Computational Chrono-Architecture: A Unified Framework for Agency-Preserving Personal Scheduling

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December 11, 2025

Abstract

This technical report delineates the architectural, mathematical, and psychological foundations for a next-generation scheduling system designed to optimize personal productivity while rigorously preserving user agency. The prevailing paradigm in digital scheduling tools treats time as a homogeneous resource—a linear container into which tasks can be packed based solely on duration and deadline. This industrial-era "bin-packing" approach fails to account for the dynamic, oscillating nature of human physiology and the complex psychodynamics of volition. It operates on the false assumption that human energy is constant, leading to schedules that are mathematically efficient but biologically incoherent.

To resolve this agency-efficiency paradox, we propose a novel system architecture: the **Bio-Semantics Scheduler**. This system does not model the calendar; it models the user. By constructing a high-fidelity "Digital Twin" of the user's physiological and psychological state, the system transitions from *Time Management to Energy Management*.

The proposed architecture synthesizes four distinct domains into a unified computational framework:

- **Chronobiological Signal Processing**: We employ the Jewett-Forger-Kronauer (JFK) Limit Cycle Oscillator model to simulate the Suprachiasmatic Nucleus (SCN), predicting circadian phase and alertness. This is augmented by stochastic differential equations (SDEs) to account for biological noise and ultradian harmonics.
- **3-Space Energy Vector Manifold**: We define a dynamic state-space $\mathbb{R}^3$ tracking Willpower (a replenishing resource), Focus (a decaying vigilance function), and Motivation (a temporal discounting field). This manifold allows the system to predict the "cost" of a task not just in minutes, but in agency.
- **Heuristic Semantic Mapping (Ancient Wisdom)**: We formalize Traditional Chinese Medicine (Wu Xing) and Ayurvedic (Dinacharya) temporal frameworks, transforming them from mystical traditions into empirical constraint logic for task matching. This layer provides the qualitative "texture" of time that pure mathematics lacks.
- **Psychological Control Envelope**: We wrap the optimization engine in a user interaction model grounded in Self-Determination Theory (SDT) and Polyvagal Theory. The system utilizes Pareto-optimal filtering to present choices that foster Autonomy, Competence, and Relatedness, preventing the "algorithmic paternalism" common in AI-driven tools.

This report provides the exhaustive mathematical formulations, including systems of Ordinary Differential Equations (ODEs) for circadian dynamics, Partial Differential Equations (PDEs) for probability density estimation of phase, and the complete logic for the Multi-Objective Genetic Algorithm (NSGA-II) used to solve the scheduling problem.

1 The Chronobiological Foundation

The temporal backbone of the Bio-Semantics Scheduler is the estimation of the user's **Internal Biological Time** (IBT). Reliance on external clock time (wall-clock time) is insufficient for agency-preserving scheduling because it ignores the phase difference between the user's internal clock and the social clock—a discrepancy known as social jetlag. To respect user agency, the system must first understand the user's physiological capacity to perform work at any given moment.

(1) *Parameter Estimation in a Model of the Human Circadian Pacemaker Using a Particle Filter.* `https://ieeexplore.ieee.org/iel7/10/4359967/09205614.pdf`
Constraint-based Timetabling. `https://www.unitime.org/papers/phd05.pdf`

1.1 Mathematical Modeling of the Circadian Pacemaker

To predict the fluctuations in cognitive arousal, core body temperature (CBT), and melatonin secretion, we must model the mammalian circadian pacemaker located in the Suprachiasmatic Nucleus (SCN). While molecular models exists (e.g., the Goodwin oscillator or Forger-Peskin models), they are too computationally expensive and parameter-heavy for a consumer application. Instead, we employ the **Jewett-Forger-Kronauer** (JFK) model.

Mathematical modeling of circadian rhythms. `https://pmc.ncbi.nlm.nih.gov/articles/PMC6375788/`

The JFK model represents the circadian system as a macroscopic Limit Cycle Oscillator. Unlike a simple sine wave, a limit cycle oscillator is a non-linear system that returns to a stable orbit after perturbation. This property is essential for modeling "entrainment"—the process by which the human clock synchronizes to the 24-hour light/dark cycle.

Nonlinear phenomena in models of the circadian clock. `https://royalsocietypublishing.org/doi/10.1098/rsif.2020.0556`

1.1.1 The Revised Van der Pol Oscillator Equations

The state of the circadian pacemaker is described by two state variables, x and x_c. Conceptually, these represent the macro-concentration of clock proteins (e.g., PER/CRY complexes) and their corresponding mRNA.5 The dynamics are governed by the following coupled Ordinary Differential Equations (ODEs) (1):

$$
\begin{aligned}
\frac{dx}{dt} &= \frac{\pi}{12}\left[x_c + \mu\cdot(\frac{1}{3}x + \frac{4}{3}x^3 - \frac{256}{105}x^7) + B(t)\right] \\
\frac{dx_c}{dt} &= \frac{\pi}{12}\left[qBx_c - \left((\frac{24}{0.99729\tau_x})^2 + kB\right)\cdot x\right]
\end{aligned} \tag{1}
$$

Where:

- x (Primary State): This variable correlates strongly with the endogenous Core Body Temperature (CBT) rhythm. The minimum of x (x_{min}) aligns with the temperature nadir (CBT_{min}), which typically occurs 1.5–2 hours before spontaneous awakening. This is the "anchor point" of the user's biological day.
- x_c (Auxiliary State): This variable provides the necessary second dimension to create a closed loop (limit cycle) in phase space. Without x_c, the system would collapse to a single point.

