

Article

Parametric Resonance as an Interpretative Framework of Coupled Large-Scale Neural Dynamics

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Abstract: This paper deals with a theoretical paradigm wherein the ElectroEncephaloGram (EEG) brain activity is interpreted as the macroscopic expression of a nonequilibrium oscillatory system influenced by synchronization and parametric resonance effects. In particular, within the proposed model, neural populations are regarded as interacting groups whose collective dynamics produce coherent rhythms that synchronize themselves across different time scales. On this ground, we investigate a collection of neural spectra recorded during wake-to-sleep and sleep-to-wake transitions and show that, within the theta-alpha frequency range examined here (4–12 Hz) the dominant oscillatory components exhibit approximately harmonic frequency relationship. These observations are consistent with a resonance-based interpretation. Furthermore, the EEG records acquired from an individual experiencing the wake-to-sleep and the sleep-to-wake transitions, analyzed by Fourier transform, suggest that energy transfers take place between different spectral bands, this latter showing pseudo-fine structures.

Keywords: brain waves; EEG; wake; sleep; Fourier analysis; parametric resonance

1. Introduction

Brain function relies on coordinated electrical activity across neuronal populations, supporting processes ranging from sensory encoding to cognition, memory, and affective states [1–4]. At the network level, synchronized synaptic and membrane-potential fluctuations contribute to local field potentials and to the large-scale electrophysiological rhythms detected by electroencephalography (EEG) [5,6]. These rhythms are conventionally classified into frequency bands, including delta, theta, alpha, beta, and gamma activity, whose relative expression varies across cognitive, behavioural, and vigilance states [7,8].

Understanding how microscopic neuronal dynamics give rise to coherent macroscopic oscillations requires a multiscale description of brain activity. Astrocytic Ca^{2+} signalling, neuromechanical interactions, and other mesoscopic processes have been proposed as possible mechanisms linking local nonlinear dynamics to large-scale electrophysiological observables [9–11]. More general dynamical-systems and open-system approaches, together with hybrid quantum–classical formulations, also emphasize the roles of environmental coupling, multiscale organization, and collective brain dynamics [12–15]. Within this framework, resonance and synchronization may provide effective mechanisms for amplifying oscillatory activity and promoting transitions between functional brain states.

Concerning synchronization phenomena, the Kuramoto model [16,17], introduced by Yoshiki Kuramoto in the 1970s, offers a general theoretical scheme for describing how synchronization can emerge in coupled systems across many domains. Within neuroscience, it can serve as a useful abstraction for representing neuronal



synchrony thought to support coordinated activity and distributed information processing among brain areas. In essence, the Kuramoto formalism considers a population of coupled oscillators, each characterized by a phase and an intrinsic (natural) frequency; the model dynamics is commonly expressed, for n oscillators, as:

$$\frac{d\alpha_l}{dt} = v_l + \frac{C}{n} \sum_{m=1}^n \sin(\alpha_m - \alpha_l)$$

Here, α_l denotes the phase of the l -th oscillator, v_l its natural frequency, C the coupling strength parameter, and n the total number of oscillators. Interpreted in terms of neuronal synchronization, each oscillator can be viewed as a neuron: the phase α_l corresponds to an electrical or firing phase, whereas v_l represents the neuron's intrinsic firing rate, which may differ across neurons due to physiological and genetic variability.

The interaction term $\frac{C}{n} \sum_{m=1}^n \sin(\alpha_m - \alpha_l)$ plays the central role in the emergence of synchrony. It encodes how the activity of one neuron affects the timing of others in the network. The sinusoidal dependence $\sin(\alpha_m - \alpha_l)$ implies that coupling is controlled by phase differences: when phases are misaligned, the coupling acts to reduce the mismatch, thereby favouring phase locking.

Figure 1 illustrates this mechanism through the classical analogy of metronomes placed on a common movable platform. The metronomes interact indirectly through the motion of the shared base and may synchronize when the coupling is sufficiently strong relative to the differences among their natural frequencies. This phenomenon provides an intuitive representation of how coupled oscillatory units, such as neurons or neuronal populations, can achieve coherent collective behaviour.

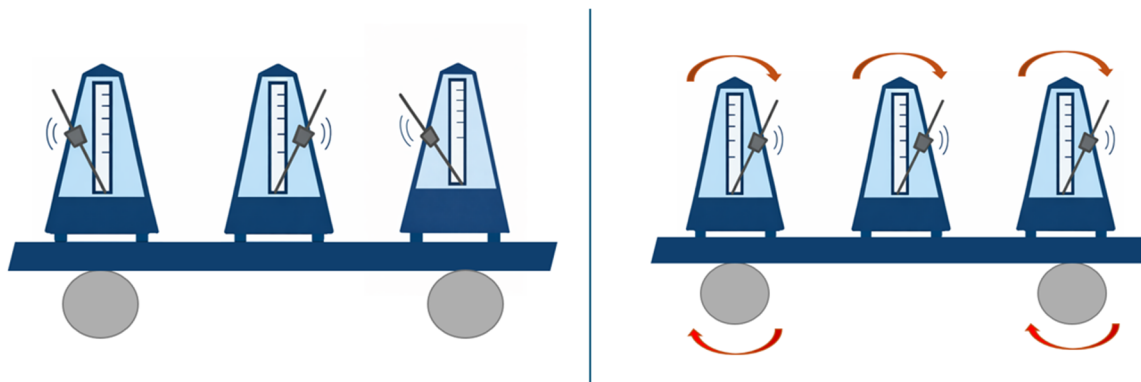


Figure 1. Mechanical analogy of synchronization among coupled neuronal oscillators. Three metronomes interact indirectly through a common movable platform and synchronize when the coupling is sufficiently strong relative to their natural-frequency differences.

