatially homogeneous behavior immediately suggests that a very low-order dynamic mechanism underlies burst suppression. Some studies have suggested that asynchronous burst suppression can arise in the case of large-scale cortical deafferentation (14, 15). In such settings, large-scale differences in regional blood supply and autoregulation may prevent the uniformity typically associated with burst suppression.

A second important feature of burst suppression is its parametric sensitivity to the level of brain depression—for instance, depth of general anesthesia. In particular, the burst suppression ratio (BSR)—the fraction of time spent in suppression—is known to increase as general anesthesia deepens (16). Eventually, with sufficient quantities of drug, a completely isoelectric (flatline) EEG can be achieved. A similar progressive increase in BSR can be observed during hypothermia (see below). Thus, the burst suppression pattern is not a discrete state, but occurs on a continuum guided by a changing underlying biophysical process.

Finally, we note the significant difference in timescales between burst suppression and other neural activity associated with an inactivated brain state, specifically, the 0.5– to 2-Hz slow/delta oscillation commonly observed during sleep and general anesthesia. Burst suppression occurs on a much slower timescale than these oscillations. Bursts may last multiple seconds interspersed with as long as 10–20 s of suppression (Fig. L4 and Fig. 2).

Author contributions: E.N.B., N.J.K., and S.C. designed modeling research; E.N.B. and P.L.P. designed experimental research; S.C. and P.L.P. performed research; S.V. contributed model concepts and parameterizations; S.C. and P.L.P. analyzed data; and S.C., E.N.B., and N.J.K. wrote the paper.

The authors declare no conflict of interest.

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The propofol-induced alpha is thought to involve potentiation of slow-wave and delta activity persists during the burst epochs (11). Suppression induced by isoflurane general anesthesia. A similar feature has been observed during burst sequence of zeros and ones. Logically, it is as if Fig. 1B displays epochs of quiescence. When a burst occurs, the alpha activity is recovered. (D) Alpha peak during deep burst suppression, general anesthesia. Spectrum was averaged from 25 4-s epochs. (E) Alpha peak during burst suppression. Spectrum was averaged from 25 burst epochs.

Moreover, unlike slow oscillations, burst suppression is not periodic (17). Indeed, it has been suggested that slow oscillations are contained within bursts (11), indicating that burst suppression may be governed by a more global dynamic process.

### Additional Data and Constraints

To develop additional constraints, we examine burst suppression EEG recordings from healthy volunteers anesthetized with the widely used anesthetic propofol. These recordings were collected as part of a larger study on the electrophysiological and behavioral effects of propofol general anesthesia (18).

Fig. 1A shows a representative epoch of burst suppression from left- and right-frontal electrodes from such a subject. As is typical in burst suppression, the bursts begin and end synchronously between hemispheres. Fig. 1B shows the spectrogram of a frontal electrode at a deep, but not burst-suppression, general anesthesia. The alpha rhythm associated, described in ref. 19, is manifest. (C) At a deeper level of general anesthesia, burst suppression is achieved (the spectrogram clearly displays epochs of quiescence). When a burst occurs, the alpha activity is recovered. (D) Alpha peak during deep burst suppression, general anesthesia. Spectrum was averaged from 25 4-s epochs. (E) Alpha peak during burst suppression. Spectrum was averaged from 25 burst epochs.

Objectives

We seek a biophysical model that accounts for the following features of burst suppression: (i) the quasiperiodic onset and offset of bursts across the scalp; (ii) the very slow timescales associated with burst and suppression duration; (iii) the parametric modulation of BSR as a function of anesthetic dose, hypothermia, or metabolic reduction; and (iv) the association of burst suppression with states of lowered cerebral metabolism.

### Approach: A Link to Metabolism

To develop a modeling approach that accounts for the above features, we look to the common aspects of the different burst suppression etiologies—specifically, their relationship to aberrant neurometabolic dynamics. Clearly, hypoxic–ischemic coma is associated with severe changes to brain metabolism and CMRO (6, 22). Early infantile encephalopathy that is not directly linked to a hypoxic–ischemic event, [e.g., Ohtahara syndrome (7, 8)], is nevertheless associated with brain atrophy and metabolic dysfunction (23).