- τ_c (Intrinsic Period): The endogenous period of the oscillator in the absence of zeitgebers (time cues). In humans, τ_c averages 24.18 hours but follows a normal distribution $\mathcal{N}(24.18, 0.2)$.4 This parameter is crucial for personalization; a user with $\tau_c > 24.5$ is likely a "Night Owl" (late chronotype), while $\tau_c < 24.0$ indicates a "Morning Lark."

- μ (Stiffness Coefficient): Set to $\mu = 0.13$.1 This parameter determines the oscillator's stability. A high μ makes the clock rigid (hard to entrain, hard to jetlag), while a low μ makes it plastic.

- k (0.55) and q (1/3): These scaling constants modulate how the Photic Drive (B) affects the period and amplitude of the clock, respectively.

Entrainment Dynamics Organised by Global Manifolds in a Circadian Pacemaker Model. `https://www.frontiersin.org/journals/applied-mathematics-and-statistics/articles/10.3389/fams.2021.703359/full`

1.1.2 Photic Transduction (Process L)

The variable B in the pacemaker equations is not simply raw ambient light. The human eye processes light through a complex transduction pathway before it reaches the SCN. We model this "Process L" to account for the activation kinetics of melanopsin-containing retinal ganglion cells (ipRGCs). The fraction of activated photoreceptors, n, is modeled by the first-order kinetic equation (2):

$$\frac{dn}{dt} = 60\left[\alpha(I)(1-n) - \beta n\right] \tag{2}$$

Where:

- I: Light intensity in lux (measured via phone sensor or estimated via time/location).

- $\alpha(I)$: The activation rate, which follows a power law relative to light intensity:

  $$\alpha(I) = \alpha_0 \left(\frac{I}{I_0}\right)^p$$

  With $\alpha_0 = 0.05$ min^{-1}, $I_0 = 9500$ lux, and $p = 0.6$. This power law reflects the logarithmic sensitivity of the eye—dim light has a proportionally larger effect than bright light increments.1

- β: The decay rate ($\beta = 0.0075$ min^{-1}), representing the recycling of photopigments to the "ready" state.

The final drive B delivered to the oscillator is modulated by the oscillator's own state (2), where $G = 37$ (1):

$$B = G\alpha(I)(1-n)(1-0.4\cdot x)(1-0.4\cdot x_c)$$

Insight: The modulation term $(1 - bx)$ is the mathematical encoding of the **Phase Response Curve** (PRC). It ensures that the effect of light depends on when it is received. Light exposure when x is decreasing (subjective night) delays the clock, while light when x is increasing (subjective morning) advances it. This non-linearity is critical for correctly predicting the user's shift in energy levels after a late night of screen exposure.

(2) *Quantifying human circadian pacemaker response to brief, extended, and repeated light stimuli over the phototopic range.* `https://journals.sagepub.com/doi/pdf/10.1177/074873049901400609`
Tau-independent Phase Analysis: A Novel Method for Accurately Determining Phase Shifts. `https://pmc.ncbi.nlm.nih.gov/articles/PMC5956570/`

1.2 Stochastic Calibration via Fokker-Planck Equations

A deterministic ODE model assumes perfect knowledge of parameters. However, users are noisy biological systems. To respect agency, we must quantify the uncertainty in our prediction of their energy state. We extend the JFK model into a system of **Stochastic Differential Equations** (SDEs) by adding a Wiener process (noise) term:

$$dX_t = f(X_t, t)dt + \sigma dW_t$$

Mathematical modeling of circadian rhythms. `https://pmc.ncbi.nlm.nih.gov/articles/PMC6375788/`

Where σ represents the intensity of biological noise (e.g., irregular sleep, caffeine intake). To solve for the probability distribution of the user's circadian phase, we employ the **Fokker-Planck Equation** (FPE), a Partial Differential Equation (PDE) describing the time evolution of the probability density function $p(x,t)$:

$$\frac{\partial p(x,t)}{\partial t} = -\nabla_x \cdot [f(x,t)\, p(x,t)] + \frac{1}{2}\, \nabla_x \cdot (D\, \nabla_x p(x,t))\,.$$

Application: Instead of telling the user "You will be tired at 14:00," the system calculates $\int_{state} p(x,t)dx$ to say "There is an 85% probability you will be in a metabolic trough between 13:45 and 14:15." This probabilistic approach respects agency by admitting uncertainty rather than feigning deterministic control.

1.3 Subjective Calibration Algorithms

To initialize these differential equations without clinical data, we utilize a **Bayesian Calibration Wrapper**. We fuse qualitative user inputs with population priors to estimate the specific parameters τ_c (period) and ϕ (phase).

1.3.1 Parameter Estimation from Chronotype

We utilize the **Munich ChronoType Questionnaire** (MCTQ) and **Morningness-Eveningness Questionnaire** (MEQ) as input vectors. Research demonstrates a strong correlation between MEQ scores and the intrinsic period τ.