When the coupling parameter C is weak, neurons predominantly follow their own intrinsic rhythms and tend to fire independently. As C grows, mutual interactions strengthen and progressively foster coordinated timing, so that neurons begin to align their firing phases. Once C exceeds a critical value, a substantial subset of neurons can lock together, producing coherent oscillatory activity at the network scale. In the limit of strong synchronization, phase differences across neurons become constant—potentially approaching zero—so that the network exhibits highly coordinated firing. Such synchronized regimes are commonly associated with rhythmic brain activities observed experimentally, including alpha, beta, and gamma oscillations.

The present study deals with a previously introduced parametric-resonance-based brain model [18] devised to describe cerebral electrical activity. In this approach, neuronal synchronization is treated as a key mechanism underlying the emergence of observable brain rhythms, particularly when large neuronal populations within defined regions act in a synchronized manner. The model builds on an analysis of brain-wave frequencies and advances the idea of a hierarchical amplification among bands. Parametric resonance refers to the situation in which a system's response becomes strongly enhanced at particular excitation frequencies, and it is widely used across scientific disciplines. Transposed to cerebral dynamics, brain waves are represented as oscillators whose amplitudes may be resonantly increased through mutual interactions. More specifically, the model posits that higher-frequency rhythms enhance the amplitude of lower-frequency rhythms, yielding a stepwise reinforcement from gamma down to delta activity. Supported by several empirical observations, this framework offers a unified interpretation of the relationships linking the principal brain-wave frequency ranges.

2. Results and Discussion

Different classes of brain waves, each defined by a characteristic frequency range, are linked to specific mental activities and psychophysiological states [19,20].

Delta waves (1.2–4 Hz) display a smooth and regular temporal profile, represent the slowest oscillatory brain activity, and exhibit the largest amplitudes; they prevail during deep, dreamless sleep and in profoundly meditative conditions, and they also constitute a hallmark of particular stages of brain maturation, especially in infancy [21].

Theta waves (4–7 Hz) occupy a slightly higher frequency range and emerge during specific phases of sleep, notably the stages 1 and 2 of non-REM sleep; they are likewise observed during deep relaxation and certain meditative practices, and are often associated with mental processes involving imagery, intuition, and memory.

Alpha waves (8–12 Hz) are characteristic of a relaxed waking state with closed eyes; they tend to dominate when the brain is calm and not heavily engaged in information processing; their amplitude can be enhanced through mindfulness and meditation, whereas they are typically suppressed during focused, open-eye cognitive activity.

Beta waves (13–30 Hz) are prominent during active and engaged mental states, such as problem solving and decision making; they correspond to the rhythm of the “working” brain, involved in logical reasoning and conscious choice.

Gamma waves (>30 Hz), while exhibiting the smallest amplitudes in EEG recordings relative to other bands, are the fastest oscillations; they are linked to higher-order cognitive functions, including perception and consciousness, and are thought to participate in the integration of information across distributed brain regions, being associated with heightened sensory awareness and insight. Moreover, each wave pattern differs not only in its frequency content but also in waveform and amplitude characteristics [22,23].

However, it is important to note that the different brain waves are not mutually exclusive phenomena; rather, they coexist across different cerebral regions, with their relative amplitudes and dominance varying according to the individual’s psychological and physiological conditions. Neuroscientific research has demonstrated that multiple types of neural oscillations can be active at the same time, pointing to a complex interplay that supports cognitive and emotional functions. The brain exhibits a highly dynamic organization in which distinct regions may concurrently generate different oscillatory activities. In humans, for example, during demanding problem-solving tasks, the frontal cortex may express beta oscillations, while posterior regions simultaneously display alpha activity characteristic of a more relaxed state.

The brain’s capacity to perform sophisticated cognitive operations relies on its ability to adjust both the intensity and the frequency of these oscillations in response to task demands. Activities requiring sustained attention and enhanced sensory processing are typically accompanied by increased beta and gamma activity in task-relevant cortical areas, whereas less engaged regions may continue to exhibit lower-frequency theta or alpha rhythms. Transitions between mental states are marked by shifts in the dominant frequency bands: the progression from wakefulness to sleep, for instance, involves a gradual change from faster beta oscillations to slower theta and delta activity. Even during sleep, different oscillatory bands coexist in intricate patterns that vary across sleep stages, reflecting layered modes of neural processing. The interactions among distinct frequency bands are further illustrated by phenomena such as cross-frequency coupling, in which the phase or amplitude of one oscillation modulates another. This mechanism is essential for cognitive flexibility and enables the efficient coordination of large-scale neural networks. Taken together, these observations emphasize the non-exclusive nature of brain waves and highlight their simultaneous expression as a fundamental feature of brain function, allowing the integration of sensory information, the regulation of consciousness, and the maintenance of cognitive adaptability across diverse tasks and states.

