MODELING CIRCADIAN RHYTHMS WITH PHYSICS-INFORMED NEURAL NETWORKS

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Circadian rhythms are generated by endogenous molecular oscillators and modulated by environmental cues such as light, food, and temperature. These rhythms can be effectively modeled as networks of coupled biological oscillators, capturing the synchronization dynamics within structures such as the suprachiasmatic nucleus (SCN) [2]. To better represent the transient dynamics of circadian systems under external perturbations (e.g. jet lag), we extend the classical Kuramoto model by incorporating inertia and damping. This leads to a second-order formulation:

$$\frac{d^2\theta_i}{dt^2} + \gamma\frac{d\theta_i}{dt} = \omega_i + \frac{K}{|N_i|}\sum_{j\in N_i}\sin(\theta_j - \theta_i) + A\sin\left(\frac{2\pi t}{T}\right) \tag{1}$$

This model accounts for delayed adaptation and realistic neuronal response times. We define a modular network of $N = 40$ oscillators partitioned into three regions: the SCN (A), an interfacial layer (I), and peripheral tissues (B), interconnected via a graph with local and random links. Oscillators in the SCN receive light-driven forcing, while those in regions I and B have slightly shorter intrinsic periods ($\omega_A = 2\pi/24$, $\omega_{I,B} = 2\pi/22$), reflecting physiological heterogeneity.

Physics-Informed Neural Networks (PINNs) are employed to infer the phase dynamics $\theta_i(t)$ and a behavioral proxy $1 - \cos(\theta_i)$ from sparse observational data. The network minimizes a composite loss function comprising three terms: physical consistency (ODE residuals), synchrony (pairwise phase alignment), and behavioral fidelity (deviation from observed outputs). To overcome the spectral bias inherent in standard neural networks, we apply Fourier feature mappings [3], which enhance the model's capacity to resolve fast phase transitions.

To validate our model, we reproduced the circadian dynamics observed under jet lag conditions as reported by Houben et al. [4]. Figure 1 shows our simulation results using the PINN framework, which accurately captures the dissociation between SCN and behavioral adaptation.

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[2] Ji, P., et al. (2014). Low-dimensional behavior of Kuramoto model with inertia in complex networks. *Scientific Reports*, **4**, 4783.

[3] Tancik, M., et al. (2020). Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains. *NeurIPS*, **33**, 7537-7547.

[4] Houben, T., et al. (2014). Adaptation to constant light requires plasticity of the circadian clock. *Journal of Biological Rhythms*, **29**(6), 509-520.

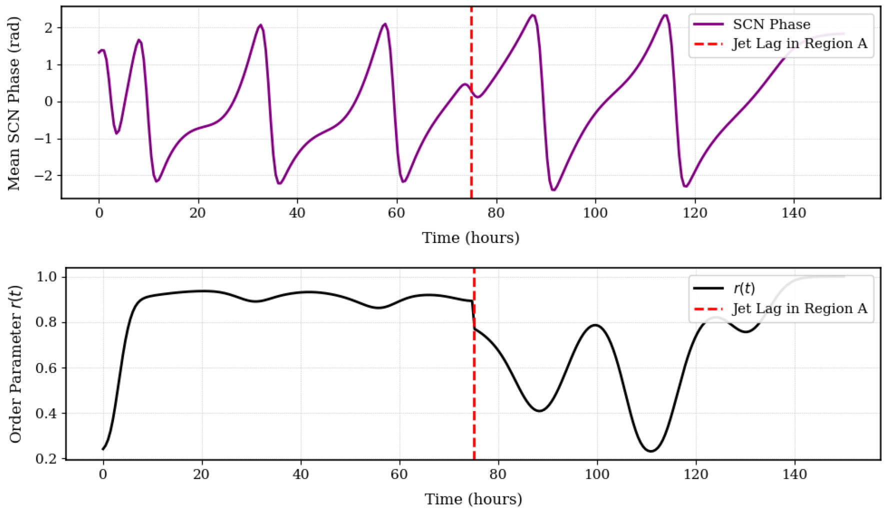

FIG. 1. SCN and network response to a T-cycle advance at hour 72 (red dashed line). **Top:** Mean SCN phase shows transient misalignment followed by gradual re-entrainment. **Bottom:** Order parameter $r(t)$ drops sharply, reflecting temporary network desynchronization.

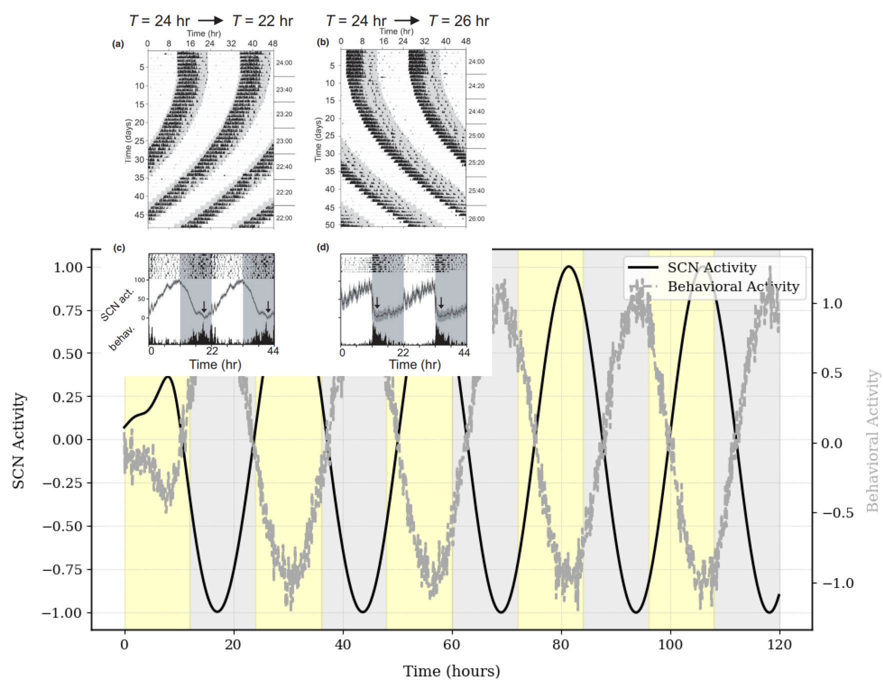

FIG. 2. Simulation results using the proposed PINN framework. The black curve represents SCN neuronal activity and the gray curve denotes behavioral activity. **Inset:** Experimental results reproduced from [4], illustrating the observed phase dissociation.