A reduced CMRO is also characteristic of burst suppression during hypothermia (3), [i.e., brain cooling, which is frequently used to induce or maintain medical coma during surgeries that involve circulatory arrest (4, 24) or for cerebral protection after cardiac arrest]. An example of this is shown in Fig. 2, which shows a frontal EEG from a patient undergoing circulatory rewarming after induced hypothermia during cardiac surgery (SI Methods). As rewarming occurs, the BSR decreases until a continuous EEG is recovered. This gradual decrease in BSR is similar to the progression observed during emergence from general anesthesia. In the context of anesthetic drugs, it is known that most intravenous GABAergic induction agents lead to significantly reduced CMRO (25). Those that are associated with increased CMRO, such as ketamine, do not lead to the classical pattern of burst suppression at clinically relevant dose levels (26).

This evidence suggests a link between reduced cerebral metabolism and the state of burst suppression. At the neuronal network level, a candidate for providing this link is the adenosine triphosphate (ATP)-gated potassium channel (K<sub>ATP</sub>), which is thought to provide neuronal protection during hypoxic–ischemic events (27, 28). It has been shown that, in certain cortical areas, this channel may lead to very slow (<0.5 Hz) oscillatory activity (29). The involvement of this channel—or one similar in behavior—in burst suppression is investigated in the subsequent sections of this paper.

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Methods

Model Structure. We construct a model consisting of biophysical cortical neurons that are described by voltage-gated conductance equations of the Hodgkin-Huxley type (30). The primary feature of the model is the aforementioned $K_{ATP}$ channel, which modulates neuronal firing as a function of ATP production. The rate of ATP production is, in turn, directly modulated by CMRO by CMRO (31, 32). The schematic of the model is shown in Fig. 3. The neuronal network consists of cortical pyramidal neurons and interneurons that produce neuronal oscillations on timescales commensurate with the EEG observed during general anesthesia (19, 20). To this network, we add dynamics associated with ATP consumption, in the form of the sodium–ATP pump, which is thought to be the major consumer of cerebral ATP (29, 33).

Regulation of neuronal ATP production is coupled to each of the etiologies associated with ATP consumption, in the form of the sodium–ATP pump dynamics. The opening of the $K_{ATP}$ channel leads to hyperpolarization and prohibits further spiking. During the suppression, [ATP] slowly recovers according to the network inhomogeneity, along with the noise, causes bursts to be initiated at variable times during the recovery of $[ATP]$ (note the time course of $[ATP]$ in Fig. 5). In the small model with no noise the burst suppression pattern is more regular and periodic.

Results

Metabolic Dynamics Lead to Burst-Like Phenomena. We demonstrate the main result using a purely cortical network consisting of reciprocally coupled interneurons and pyramidal cells. As shown previously (20, 37), such a network can be used to explain the progressive reduction in frequency of EEG oscillations observed during induction of general anesthesia via propofol. The mechanism in those models was a drug-induced potentiation of GABA$_A$ inhibitory postsynaptic potentials. Here, we build upon these models by adding metabolic dynamics.

Fig. 4 shows the simulated local field potential (LFP) obtained from a network of 14 cells—10 pyramidal cells and 4 interneurons—for baseline and lowered levels of ATP regeneration, respectively. The traces are from a representative network but are repeatable and robust to model noise. As is shown, when the ATP regeneration is lowered to 50% of baseline, continuous neural activity gives way to epochs of quiescence. Bursts and suppression epochs are on the order of 4–10 s and alternate quasiperiodically. When ATP regeneration is lowered further to 30% of baseline (Fig. 4C), a notable increase in the BSR occurs. Fig. S1 shows the computed BSR as a function of $J_{ATP}$ over the 30–50% range. From Fig. S1 we note that the length of bursts becomes more variable as $J_{ATP}$ increases.

The mechanisms that underlie this phenomenon can be established using a minimal network consisting of only a single pyramidal cell and a single interneuron. Using this configuration, Fig. 5 shows the output of a cortical pyramidal neuron for 50% and 30% reductions in ATP regeneration rate. Fig. 5A shows the bursting activity, where the spiking within the bursts has alpha periodicity, consistent with ref. 20. The transition from burst to suppression can be understood in terms of the intracellular ATP concentration [ATP]. As shown in Fig. 5B, as a burst occurs, [ATP] decreases by $\sim$25%. This decrease causes an increase in the conductance $g_{K_{ATP}}$ (9) as shown in Fig. 5C. The opening of the $K_{ATP}$ channel leads to hyperpolarization and prohibits further spiking. During the suppression, [ATP] slowly recovers according to the network inhomogeneity, along with the noise, causes bursts to be initiated at variable times during the recovery of [ATP] (note the time course of $[ATP]$ in Fig. 5). In the small model with no noise the burst suppression pattern is more regular and periodic.