Sleep stages were classified according to the American Academy of Sleep Medicine (AASM) criteria [24], based on the combined evaluation of EEG, electrooculographic, and electromyographic signals in 30-s epochs. Wakefulness is typically associated with prominent occipital alpha activity, whereas the transition to N1 sleep is marked by alpha attenuation and the emergence of low-amplitude mixed-frequency activity dominated by theta oscillations. Stage N2 is characterized by sleep spindles and K-complexes, while stage N3 is dominated by high-amplitude delta activity.

As sleep onset occurs, the brain enters the first stage of non-rapid eye movement sleep, designated as stage N1. This stage represents the initial shift from wakefulness to sleep and corresponds to very light sleep. From an electrophysiological perspective, EEG activity during N1 is characterized by low-amplitude, mixed-frequency oscillations, with a clear dominance of theta-band activity and a concomitant reduction of alpha rhythms. In healthy adults, this stage generally accounts for approximately 5–10% of total sleep duration.

Progressing further into sleep, the brain transitions into stage N2, the second stage of non-rapid eye movement sleep, which constitutes the most prevalent sleep stage in adults, typically comprising about 40–55% of total sleep

time. Stage N2 is distinguished by specific EEG signatures, most notably the appearance of sleep spindles in the 11–16 Hz frequency range and K-complexes. These electrophysiological features are thought to contribute both to the stabilization of sleep and to processes of memory consolidation. Relative to wakefulness, this stage is associated with a further reduction in muscle tone and a decreased sensitivity to external sensory inputs.

The deepest phase of non-rapid eye movement sleep is stage N3, commonly referred to as slow-wave sleep. This stage is defined by the dominance of high-amplitude, low-frequency delta oscillations in the EEG signal. According to established scoring criteria, delta activity must occupy at least 20% of a 30-s epoch for the stage to be classified as N3. Functionally, this stage is closely linked to physical restoration, hormonal regulation, and fundamental restorative processes, reflecting a state of maximal neural synchronization and minimal responsiveness to the external environment.

The EEG recordings analyzed in this study were obtained from the ANPHY-Sleep database [25], an open-access high-density sleep EEG dataset from healthy adults, including synchronized EEG, EOG, EMG, and ECG signals with AASM-based sleep-stage annotations. For the present analysis, a 44-year-old female participant was selected. Her polysomnographic recording lasted 417 min, including approximately 310 min of sleep. Each 30-s epoch was assigned to a vigilance state according to AASM criteria. The main sleep parameters and stage durations of the selected recording are summarized in Table 1.

Table 1. Normative values reported here derive from large-scale polysomnographic studies of healthy adult populations and from the standardized definitions provided by the *American Academy of Sleep Medicine*. In adults, normal nocturnal sleep is typically characterized by a sleep efficiency exceeding 85%, a sleep onset latency below 30 min, and a wake-after-sleep-onset duration generally below 40 min. Sleep architecture is dominated by N2 sleep, with slow-wave sleep (N3) and REM sleep occupying progressively smaller yet physiologically essential fractions of total sleep time. Deviations from these ranges are commonly interpreted in terms of sleep fragmentation, altered sleep regulation, or age- and state-dependent variability, all of which are central to analyses of sleep–wake transitions and brain dynamical regimes.

Domain	Metric	Abbreviation	Reference Subject	Normative Range (Healthy Adults)
Recording Duration	Total Recording Time	TRT	417.0 min	360–480 min
Sleep Quantity	Total Sleep Time	TST	310.5 min	360–420 min
Sleep Quality	Sleep Efficiency	SE	74.5%	≥85%
Sleep Initiation	Sleep Onset Latency	SOL	4.5 min	<30 min
Sleep Continuity	Wake After Sleep Onset	WASO	102.0 min	<40 min
Sleep Architecture	Stage N1	N1	35.5 min (11.4%)	5–10% of TST
Sleep Architecture	Stage N2	N2	137.0 min (44.1%)	45–55% of TST
Sleep Architecture	Stage N3 (SWS)	N3	88.0 min (28.3%)	15–25% of TST
Sleep Architecture	REM Sleep	REM	50.0 min (16.1%)	20–25% of TST

The analysis focused on the occipital O1 channel, whose location is shown in Figure 2. The occipital region was selected because it is particularly sensitive to the attenuation and re-emergence of alpha activity during transitions between wakefulness and light sleep. The selection of the occipital region is not arbitrary; this cortical area is particularly sensitive to the rhythmic variations associated with the transition between wakefulness and sleep. It exhibits well-defined oscillations in the alpha and theta bands, which are considered fundamental markers for characterising the transitions from Wake to N1-Sleep and vice versa.