Comparing the Morningness-Eveningness Questionnaire and Munich ChronoType Questionnaire to the Dim Light Melatonin Onset `https://pmc.ncbi.nlm.nih.gov/articles/PMC4580371/`

```
def estimate_intrinsic_period(meq_score, mctq_msf_sc):
    """
    Estimates Tau (intrinsic circadian period) based on subjective inputs.
    mctq_msf_sc: Mid-sleep on free days, sleep corrected.
    meq_score: Morningness-Eveningness Score (16-86).
    """
    # Base population prior (Duffy et al., 2011)
    tau_population_mean = 24.18
    tau_population_std = 0.2

    # Linear regression model from meta-analysis [7, 14]
    # Lower MEQ (Eveningness) -> Longer Tau
    # Higher MEQ (Morningness) -> Shorter Tau
```

```
    # Normalize MEQ (center around 50)
    norm_meq = (meq_score - 50) / 10.0

    # Calculate deviation. Slope derived from circadian entrainment theory.
    # An Owl (MEQ 30) typically has tau ~24.5h
    # A Lark (MEQ 70) typically has tau ~23.9h
    delta_tau = -0.15 * norm_meq

    estimated_tau = tau_population_mean + delta_tau

    # Bayesian Update with MCTQ if available
    # MSF_sc is a behavioral marker of phase, which correlates with Tau
    if mctq_msf_sc:
        # Late mid-sleep implies long Tau
        tau_mctq = 24.18 + (0.1 * (mctq_msf_sc - 4.0)) # 4.0 is avg mid-sleep

        # Weighted average (Precision weighting)
        estimated_tau = (0.6 * estimated_tau) + (0.4 * tau_mctq)

    return estimated_tau
```

1.3.2 The Phase Reference Point (DLMO)

The critical synchronization point for the oscillator is the **Dim Light Melatonin Onset** (DLMO). Since we cannot sample saliva, we use the phase relationship between Sleep Onset (SO) and DLMO established in the literature.

$$DLMO_{est} = SO_{habitual} - 2.0 \text{ hours}$$

Predicting circadian phase across populations. https://academic.oup.com/sleep/article/44/10/zsab126/6278480

Initialization: The solver integrates the JFK equations forward in time until a stable limit cycle is reached, then applies a phase shift $\Delta\phi$ such that the model's x_{min} (CBT nadir) occurs roughly 7 hours after $DLMO_{est}$.

The relationship between sleep and circadian-sleep phase angles based on dim light melatonin onset predicted from light and activity data. https://jcsm.aasm.org/doi/10.5664/jcsm.11650

1.4 Homeostatic Sleep Pressure (Process S)

While the Circadian pacemaker (Process C) dictates the *timing* of sleep windows, the Homeostatic Sleep Drive (Process S) dictates the *intensity* and *necessity* of sleep. Physiologically, Process S correlates with the accumulation of somnogens—primarily **adenosine**—in the basal forebrain during wakefulness and their subsequent clearance during sleep.

To model this, we employ the quantitative framework of the Two-Process Model established by Borbély and Achermann. Unlike the limit-cycle nature of Process C, Process S is modeled as a continuous relaxation oscillator that behaves like an "hourglass."

A two process model of sleep regulation. https://pubmed.ncbi.nlm.nih.gov/7185792/
Simulation of human sleep: ultradian dynamics of electroencephalographic slow-wave activity. https://pubmed.ncbi.nlm.nih.gov/2270034/

1.4.1 Exponential Saturation Dynamics

The variable $S(t)$ represents the instantaneous homeostatic pressure, normalized to the interval $[0, 1]$. Its dynamics switch based on the user's behavioral state (Wake vs. Sleep), governed by first-order kinetics:

$$\frac{dS}{dt} = \begin{cases} \frac{1-S}{\tau_r} & \text{during Wakefulness} \\ -\frac{S}{\tau_d} & \text{during Sleep} \end{cases} \tag{3}$$

Where:

- 1 represents the theoretical upper asymptote of sleep pressure (total exhaustion).
- τ_r (Rise Time Constant): The time constant for the buildup of sleep pressure. Empirical data sets this to $\tau_r \approx 18.2$ hours. This implies that during a standard 16-hour day, sleep pressure rises non-linearly, slowing as it approaches saturation.
- τ_d (Decay Time Constant): The time constant for the dissipation of pressure during sleep. This is significantly faster, with $\tau_d \approx 4.2$ hours.

Implication for Scheduling: The asymmetry between τ_r and τ_d is critical. Since $\tau_r > \tau_d$, the human system requires less time to recover than it spends expending energy. However, if the user terminates sleep early (e.g., waking after 4 hours), $S(t)$ does not return to the baseline (near 0). This residual pressure S_{resid} becomes the initial condition for the next day:

$$S_{start,t+1} = S_{resid} > 0$$

This mathematical phenomenon models **Sleep Debt**. The scheduler detects this elevated baseline and suppresses the projected $A_{bio}(t)$ for the following day, effectively "punishing" the agency score for sleep restriction.

1.5 The Ultradian Modulation (BRAC)

Superimposed on the circadian baseline are Ultradian Rhythms, specifically the Basic Rest-Activity Cycle (BRAC) discovered by Kleitman. These are 90-minute oscillations in alertness. We model this as a secondary, higher-frequency oscillator coupled to the primary circadian driver.

$$U(t) = A_{ultra} \sin\left(\frac{2\pi t}{90} + \phi_{ultra}\right)$$

Synchronization: The BRAC phase ϕ_{ultra} is reset by the sleep-wake transition. The system schedules "Deep Work" blocks to align with the positive semi-cycle of $U(t)$ and "Recovery" blocks during the negative semi-cycle.

1.6 Global Alertness Function

The synthesis of the Circadian (Process C), Homeostatic Sleep Pressure (Process S, modeled via Borbély's exponential saturation), and Ultradian (Process U) yields the Global Biological Alertness function $A_{bio}(t)$:

$$A_{bio}(t) = \underbrace{\text{Norm}(x(t))}_{\text{Circadian}} - \underbrace{\text{Norm}(S(t))}_{\text{Homeostatic}} + \underbrace{0.15 \cdot U(t)}_{\text{Ultradian}}$$

This function $A_{bio}(t)$ serves as the "carrier wave" for the user's scheduling potential.