Spectral Content Is Preserved Within Bursts. The model confirms that spectral content remains intact within burst epochs. Fig. 6 shows the spectrograms of the simulations of baseline and burst-suppression activity. In Fig. 6A we see the 10- to 12-Hz alpha
oscillation that is associated with surgical levels of general anesthesia (20). In Fig. 6B, we see that this alpha activity persists during the burst intervals. The phenomenon is again due to the underlying dynamics of the $g_{KATP}$ channel. As shown in Fig. 5B, during the periods of activity, $g_{KATP}$ operates near baseline. Consequently, the neuronal network operates in a normal dynamic range and thus the alpha oscillation is recovered. As the burst progresses, $g_{KATP}$ eventually moves away from baseline, leading to intraburst frequency variations. Such variability is studied below.

**Spectral Drift Within Burst.** The model exhibits an interesting emergent phenomenon: a progressive slowing in frequency toward the end of a burst. Fig. 7 shows the spectrogram of a 40-s period of burst suppression generated from the model using a parameterization for 30% reduction in ATP production. Here, bursts are 4–6 s in duration. Note that the frequency within each burst slowly decreases from an initial value >10 Hz to a final value near 8 Hz.

As such, the model suggests that the burst suppression morphology is not simply that of an “on–off” switching function. Indeed, the activity appears to wax and wane, with a notable reduction in frequency toward the end of a burst. As seen in Fig. 5, this behavior can be attributed to the slow variation in the $g_{KATP}$ channel as the burst progresses. As $g_{KATP}$ increases, the pyramidal cell transitions through a regime where spiking occurs but is slowed. Such dynamics are analogous to calcium fluctuations in certain thalamic cells, (i.e., so-called calcium bursts), but on a much slower and irregular timescale. They are a novel property of this model and have yet to be verified in experimental data.

**Limits in High-Frequency Intraburst Activity.** The model predicts limitations to high-frequency neuronal activity during a compromised metabolic regime. Fig. 8 shows the maximum frequency of action potential firing for a pyramidal cell from the model as a function of the time constant and conductance of GABA-ergic inhibition. Note that a $3–4 \times$ potentiation in GABA is consistent with common general anesthetics (20) ($1 \times$ corresponds to an unanesthetized baseline). When the model is parameterized with baseline values of ATP production, the timescale of inhibition sets the firing rate of the network (and of this pyramidal cell) (38), leading to a progressive reduction in firing from the gamma to the alpha range. Fig. 8 also shows the frequency output over the same range of GABA potentiation for a 30% reduction in $J_{ATP}$. In this scenario, the network produces burst suppression. However, within each burst the spiking frequency is restricted to the 10-Hz range; (i.e., high-frequency firing is impeded by metabolic modulation and not through inhibitory synaptic effects).

**Discussion**

**Neuronal–Metabolic Model for Burst Suppression.** We have developed a model for burst suppression that combines effects at the local circuit level with broader effects on neural metabolism. In the model, the link between these two levels of physiology is through the ATP-gated potassium channel, which is known to be expressed in cortex and subcortical structures (28). Activation of this channel serves to stabilize cell membranes, leading to seconds-long periods of alternating activity and suppression.

It is known that altered neurometabolic dynamics can occur in each of the conditions associated with burst suppression: in general anesthesia, through a reduction in neural activity and subsequent reductions in CMRO (25, 36); in hypoxic/ischemic injury, through aberrant reductions in metabolic regulation due to diffusion injuries or through direct oxidative stress (6, 22); in hypothermia, through direct reductions in metabolic rate (3, 35); and in developmental encephalopathy, through neural and metabolic dysfunction (23). Implicating brain metabolism in the neural mechanisms of burst suppression establishes a unifying physiologic connection between the main etiologies of the phenomenon.