Figures 3 and 4 show the O1-channel EEG power spectra computed by Fourier analysis in the time windows preceding and following two physiological transitions: from wakefulness (W) to stage N1-Sleep (see Figure 3), and from stages N1/N2 back to wakefulness (see Figure 4). In both the cases, the curves represent the average power per frequency bin, with the before condition shown in blue and the after condition shown in orange.

During the Wake to N1-Sleep transition, which reflects a gradual shift toward light sleep, a clear redistribution of spectral energy emerges. Specifically, there is an increase in low-frequency power, mainly in the delta (1.2–4 Hz) and theta (4–7 Hz) bands, while the occipital alpha activity (8–12 Hz), characteristic of relaxed wakefulness, decreases. This pattern is consistent with the well-known attenuation of alpha rhythm during sleep onset.

Conversely, during the N1/N2-Sleep to Wake transition (see Figure 4), the spectral profile reorganizes in the opposite direction. In the condition after the return to wakefulness, a pronounced increase in alpha-band power is observed, reflecting the re-emergence of the occipital alpha rhythm. At the same time, a reduction in delta and theta activity, typically enhanced during light sleep, becomes evident. The color-coded shading of the frequency bands in the figures facilitates the visual interpretation of these spectral changes.

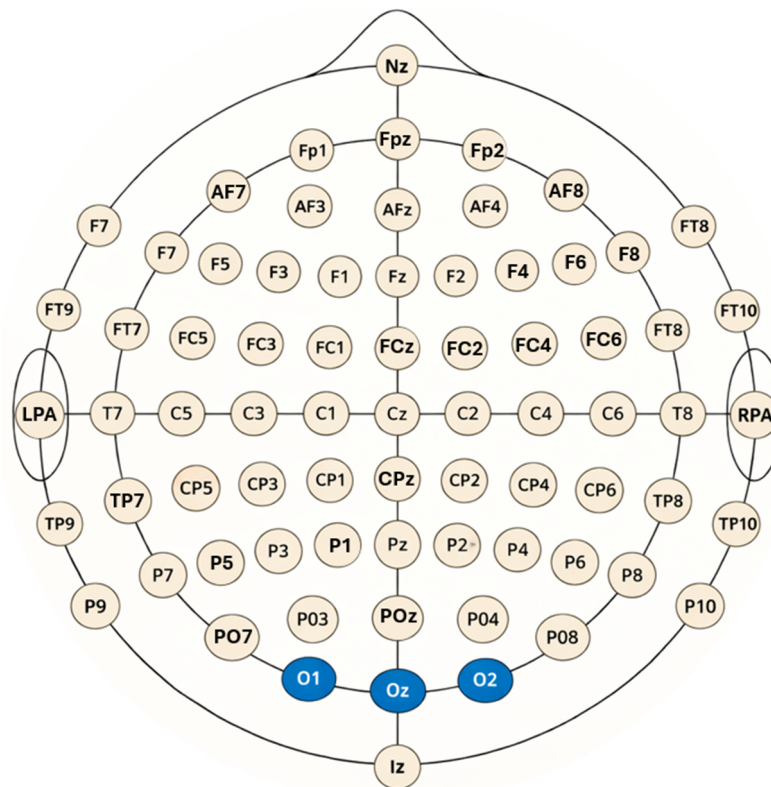


Figure 2. Schematic representation of the EEG electrode layout according to the international 10–20 system, with the occipital region highlighted. The present analysis was performed on the O1 channel.