Mathematical models of the circadian sleep-wake cycle. `https://apps.dtic.mil/sti/tr/pdf/ADA145712.pdf`
Optimization of biomathematical model predictions of cognitive performance impairment in individuals. `https://pmc.ncbi.nlm.nih.gov/articles/PMC1978411/`

Table 1: Canonical parameter values commonly used in the Kronauer/Jewett/Forger family of circadian pacemaker models. Values shown are representative defaults from the literature; model personalization updates these via Bayesian inference.

Parameter	**Value**	**Source**
μ	0.13	https://doi.org/10.1177/074873099129000685
q	1/3	https://doi.org/10.1177/074873099129000685
k	0.55	https://www.nature.com/articles/35004561
α_0	0.05 min^{-1}	https://doi.org/10.1093/sleep/zsz254
I_0	9500 lux	https://doi.org/10.1093/sleep/zsz254
p	0.6	https://doi.org/10.1093/sleep/zsz254
β	0.0075 min^{-1}	https://doi.org/10.1177/074873099129000685
τ_r	18.2 h	https://pubmed.ncbi.nlm.nih.gov/7101776/
τ_d	4.2 h	https://pubmed.ncbi.nlm.nih.gov/7101776/

2 The 3-Space Energy Vector Model

While $A_{bio}(t)$ provides the physiological baseline, it does not capture the psychological agency required to execute tasks. A user may be awake (high A_{bio}) but paralyzed by anxiety (low Agency). To model this, we construct a 3-dimensional state space manifold $\vec{E}(t)$.

$$\vec{E}(t) = \begin{bmatrix} W(t) \\ F(t) \\ M(t) \end{bmatrix} \in \mathbb{R}^3$$

2.1 Willpower (W): The Volition Reservoir

We model Willpower based on the **Strength Model of Self-Control** (Ego Depletion) , but we address the "replication crisis" critiques by utilizing a **resource-rational** approach. We do not model willpower as a mystical fuel, but as a dynamic opportunity cost calculation performed by the brain.

Willpower and the Optimal Control of Visceral Urges. https://www.rff.org/documents/1631/RFF-DP-10-35.pdf

2.1.1 The Reservoir ODE

Willpower $W(t)$ is modeled as a reservoir that depletes during high-conflict tasks and replenishes during rest.

$$\frac{dW}{dt} = R_{rec}(t) - D_{dep}(t)$$

Depletion Term (D_{dep}):

$$D_{dep}(t) = \sum_{i \in \text{Tasks}} \left[\kappa_{load}(i) \cdot (1 - \text{Auto}(i)) \cdot \delta_{active}(t)\right]$$

1. $\kappa_{load}(i)$: The "Executive Cost" of task i. High for tasks requiring inhibition (e.g., ignoring distractions) or complex decision-making.

   An Analysis of the Ego-Depletion Effects of Emotion Versus Attention Draining Tasks. https://openworks.wooster.edu/cgi/viewcontent.cgi?article=10174&context=independentstud

2. Auto(i): The **Autonomy Index** (from SDT, see Part IV). This is a scalar.
   (a) If Auto ≈ 1 (Intrinsic Motivation), the effective depletion is nearly zero.
   (b) If Auto ≈ 0 (External Coercion), the depletion is maximal.
   (c) *Insight*: This mathematically validates the SDT finding that autonomous action is less depleting.

Why Self-Determination Theory Needs Computational Modelling: The Case of Competence and Optimal Challenge. `https://osf.io/preprints/psyarxiv/n6x8s_v1`
Methodological Overview of A Self-Determination Theory-Based Computerized Intervention to Promote Leisure-Time Physical Activity. `https://pmc.ncbi.nlm.nih.gov/articles/PMC2900852/`

Recovery Term (R_{rec}):

$$R_{rec}(t) = \begin{cases} R_{sleep} & \text{if } S_{state} = \text{Sleep} \\ R_{rest} \cdot Q_{rest} & \text{if } S_{state} = \text{Break} \\ 0 & \text{if } S_{state} = \text{Work} \end{cases}$$

Q_{rest} represents the "quality" of the break. Scrolling social media ($Q_{rest} \approx 0.1$) provides minimal recovery compared to Non-Sleep Deep Rest (NSDR) ($Q_{rest} \approx 1.0$).

2.1.2 The Fundamental Discontinuity

Following economic models of willpower, we implement a discontinuity function. When $W(t)$ falls below a critical threshold W_{crit}, the cost of self-control approaches infinity.

$$\text{Cost}(task) \propto \frac{1}{W(t) - W_{crit}}$$

At this singularity, the system must schedule a state-break; no amount of motivation can force the user to work without causing burnout.

2.2 Focus (F): The Vigilance Decrement

Focus is distinct from Willpower. It is the capacity to sustain selective attention. We model Focus using the **Vigilance Decrement** framework (Mackworth Clock test results) and **Cognitive Load Theory**.

The Role of Mathematical and Trait Anxiety in Mental Fatigue: an EEG Investigation. `https://psychologyinrussia.com/volumes/?article=7576`

2.2.1 The Leaky Integrator Model

Focus behaves as a leaky integrator. It can be boosted by stimuli but decays exponentially over time-on-task.

$$\frac{dF}{dt} = -\lambda_{decay}(F(t) - F_{min}) + \text{Input}(t)$$

Where:

1. F_{min}: The asymptotic baseline, which is dynamically set by the Circadian Alertness $A_{bio}(t)$.

$$F_{min}(t) = F_{base} \cdot A_{bio}(t)$$

2. λ_{decay}: The rate of focus loss. This parameter is sensitive to Sleep Pressure (S).

$$\lambda_{decay}(t) = \lambda_0(1 + \gamma S(t))$$

   Implication: As the user gets more tired (high S), their focus degrades faster. This necessitates shorter work blocks (pomodoros) in the evening compared to the morning.