The model provides an explanation of the central features of burst suppression: (i) The progressive and continuous increase in BSR with deeper levels of inactivation is due to a progressive reduction in metabolism, for instance through a decrease in CMRO; (ii) the spatial synchrony of burst onset and offset may arise through the broad manifestation of such metabolic changes, including in subcortical structures (noting that the present model is spatially compact); and (iii) the recovery of rhythms within bursts is due to recovery of basal dynamics at the neuronal circuit level caused by transient increases in energetics.

In addition, the model suggests new phenomenological features: (iv) a drift in the rhythmic activity through the course of a burst due to slow depletion and subsequent increase in $g_{KATP}$ and (v) a limitation in high-frequency intraburst activity independent of the strength of synaptic inhibition.
Consistency with Previous Studies. The model is consistent with descriptions of burst suppression in general anesthesia, hypoxic–ischemic brain injury, and childhood encephalopathy (25). At the cellular level, the model is compatible with ref. 10, which showed wide synchrony of bursts and a strong correlation between cortical spiking and burst activity as measured by field potentials. The fact that some subcortical cells produce spikes during cortical quiescence may be due to differential expression of the KATP channel in these structures.

It was shown in ref. 11 that burst activity is correlated with a decrease in extracellular calcium. As suggested in ref. 40, the depletion of extracellular calcium would prohibit synaptic transmission, leading to alternating periods of burst and quiescence. Such a mechanism does not immediately account for features such as burst quasiperiodicity or continuous changes in BSR, nor does it provide a transparent link to the range of burst suppression etiologies. Nevertheless, aberrant calcium regulation may certainly be a companion to the mechanisms suggested in our model. Indeed, compromised brain metabolism and ATP production may impair the homeostatic neuronal pumps for maintenance of calcium levels, leading to their depletion through the course of a burst. Suppressing neuronal firing via opening of the K$_{ATP}$ channel maximizes the energetics available for restoration of calcium.

In ref. 11, the authors also show that after the occurrence of a burst, there is a refractory period during which neural activity cannot be induced by external microstimulation. This result is again consistent with our model, in which the K$_{ATP}$ channel remains open after cessation of spiking (due to the time constant of the gating variable $z$ in ref. 9) (Fig. 5). Thus, excitability of neurons is severely diminished for the period immediately following burst offset. As ATP recovers, it becomes gradually easier to initiate a burst, which may correspond to enhanced excitability (11) and higher variance in burst duration (Fig. S1).

We additionally note that the relationship between metabolism and physiological oscillations has been well studied at the level of mitochondria and cardiac dynamics (41). In this context, models have been developed that suggest how oxidative stress may lead to slow, large-amplitude oscillations and arrhythmia through mechanisms that involve ATP-gated membrane channels (42). Such mechanisms are similar to those in our model for burst suppression.

Model Predictions. The model predicts the manifestation of burst suppression in scenarios involving severely compromised brain metabolism. The practice of induced hypothermia (4) during cardiac surgeries provides a powerful, parametric means of testing this mechanism. In these scenarios, we would expect burst suppression to manifest independently from the anesthetic regimen. Different anesthetic drugs may induce different spectral signatures in the EEG. Accordingly, we expect the spectral signature within a burst to be the same as that of the time period immediately preceding the onset of burst suppression.

The limitation in high-frequency activity during burst suppression may be an additional mechanism that impairs normal cortical function. This is an emergent property of the model and has not yet been investigated in experiments.

Whereas we have specifically implicated the K$_{ATP}$ channel, it is likely that other channels may exhibit similar behavior. Moreover, the mechanism outlined herein is almost certainly related to secondary effects such as the aforementioned regulation of extracellular calcium. The autoregulation of physiological processes such as cerebral blood flow may also be important in burst suppression (39, 43).

The present model does not possess the spatial scale to describe the relationship between disparate brain regions during burst suppression. However, on the basis of the model, we anticipate some degree of variation due to regional metabolic differences.

Relationship with Other Slow Activity Brain Development. Burst suppression is different from slow-wave activity in general anesthesia or sleep. Slow oscillations are thought to be spatially
local, both in cortical location and in depth (44, 45), and occur on a timescale that is faster than that of burst suppression. Moreover, burst suppression does not appear in normal sleep (2). From our model, we anticipate that these oscillations are recovered during bursts.