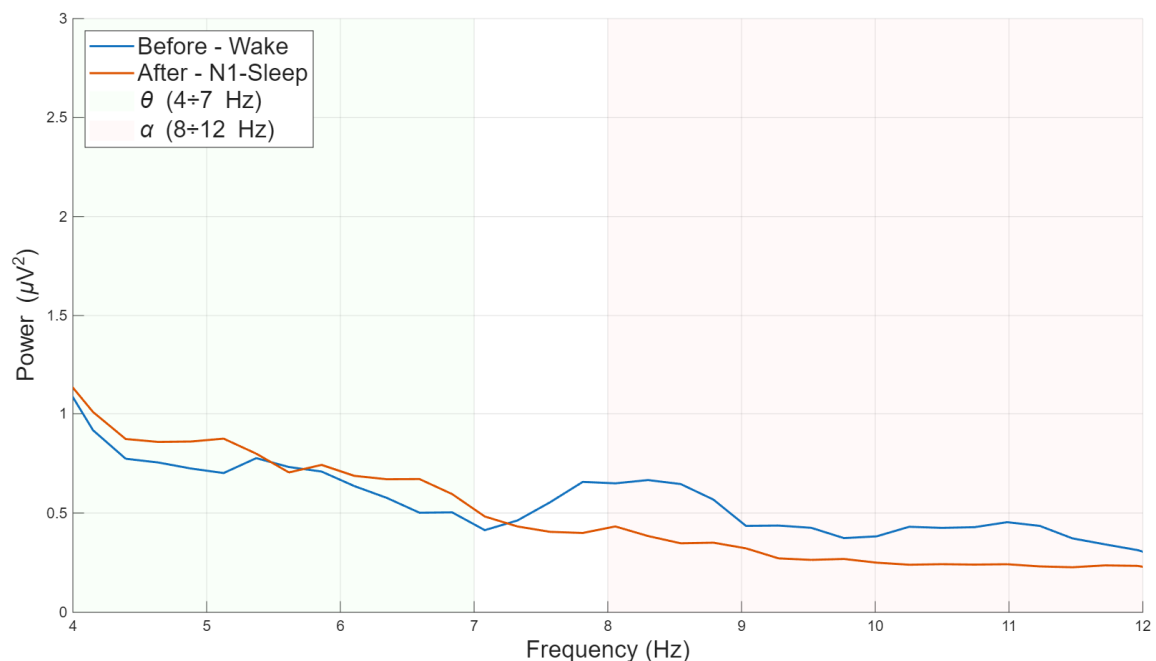


Figure 3. EEG power spectrum (channel O1) across the Wake to N1-Sleep transition, computed via Fourier analysis. The blue curve represents the Wake condition, while the orange curve corresponds to the N1-Sleep condition. The transition to Sleep is characterized by a redistribution of spectral energy, with increased power in the theta sub-bands (4–7 Hz) and a marked reduction in occipital alpha sub-bands (8–12 Hz), typical of relaxed wakefulness. Shaded regions highlight the canonical EEG frequency bands to support visual interpretation of the spectral changes (see captions inside the figure).

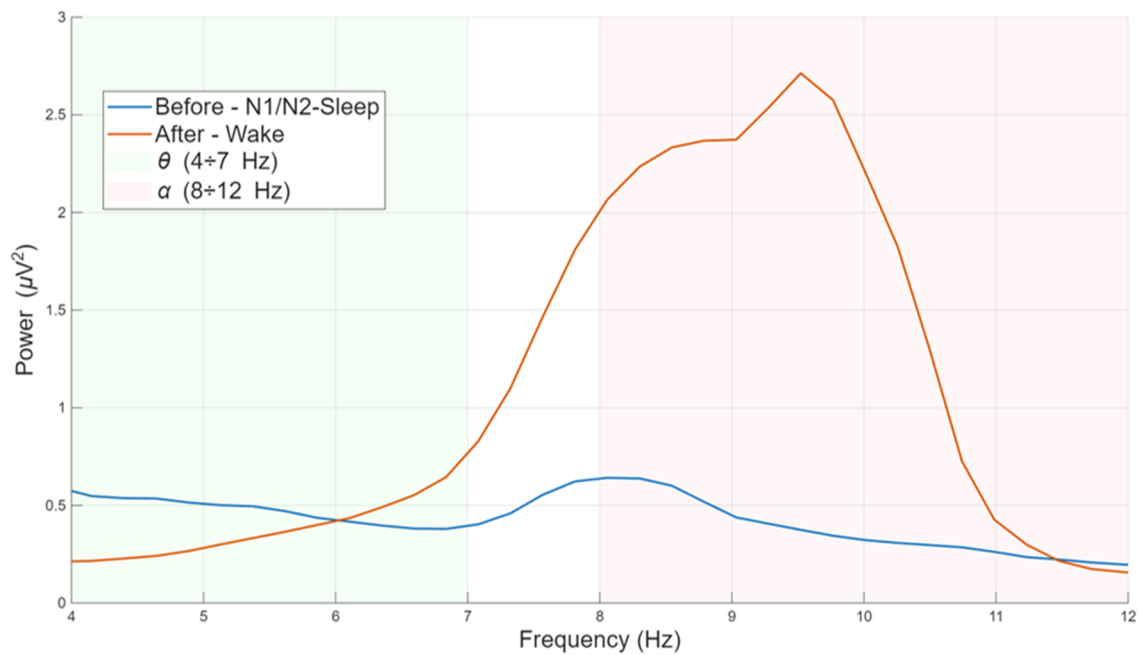


Figure 4. EEG power spectrum (channel O1) during the N1/N2-Sleep to Wake transition, computed via Fourier analysis. The blue curve represents the N1/N2-Sleep condition, while the orange curve shows the Wake condition. A marked increase in the alpha-band power (8–12 Hz) is observed after the return to wakefulness, reflecting the re-emergence of the occipital alpha rhythm. Conversely, power in the theta sub-band (4–7 Hz) decreases, consistent with the reduction of low-frequency activity typical of light sleep. Shaded regions indicate the canonical EEG frequency bands to facilitate visual interpretation (see the captions inside the figure).

Overall, the spectral analysis highlights the bidirectional modulation of EEG rhythms that accompanies transitions into and out of light sleep, with low-frequency activity increasing during sleep onset and alpha activity reappearing upon awakening.