3. Input(t): Exogenous shocks (caffeine, exercise) or Endogenous triggers (interest, flow).

Computational Cognitive Modeling of the Temporal Dynamics of Fatigue from Sleep Loss. https://pmc.ncbi.nlm.nih.gov/articles/PMC5559350/

2.3 Motivation (M): Temporal Dynamics & Dopamine

Motivation is the vector magnitude that initiates action. We utilize **Temporal Motivation Theory** (TMT) by Piers Steel, which unifies Expectancy Theory and Hyperbolic Discounting.

Temporal Motivation Theory - BCL. https://bcltraining.com/learning-library/temporal-motivation-

2.3.1 The TMT Equation

The instantaneous motivation to perform task i at time t is:

$$M_i(t) = \frac{E_i \times V_i}{\Gamma_i \times (D_i(t) + \epsilon)}$$

Where:

- E_i **(Expectancy)**: Self-efficacy ("Can I do it?"). Modeled as a function of the user's recent completion rate for similar task tags.
- V_i **(Value)**: The subjective utility of the task. (Modulated by Ancient Wisdom layers, see Part III).
- Γ_i **(Impulsiveness)**: Sensitivity to delay. High for users with ADHD traits.
- $D_i(t)$ **(Delay)**: Time until deadline ($T_{deadline} - t$). As $D \to 0$, $M \to \infty$ (The "Deadline Rush").

2.3.2 Dopamine Prediction Error (RPE) Integration

To make $M(t)$ dynamic within a task execution, we couple it with a Dopamine (DA) model. Motivation is not just about the static reward, but the rate of progress.

$$\frac{d(DA)}{dt} = \alpha \cdot \text{RPE}(t) - \beta(DA(t) - DA_{base})$$

$$\text{RPE}(t) = (\text{Reward}_{received} - \text{Reward}_{predicted})$$

Motivating Machines: The Potential of Modeling Motivation as MoA for Behavior Change Systems. https://www.mdpi.com/2078-2489/13/5/258
Neural mechanisms underlying the effects of cognitive fatigue on physical effort-based choice. https://www.biorxiv.org/content/10.1101/2024.12.06.627274v1.full-text

Implementation: The system breaks tasks into micro-milestones. Completing a milestone triggers a positive RPE, spiking $DA(t)$. We feed this back into the TMT equation by temporarily lowering Impulsiveness Γ:

$$\Gamma_{effective}(t) = \frac{\Gamma_{base}}{1 + \delta \cdot DA(t)}$$

This mathematical loop models "Momentum"—the more you do, the easier it is to focus, as dopamine suppresses the desire for immediate distraction.

The Dopamine Equation: How Math Explains Motivation. https://medium.com/the-quantastic-journal/the-dopamine-equation-how-math-explains-motivation-5954a6509698

Table 2: The Computational Wu Xing Matrix

Time	**TCM Phase**	**Element**	**Physiological Correlate**	**Keyword**	**Antonym**
03:00 - 05:00	Lung	Metal	Respiratory peak, cortisol rise	Purge, Stillness, Release, Maintenance, Creative	Logic
05:00 - 07:00	Large Intestine	Metal	Elimination, peristalsis	Purge, Stillness, Release, Maintenance	Rest
07:00 - 09:00	Stomach	Earth	Ghrelin/leptin flux, digestion	Intake, Learning, Logic, Maintenance	
09:00 - 11:00	Spleen	Earth	Glucose transport, anabolism	Intake, Learning, Logic, Maintenance, Important	Rest
11:00 - 13:00	Heart	Fire	High HR, social engagement	Connection, Execution, Intake, Rest	Resolution
13:00 - 15:00	Small Intestine	Fire	Sorting nutrient/waste	Connection, Execution, Intake, Processing	Creative
15:00 - 17:00	Bladder	Water	Homeostatic regulation	Maintenance, Planning, Exertion	
17:00 - 19:00	Kidney	Water	Adrenal recovery, repair	Maintenance, Planning, Intake, Purge	Initiation
19:00 - 21:00	Pericardium	Fire	Circulation, emotional balance	Connection, Devotion, Release, Rest	
21:00 - 23:00	San Jiao	Fire	Metabolic balance, preparation for rest	Connection, Devotion, Release, Rest	Exertion
23:00 - 01:00	Gallbladder	Wood	Detox, decision processing	Rest, Creative	Exertion, Initiation
01:00 - 03:00	Liver	Wood	Detox, blood cleansing, repair	Rest	Exertion, Execution, Initiation

3 Heuristic Semantic Mapping (Ancient Wisdom)

While the differential equations provide the quantitative landscape (how much energy is available), they lack the qualitative nuance (what kind of energy). Ancient systems like Traditional Chinese Medicine (TCM) and the Benedictine Horarium represent millennia of empirical observation regarding what time aligns with what act. We formalize these not as mysticism, but as Semantic Classifiers or Heuristic Masks that overlay the circadian model.

Traditional Chinese Organ Body Clock. https://www.nirvananaturopathics.com/blog/traditional-chine
What is Dinacharya? https://piorliving.com/blogs/ayurvedic-routine/dinacharya/

Set the hour 12 to the most wakeful moment of the user, and through the many wisdom of spiritualities we may translate that daily cycle into a map from moments to qualities which are also attributed to the potential plans.