A phenomenon that may also be related to our model is the so-called trace alternant—a burst suppression-like EEG pattern—observed in some healthy newborns (46). The mechanism of our model implies that burst suppression is a means of cell preservation, allowing maximum energetics for basic cell functions, thus preventing collapse of membrane potential in low metabolic states. Similarly, the trace alternant may be associated with optimal brain energetics in the absence of higher-order functions during early development.

Clinical Interpretations and Potential Implications. The mechanisms of burst suppression presented here reveal the hierarchy in which neural activity is abolished in states of severely reduced brain function. Each successive burst can be viewed as an attempted recovery of basal cortical dynamics. Suppression ensues when there is an imbalance in neuronal activity and available energetics.

In extreme cases, such as ischemia, even complete isoelectricity may be associated with opti-

cmal brain energetics in the absence of higher-order functions during early development.

These mechanisms have potential implications for brain monitoring and intraoperative care. For instance, a detailed charac-
terization of the burst suppression pattern may enable the de-
tection of cerebral ischemia during surgery (47), perhaps through a change in the spectral characteristic within bursts. Such characterization may also help to differentiate “bursting” in an inac-
tivated brain versus one in a state of seizure (9, 40).

Burst suppression is often used as a target in medically induced coma for brain protection during intensive care (3). The model provides further justification for this technique and may eventually help design paradigms for optimally achieving this brain state using anesthetic drugs and/or hypothermia. For instance, clari-

fying the metabolic differences between a low BSR—say, a few short bursts per minute—and complete isoelectricity would help refine targets for neuroprotection.

Finally, the model provides a means to explore new thera-

peutic strategies and pharmacology. It has been reported in animal studies that pyruvate may prolong neural survival during ischemic infarctions (48, 49). Pyruvate is known to stabilize ox-

idative metabolism by increasing ATP production during hypoxic events. Our model suggests that such an effect should manifest in terms of the BSR—a clinically relevant and testable hypothesis.

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Supporting Information

Ching et al. 10.1073/pnas.1121461109

SI Methods

Data Collection. The electroencephalogram (EEG) time trace from Fig. 2 was obtained from a Sedline (Masimo) clinical anesthesia monitoring system. This recording was obtained during an aortic-arch repair procedure at Massachusetts General Hospital. The collection of these data was approved by the Human Research Committee at Massachusetts General Hospital.

Model Equations. The model consists of cortical pyramidal (PY) cells and fast-spiking (FS) interneurons. These cells are derived from ref. 1, with metabolic dynamics adapted from ref. 2.

Pyramidal cells. Pyramidal cells are based on the model of refs. 1 and 3. The membrane potential for each cell is given by

\[ V = I_{app} - I_N - I_K - I_{K_{st}} - I_{Leak}. \]

Sodium current:

\[ I_N = g_{Na}m^3h(V - E_{Na}), \]  

\[ m = a_m(V)(1 - m) - \beta_m(V)m \]

\[ h = a_h(V)(1 - h) - \beta_h(V)h \]

\[ a_m(V) = \frac{0.32(V + 54)}{1 - \exp(-(V + 54)/4)} \]

\[ \beta_m(V) = \frac{0.08(V + 27)}{1 - \exp(-(V + 27)/5)} \]

\[ a_h(V) = 0.128(-(V + 50)/18), \beta_h(V) = \frac{0.5(-(V + 57)/40)}{1 + \exp(-(V + 27)/5)} \]

\[ g_{Na} = 50, E_{Na} = 100. \]

Potassium current:

\[ I_K = g_{K}m^4(V - E_K) \]

\[ m = a_m(V)(1 - m) - \beta_m(V)m \]

\[ \alpha_m(V) = \frac{0.052(V + 52)}{1 - \exp(-(V + 52)/5)} \]

\[ \beta_m(V) = \frac{0.5(V + 57)/40}{40} \]

\[ g_{K} = 80, E_{K} = -100. \]

Leak current:

\[ I_{Leak} = 0.1(V + 61) \]

Adenosine triphosphate (ATP)-gated potassium membrane channel (2, 4):

\[ I_{K_{st}} = g_{K_{st}}z(V - E_K). \]

\[ z = \frac{1}{(1 + 10[ATP])} \]

\[ [Na] = F[I_{Na} - 3K_{m}[Na]^{3}[ATP] \]

\[ [ATP] = J_{ATP}([ATP]_{max} - [ATP]) - K_{m}[Na]^{3}[ATP]. \]

The kinetic constants are set as \( F = 8.8 \times 10^{-5} \) and \( K_{m} = 6 \times 10^{-8} \). The parameter \( J_{ATP} \) is set to 2 at baseline. The applied current is \( I_{app} = 1.8 + I_u \), where \( I_u \sim N(0, 0.1) \).