To quantitatively assess the similarity between EEG power spectra recorded during wakefulness and N1-Sleep we computed the spectral distance (SD) using the Euclidean metric ($p = 2$). Given two records I_1 (Wake) and I_2 (N1-Sleep), the spectral distance is defined as:

$$d_p(I_1, I_2) = \left(\sum_{\lambda} |i_{1,\lambda} - i_{2,\lambda}| \right)^{1/p}, \quad p = 2$$

In order to provide a characterisation of these localised spectral changes during the two transitions, a multiresolution spectral-difference map was constructed by means of the partitioning of the investigated frequency range into a set of progressively finer sub-bands, corresponding to smaller and smaller scales. In particular, the original frequency interval of interest (4–12 Hz) was subdivided into 2^n contiguous frequency sub-bands, and within each range the power spectral difference was computed. The procedure yields a hierarchical representation, whereby coarse scales capture global spectral variations, while finer scales emphasise frequency-specific, localised differences.

Rather than relying solely on unsigned distance measures, a signed spectral difference was retained at each scale, computed as the mean difference between the two power spectra within each frequency band. This methodology preserves the sign of the spectral variation, thereby enabling the distinction of increases and decreases in spectral power across the two transitions. The resulting signed values were then replicated across the corresponding frequency bins to generate a two-dimensional multiresolution frequency representation in which spectral differences can be examined across progressively finer frequency scales.

The multiresolution spectral-difference map was then subjected to visualisation using a colour scale ranging from blue to red, with blue tones signifying negative spectral differences and red tones denoting positive differences. The colour limits were symmetrically normalized around zero in order to ensure a balanced representation of opposite spectral changes.

The use of spectral distance functions allows one to highlight key features of the transitions, showing that energy exchanges do not involve the entire EEG record but are instead localized within specific frequency bands.

Figure 5 shows, as an example, the map obtained during the Wake to N1-Sleep transition; two regions of negative differences (the blue bands) emerge at high frequencies, which reverberate as positive differences at low

frequencies (the yellow bands). This pattern indicates a redistribution of energy from faster to slower spectral components, consistent with the physiological dynamics of sleep onset.

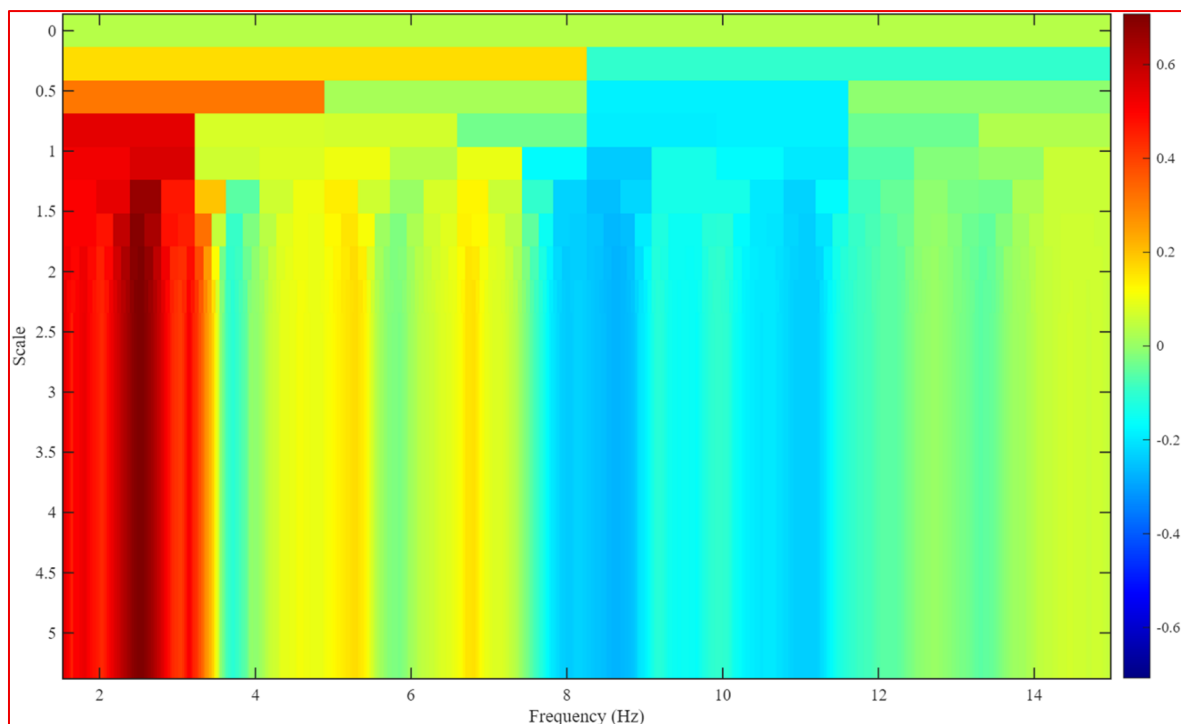


Figure 5. Spectral distance analysis during the Wake to N1-Sleep transition. Two regions of negative differences (blue bands) emerge at high frequencies while positive differences emerge at low frequencies (yellow bands). The figure highlights a frequency-dependent spectral reorganization accompanying sleep onset, characterized by a reduction of alpha-band activity and a concurrent enhancement of lower-frequency components within the theta range.