Algorithm: The system calculates a **Alignment Score** (S_{wis}) for a task i at time t by querying a Compatibility Matrix from tradition j $\mathbf{C}_j$.

$$S_{\text{wis}}(i,t) = \sum_{j \text{ in traditions}} \mathbf{C}_j(i,t)$$

Where:

$$\mathbf{C}_j(i,t) = \begin{cases} +1 & \text{if a keyword from } i \text{ matches the current phase of tradition } j, \\ 0 & \text{if no match,} \\ -1 & \text{if a keyword from } i \text{ is an antonym for the current phase.} \end{cases}$$

The keywords are: 'Initiation', 'Planning', 'Execution', 'Logic', 'Maintenance', 'Connection', 'Resolution', 'Exertion', 'Intake', 'Processing', 'Purge', 'Rest', 'Stillness', 'Creative', 'Learning', 'Devotion', 'Release', 'Important'.

3.1 The Wu Xing (Five Elements) Organ Clock

The TCM clock divides the 24-hour cycle into 12 two-hour windows, each associated with an Organ System and an Element (Wood, Fire, Earth, Metal, Water). We map these biological functions to modern knowledge work archetypes.

Systems Biology Insight: The "Spleen" time (09:00-11:00) corresponds closely to the steepest rise in core body temperature and cortisol, biologically supporting maximum executive function. The "Small Intestine" time (13:00-15:00) aligns with the post-prandial glucose dip, where "sorting" (low cognitive load) is more viable than "creation".

The Role of the TCM Clock in Holistic Health. https://ccatcm.ca/tcm-clock-for-better-wellness/
Understanding Traditional Chinese Medicine Therapeutics: An Overview of the Basics and Clinical Applications. https://pmc.ncbi.nlm.nih.gov/articles/PMC8000828/

3.2 Ayurvedic Dosha Cycles (Dinacharya)

Ayurveda operates on a broader 4-hour cycle of metabolic states (Doshas). We use this to modulate the Value (V) parameter in the Motivation equation.

Dinacharya - How having an Ayurvedic daily routine will change your life. https://www.suryaprananutrition.co.uk/blog/ayurvedic-daily-rituals
AYURVEDIC LIFESTYLE PLANNER. https://www.modernayurvedic.com.au/pages/ayurvedic-routine

3.3 The Benedictine Algorithm: The Power of Interruption

The Rule of St. Benedict is not merely a religious text; it is a manual for sustaining high output in a closed system without burnout. Its core innovation is the Immutable Interrupt. Unlike "Flow State" theories which advocate for uninterrupted marathon sessions, the Benedictine *Horarium* forces the user to stop working *before* they are exhausted.

Mechanism: The system inserts "Liturgy Blocks" (hard stops) to prevent the *Law of Diminishing Returns.*

Table 3: Ayurvedic Dosha Cycles: Scheduling Logic & Equation Modifications

Dosha	Time	Keywords	Antonyms	Logic
Vata 1	**02:00-06:00**	Stillness, Purge, Creative, Planning	Rest, Intake, Execution	$\lambda_{\text{decay}} \leftarrow \lambda_{\text{decay}} \times 1.3$
Kapha 1	**06:00-10:00**	Exertion, Maintenance, Connection	Logic, Rest, Initiation	$\kappa_{\text{load}} \leftarrow \kappa_{\text{load}} \times 1.2$
Pitta 1	**10:00-14:00**	Execution, Intake, Logic, Resolution, Important	Stillness, Maintenance, Creative	$V_{\text{task}} \leftarrow V_{\text{task}} \times 1.5$
Vata 2	**14:00-18:00**	Connection, Initiation, Learning, Exertion, Planning	Execution, Resolution, Intake	$\lambda_{\text{decay}} \leftarrow \lambda_{\text{decay}} \times 1.3$
Kapha 2	**18:00-22:00**	Connection, Maintenance, Devotion, Release, Intake, Rest	Execution, Logic, Important	$\kappa_{\text{load}} \leftarrow \kappa_{\text{load}} \times 1.2$
Pitta 2	**22:00-02:00**	Rest, Processing, Purge	Intake, Execution, Connection, Study	$V_{\text{task}} \leftarrow V_{\text{task}} \times 1.5$

Table 4: The Benedictine Horarium: Task Mapping Logic

Hour	Time	Psychological State	Keyword	Antonym
Vigils	03:30 – 06:00	*Nocturnal Silence.*	Devotion, Stillness, Learning, Initiate	Exertion, Connection
Lauds	06:00 – 09:00	*Inception.*	Planning, Maintenance, Exertion, Connection	Rest, Stillness
Terce	09:00 – 12:00	*Labora* (Work).	Exertion, Devotion, Important	Creative, Stillness
Sext	12:00 – 15:00	*The Meridian.*	Execution, Important, Intake, Rest	Exertion
None	15:00 – 18:00	*The Danger Zone.* Risk of *Acedia*	Maintenance, Release, Connection, Resolution	Creative
Vespers	18:00 – 21:00	*Lucernarium*	Connection, Devotion, Intake, Release, Processing	Execution, Exertion
Compline	21:00	*The Great Silence.* Release of control.	Rest, Stillness, Purge, Release	Execution, Exertion

3.4 The Kabbalistic Toggle: Chesed vs. Gevurah

Jewish timekeeping (*Zmanim*) combined with Kabbalistic structure offers a powerful binary for classifying work types. The day is not a monolith; it is divided into a Morning of Expansion (*Chesed*) and an Afternoon of Restriction (*Gevurah*).**The Scheduling Heuristic:**

- Morning (Shacharit - Chesed): The energy is "Kindness/Flow." Schedule tasks that require Generation: brainstorming, drafting, exploring, saying "Yes" to ideas.