FS cells. FS cells are adapted from ref. 1. The membrane potential for each cell is given by

\[ \dot{V} = I_{app} - I_N - I_K - I_{Leak}, \]

where the sodium, potassium, and leak currents are given by Eqs. S1, S2, and S3, respectively. The mean applied current is \( I_{app} = 0.5 \).

Synaptic connectivity. Synaptic connectivity is modeled as follows:

AMPA

\[ I_{AMPA} = g_{AMPA}(V - E_{AMPA}) \]

\[ \dot{x} = 5(1 + \tanh(V/4))(1 - x) - x/2, \]

where \( E_{AMPA} = 0 \). Similarly, for Gamma aminobutyric acid (GABA),

\[ I_{GABA} = g_{GABA}(V - E_{GABA}) \]

\[ \dot{x} = 2(1 + \tanh(V/4))(1 - x) - x/\tau_{GABA}, \]

where \( E_{GABA} = -80 \) and \( \tau_{GABA} = 5 \).

The baseline conductances in the model are as follows:

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<th>Cell Type</th>
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<td>0.1</td>
<td>2</td>
</tr>
<tr>
<td>( g_{GABA} )</td>
<td>0.64</td>
<td>1</td>
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All conductances are scaled according to the number of cells in the network. In networks larger than two cells, connectivity is all-to-all from pyramidal to interneuron and vice versa.

Additional noise and parametric uncertainty. To ensure network inhomogeneity, all parameters are chosen equiprobably from a range of 95-105% of their indicated values. Moreover, pyramidal cells receive an additional noise input in the form of a Poisson train of excitatory synaptic events, with rate 0.1 Hz.

Simulated LFP. The simulated LFP in Fig. 4 is generated by low-pass filtering the mean AMPA synaptic current over all cells. The filter cutoff is set to 100 Hz. The main phenomenology (alternating burst and suppression within the network) is independent from the choice of simulated LFP.

Numerics. Simulations were run either in MATLAB (MathWorks) or using custom software developed in C++. A fourth-order Runge-Kutta algorithm for solving differential equations was used in all cases.

Analysis Methods. Fig. 1 B and C was obtained by computing spectrograms from bipolar-referenced frontal EEG (1). A 4-s window with 50% overlap was used. Fig. 1 D and E was computed by obtaining the power spectral density over 50 4-s epochs from EEG in non-burst suppression and burst suppression, respectively.

The signal shown in Fig. 2 is high-pass filtered above 0.5 Hz. Fig. 6 is a spectrogram of the simulated LFP, computed using 0.5-s windows with no overlap. Fig. 7 is computed in the same manner.

Fig. 8 is computed from the mean interspike period of the pyramidal cell over a 10-min simulation. Suppression epochs are not included as an interspike period.

Fig. S14 is computed by using an amplitude threshold to classify bursts and suppressions. After thresholding, the burst
suppression ratio (BSR) is obtained by obtaining the ratio of suppression duration to total duration of the simulated signal. Fig. S1B is obtained by computing a cross-covariance of the burst signal. This is a binary signal that takes the value 1 during a burst epoch and 0 elsewhere. Bursts and suppressions are classified according to an amplitude threshold set by visual inspection.

In all spectral analyses, a multitapered fast Fourier transformation (with eight tapers), implemented in the Chronux data analysis package (5), is used.


Fig. S1. Mean BSR and cross-covariance as function of $J_{\text{ATP}}$. $n = 10$ simulations. (A) The BSR (fraction of time in suppression) decreases as $J_{\text{ATP}}$ increases. As $J_{\text{ATP}}$ increases the model exhibits more variation in the length of bursts (note the larger SE). (B) The cross-covariance of the burst signal (SI Methods, Analysis Methods) exhibits a sharp peak at 0 s, reflecting the quasiperiodic nature of burst onset/offset. A secondary, but much smaller peak, can sometimes be seen between 3- and 6-s lag, indicating the occasional recurrence of interburst intervals of similar duration.