The central frequencies (centroids) of the EEG spectral components were estimated from the power spectrum computed on the O1 channel. For the Wake epoch (6780–6810 s), two alpha sub-bands (8–10 Hz and 10–12 Hz) were analysed, whereas for the N1 epoch (6810–6840 s), two theta sub-bands (4–6 Hz and 6–7 Hz) were considered. For each sub-band frequency interval, the dominant spectral peak was identified, and its centroid frequency was computed as the power-weighted average frequency within the peak region. The peak boundaries were defined as the frequencies at which the spectral power decreased below 50% of the peak value, FWHM (Full-Width at Half Maximum criterion). The use of spectral centroids provides a more robust estimate reducing sensitivity to local fluctuations and spectral-noise effects. The resulting centroid frequencies were 8.80 Hz and 11.63 Hz for the alpha components during wakefulness, and 5.23 Hz and 6.23 Hz for the theta components during N1 sleep. Frequency ratios were subsequently obtained by dividing the alpha centroids by the corresponding theta centroids, yielding $8.80 \text{ Hz} / 5.23 \text{ Hz} = 1.68$ and $11.63 \text{ Hz} / 6.23 \text{ Hz} = 1.87$. These counted ratios ranged from approximately 1.7 to 1.9, corresponding to deviations of about 5–15% from the ideal 2:1 relationship. Considering the intrinsic variability of EEG oscillations and the use of centroid-based frequency estimates, these values were regarded as approximately consistent with a harmonic 2:1 scaling relationship.

The experimental observations are compatible with the previously proposed parametric-resonance framework [18], which offers a possible interpretation of the frequency relationships observed within the complex dynamics of brain activity. In particular, the approximate frequency relationships and spectral reorganizations observed during Wake-N1 transition are consistent with a parametric resonance interpretation, although alternative physiological mechanism cannot be excluded. A central element of this approach is neuronal synchronization, whereby extensive populations of neurons discharge coherently within circumscribed brain regions, giving rise to synchronized electric fields that are experimentally observable. Such collective synchronization is essential for the emergence of coherent brain rhythms and supports efficient information transfer among distributed neural assemblies.

Within this theoretical setting, brain-wave frequencies do not merely correspond to distinct functional or vigilance states, but appear to be organized according to a hierarchical structure characterized by an approximately constant scaling factor. The frequency relationships observed during wake–sleep transitions are consistent with a resonance-based interpretation and may reflect interactions among oscillatory modes operating across multiple temporal scales. At the same time, alternative physiological mechanisms cannot be excluded. In particular, the

progressive reduction of cholinergic neuromodulatory activity during sleep onset is known to affect cortical excitability and network synchronization, potentially contributing to the simultaneous reorganization of multiple oscillatory generators. From this perspective, neuromodulatory changes may act as a global control parameter facilitating the emergence of the resonance-like spectral patterns observed in the EEG.

It is worth noting that the direction of interaction suggested by the present resonance-based framework differs from the conventional interpretation commonly reported in the cross-frequency coupling literature. Phase-amplitude coupling studies typically describe a modulation of faster oscillations by the phase of slower rhythms. However, these findings mainly concern theta–gamma or delta–gamma interactions, whereas the present work focuses on the theta–alpha frequency range and does not directly assess coupling directionality.

Accordingly, the proposed fast-to-slow resonance interpretation should not be regarded as a demonstrated causal mechanism but rather as a theoretical framework capable of accounting for the observed frequency relationships. Future studies employing dedicated directionality measures will be required to determine whether preferential interactions exist between the oscillatory components identified here [26–28].

Computational studies on single-neuron models have shown that resonance-related mechanisms, including stochastic resonance, can enhance weak-signal detection in the presence of background synaptic activity. In particular, Type-II Morris–Lecar neurons subjected to excitatory and inhibitory presynaptic bombardments exhibit frequency-selective responses. Although the present work addresses large-scale EEG dynamics, these findings suggest that resonance phenomena may operate across multiple organizational levels of the nervous system. The proposed parametric-resonance interpretation should therefore be viewed as complementary to other resonance-based mechanisms described at the neuronal level [29].

Accordingly, proposed framework suggests that higher-frequency brain rhythms may contribute to the modulation of lower-frequency oscillations through parametric-like interactions. The systematic growth in oscillation amplitude observed when moving from faster to slower brain waves further indicates that brain rhythms are not independent, but instead form an interconnected, multilayered system of interactions. Such a pattern is consistent with the possibility of a structured resonance cascade, in which each frequency band may contribute to shaping and reinforcing the dynamics of the immediately lower band.

In synthesis, in this work, we propose a theoretical framework in which EEG activity is interpreted as the macroscopic manifestation of a nonequilibrium oscillatory system governed by synchronization and potentially influenced by resonance-related mechanisms. By moving beyond the conventional band-based classification of brain rhythms, our analysis reveals an underlying spectral organization within the theta-alpha frequency range (4–12 Hz) characterized by approximate scaling relationships between dominant oscillatory modes.