  Keywords: Initiation, Planning, Execution, Maintenance, Connection and Creative.

- Afternoon (Mincha - Gevurah): The energy is "Severity/Judgment." Schedule tasks that require Constraint: editing, debugging, auditing, financial review, saying "No."

  Keywords: Resolution, Exertion, Intake, Processing, Purge, Rest, Stillness and Logic

3.5 The Sikh Watch System: The 8 Pahars

The Sikh tradition divides the 24-hour cycle into 8 Pahars (watches) of roughly 3 hours each. This aligns perfectly with modern ultradian rhythm research (approx. two 90-minute cycles per Pahar). The most critical contribution of this system is the formalization of the Amrit Vela.

Table 5: The Sikh 8-Pahar Daily Flow

Pahar	Time	Concept	Keywords	Antonyms
Pahar 8	03:00 – 06:00	**Amrit Vela** The veil between the physical and spiritual is thinnest. High-Value Creative Download.	Stillness, Devotion, Creative, Release, Rest	Logic, Maintenance
Pahar 1	06:00 – 09:00	Engagement with the World.	Initiation, Exertion, Planning, Intake	Rest
Pahar 2	09:00 – 12:00	High Noon / Peak Heat. The time for the hardest tasks.	Execution, Logic, Important	Stillness
Pahar 3	12:00 – 15:00	The Decline.	Maintenance, Learning, Processing, Rest, Connection, Devotion	Exertion
Pahar 4	15:00 – 18:00	*Sodar* (Preparation for Evening).	Resolution, Release, Purge, Maintenance, Processing, Resolution	Initiation
Pahar 5	18:00 – 21:00	*Rehras* (Evening Prayer).	Connection, Devotion, Intake	Execution
Pahar 6	21:00 – 00:00	*Sota* (Sleeping Time). Withdrawal of senses.	Rest, Release, Processing, Purge, Stillness	
Pahar 7	00:00 – 03:00	*Ghugh* (Deep Silence). Complete suspension of will.	Rest, Stillness	Initiation, Planning, Execution, Logic, Exertion, Intake, Learning, Important

4 The Optimization Engine (The Solver)

We frame personal schedule generation as a **Phase-Level Multi-Objective Scheduling Problem**. Instead of attempting to optimize the entire day at once, the day is decomposed into P sequential **phases** (typically $P = 5$). During each phase, the system considers a small, contextually filtered set of approximately 15 candidate tasks that are appropriate for the current moment, user state, and remaining obligations.

Each phase is then solved independently using a **lightweight multi-objective evolutionary search**, producing a compact Pareto frontier of locally optimal options. After a task is selected for the phase, the user's physiological and cognitive state is updated, and the solver proceeds to the next phase. This phased approach preserves multi-objective optimality while maintaining real-time computational tractability on mobile hardware.

This design draws inspiration from multi-objective evolutionary optimization as applied to scheduling and time-of-day allocation:

Multi-Objective Portfolio Optimization: An Application of the Non-Dominated Sorting Genetic Algorithm III. `https://www.mdpi.com/2227-7072/13/1/15`

4.1 Integration of a Random Forest Success Predictor

A core component of the solver is a **Random Forest success probability model** that predicts the likelihood of successfully completing a candidate task if executed within the current phase. For any task i considered for the present phase p, the model produces

$$P_{\text{succ}}(i,p) = \text{RF}\Big(\text{Features}(i,p,\vec{E}(p),\text{history})\Big),$$

where the feature set includes:

- Task attributes: difficulty, semantic category, intrinsic load
- Chronobiological alignment: alertness $A_{\text{bio}}(p)$ and fatigue
- Cognitive resources: motivation $M(p)$, focus $F(p)$, willpower $W(p)$
- Historical performance patterns
- Contextual markers (preceding task type, time since last rest, etc.)

The Random Forest contributes:

1. **Probabilistic realism**: tasks are selected not only for fitness but feasibility.
2. **Personalization**: model accuracy improves as the user generates more data.
3. **Exploration–exploitation balance**: difficult or historically low-probability slots are naturally deprioritized.

We define the success objective used by the NSGA-II solver as:

$$J_{\text{succ}} = \sum_{i\in\mathcal{C}_p} x_i \cdot P_{\text{succ}}(i,p),$$

where $\mathcal{C}_p$ is the candidate task set for phase p.

4.2 Phase-Level Optimization Problem

For each phase p, we define:

Decision Variables:

Let X_p be a binary vector where

$$x_i = \begin{cases} 1 & \text{if task } i \text{ is selected for phase } p, \\ 0 & \text{otherwise.} \end{cases}$$

Objective Functions:

Each candidate task is evaluated with the following objectives:

- **Bio-Fit Alignment:**

$$J_{\text{bio}} = \sum_i x_i \cdot (A_{\text{bio}}(p) \cdot \text{Fit}(\text{Tag}_i, F_{\text{vector}}))$$

- **Wisdom Alignment:**

$$J_{\text{wis}} = \sum_i x_i \cdot S_{\text{wis}}(i, p)$$

- **Energetic Impact:**
  Each task produces an estimated shift in the Energy Space:

$$\Delta\vec{E}(i, p) = (\Delta W, \Delta F, \Delta M)_{i,p},$$

  derived from:

  - task difficulty and cognitive load profile,
  - semantic category (creative, administrative, social, etc.),
  - user's current state $\vec{E}(p)$,
  - historical user responses to similar tasks,
  - time-of-day factors (circadian and ultradian modulation).