The Fourier-based investigation of EEG signals during the wake–sleep and the sleep–wake transitions provide clear evidence of systematic energy redistribution across frequency bands. In both transition directions, the ratios between the sub-band center frequencies are consistently close to two, suggesting the interpretation of a parametric resonance process.

Within this perspective, neuronal synchronization plays a central role by enabling large neural populations to behave coherently, thereby generating oscillatory modes capable of interacting through parametric amplification. Higher-frequency rhythms appear to modulate and enhance lower-frequency oscillations, producing a structured cascade in which amplitudes progressively increase toward slower dynamics. This hierarchical organization mirrors classical parametric-resonance phenomena observed in nonlinear driven systems and provides a unifying interpretation of cross-frequency interactions in the brain.

The proposed model offers a coherent physical interpretation of EEG spectral transitions and suggests that parametric resonance may represent a plausible mechanism underlying the emergence, modulation, and stability of large-scale brain rhythms. However, the present results should be regarded as supporting the consistency of such an interpretation rather than demonstrating a unique underlying mechanism.

3. Conclusions

In this work, EEG brain activity has been interpreted within a theoretical framework in which large-scale neural dynamics are viewed as the macroscopic expression of a nonequilibrium oscillatory system. Within this perspective, neural populations are described as interacting ensembles whose collective behavior may give rise to coherent rhythms, synchronization phenomena, and resonance-like effects across different temporal scales. The analysis of EEG spectra recorded during wake-to-sleep and sleep-to-wake transitions highlights the presence, within the theta-alpha frequency interval examined here, of dominant oscillatory components displaying approximately harmonic frequency relationships. This finding suggests that the observed spectral organization cannot be regarded merely as a random distribution of independent frequencies, but may instead reflect the

emergence of structured relationships among neural oscillatory modes. The Fourier analysis of the EEG records further indicates that transitions between vigilance states are accompanied by a redistribution of spectral energy among different frequency bands. Such redistribution appears to be associated with the appearance of pseudo-fine spectral structures, which may be interpreted as signatures of modulation, coupling-like behavior, or energy exchange among neural rhythms. In this sense, wake-to-sleep and sleep-to-wake transitions provide a privileged dynamical context in which the brain's oscillatory organization becomes particularly evident. Several limitations of the present study should, however, be acknowledged. First, the analysis was performed on a single subject and focused on a single occipital EEG channel, O1. Consequently, the reported frequency relationships should be regarded as descriptive observations rather than statistically generalizable findings. Future studies involving larger cohorts and multiple EEG channels will be necessary to assess the reproducibility, inter-subject variability, and statistical significance of the observed frequency-ratio distributions. Second, the present analysis is based on spectral comparisons and frequency-ratio estimation and does not include dedicated measures of causal directionality or nonlinear cross-frequency interactions. Therefore, although the observed frequency relationships are consistent with the proposed resonance-based framework, they do not establish a direct dynamical coupling between oscillatory components. Future investigations may complement the present approach with bispectral and bicoherence analyses, as well as statistical directionality measures such as Cross-Frequency Directionality and Phase Transfer Entropy.

Finally, alternative explanations cannot be excluded. In particular, the observed spectral reorganization may also reflect state-dependent oscillatory changes, common neuromodulatory influences associated with sleep onset, including the progressive withdrawal of cholinergic activity, or other forms of cross-frequency interactions reported in the literature. Accordingly, the proposed parametric-resonance interpretation should be regarded as a plausible theoretical framework consistent with the observations, rather than as a uniquely demonstrated mechanism. Overall, the results support the idea that synchronization and parametric resonance may provide useful conceptual tools for interpreting the collective behavior of neural systems. Rather than considering EEG rhythms as isolated frequency bands, the proposed approach emphasizes their possible mutual relationships and their role within a broader resonant architecture of brain activity. Although exploratory, this framework opens the way to further investigations aimed at testing resonance-based interpretations on larger EEG datasets, across different sleep stages, and through complementary time-frequency and nonlinear analytical methods.

Author Contributions

M.T.C.: conceptualization, methodology, data curation, formal analysis, visualization, writing-original draft preparation; K.A.: data curation, investigation, formal analysis, validation, writing-original draft preparation; A.S.: methodology, validation. S.M.: conceptualization, supervision, methodology, writing-reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical review and approval were not required for the present study, as it involved the secondary analysis of publicly available, anonymized data. The original ANPHY-Sleep study was approved by the Research Ethics Board of the Montreal Neurological Hospital and Institute (protocol code MP-37-2018-3886).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the original study. No additional informed consent was required for the present secondary analysis of publicly available, anonymized data.

Data Availability Statement

The data analyzed in this study are publicly available in the ANPHY-Sleep dataset at OSF (<https://doi.org/10.17605/OSF.IO/R26FH>) (accessed on 30 January 2026). No new data were generated in the present study.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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