  We scalarize the vector displacement with a function Φ:

$$J_{\text{impact}} = \sum_i x_i \cdot \Phi\big(\Delta\vec{E}(i, p), \vec{E}(p)\big),$$

  where Φ encodes:

  - penalties for entering depletion zones in W, F, M,
  - rewards for restorative or state-aligned movements,
  - alignment with user-configured daily strategic intent (e.g., "focus day," "recovery day," "build momentum day"),
  - avoidance of trajectories that push the user outside sustainable performance regions.

- **Flow Preservation (Minimize Context Switching):**

$$J_{\text{flow}} = -\,\text{ContextSwitch}(i)$$

- **Success Probability:**

$$J_{\text{succ}} = \sum_i x_i \cdot P_{\text{succ}}(i, p)$$

- **Urgency / Deadline Pressure:**

$$J_{\text{urg}} = \sum_i x_i \cdot U(i, p),$$

  where $U(i, p)$ incorporates task deadline proximity or accumulated neglect.

4.3 NSGA-II for Phase-Level Optimization

To solve the phase's multi-objective decision, we employ a **micro-scale NSGA-II**, which operates efficiently due to the small action set and low-dimensional search space.

Optimization of Time of Day Plan Scheduling Using a MultiObjective Evolutionary Algorithm. https://digitalcommons.unl.edu/context/civilengfacpub/article/1020/viewcontent/Sharma_TRB84_2005_Optimization_of_Time_Delay_Plan_Scheduling_Using_a_Multi_Objective_DC_ver_UPLOADED.pdf

Before the algorithm is run the user is prompted with a screen asking them if they want an easy day (enhance weights on success probability) a productive day (enhance weights of ridding up urgent work) a restorative day (extra weights for energetic impact) or a balanced day (extra weights on alignment. **Algorithm steps for each phase p:**

1. **Candidate Set Construction:** Select $\mathcal{C}_p$ (typically 10–20 tasks) based on feasibility, relevance, and state.
2. **Initialization:** Create a small population (20–40 individuals), each proposing a single-phase set of plans.
3. **Evaluation:** Compute the objective vector $[J_{\text{bio}}, J_{\text{wis}}, J_{\text{will}}, J_{\text{flow}}, J_{\text{succ}}, J_{\text{urg}}]$ for each candidate.
4. **Non-Dominated Sorting:** Identify Pareto fronts $\mathcal{F}_1, \mathcal{F}_2, \ldots$.
5. **Crowding Distance:** Preserve diversity in the set of trade-off solutions.
6. **Evolutionary Operators:** Tournament selection, mutation (task swaps), and light crossover, tuned for the small discrete search space.
7. **Termination:** After a few generations (10–20), output the top frontier $\mathcal{F}_1$.

4.4 Dynamic Re-Planning (Phase-by-Phase Receding Horizon Control)

The scheduling process forms a **receding horizon loop** across the phases of the day.

At the end of each completed phase:

1. Update the Energy State Vector $\vec{E}(p+1)$.
2. Update task states: remaining durations, urgency, deadlines.
3. Update the Random Forest training buffer with observed outcomes.
4. Construct the next candidate set $\mathcal{C}_{p+1}$.
5. Run the NSGA-II solver for the next phase.

This produces a flexible, adaptive schedule that evolves continuously with the user's physiological condition, cognitive resources, and actual performance.

5 The Psychological Control Envelope

A mathematically optimal schedule that ignores the user's emotional and cognitive state risks acting as a tyrant rather than a supportive tool. To preserve autonomy and psychological well-being, the optimization engine is wrapped in a control layer informed by **Self-Determination Theory** (SDT) and **Polyvagal Theory**.

Guidelines for human-AI interaction design. https://www.microsoft.com/en-us/research/blog/guidelines-for-human-ai-interaction-design/
Research-Based Guidelines for Supporting Psychological Wellbeing in User Experience. https://selfdeterminationtheory.org/wp-content/uploads/2022/08/2022_Peters_WellbeingSupportiveDes pdf

5.1 Self-Determination Theory (SDT) Integration

SDT identifies three basic psychological needs for autonomous motivation: **Autonomy**, **Competence**, and **Relatedness**. Our implementation supports each through both interface design and algorithmic weighting of objectives.

5.1.1 Autonomy: Weighted Objectives and Breadth of Choice

To avoid algorithmic paternalism ("Do this now"), the system employs two complementary mechanisms:

1. **Weighted Objectives:** At the start of each day, the user selects a *daily strategy* (e.g., Focus, Recovery, Momentum). Each strategy defines a weight vector

$$\vec{w} = \big(w_{\mathrm{bio}}, w_{\mathrm{wis}}, w_{\mathrm{impact}}, w_{\mathrm{flow}}, w_{\mathrm{succ}}, w_{\mathrm{urg}}\big)$$

   applied to the phase-level objectives:

$$J_{\mathrm{total}} = \sum_i x_i \sum_j w_j J_j(i).$$

   By allowing the user to adjust $\vec{w}$, they can shape the optimization according to their current priorities without being forced into a rigid global optimum.

2. **Breadth of Choice:** Rather than a single optimal schedule, the system presents a small set of Pareto-efficient paths for each phase or for the full day.

   Compatibility of Support and Autonomy in Personalized HCI. https://fietkau.science/support_and_autonomy_in_personalized_hci

Example User Interaction:

- **Path A (Flow):** Maximize deep work, early finish (high w_{bio}, high w_{flow}).
- **Path B (Resilience):** Complete small tasks, moderate activation (balanced w_j).
- **Path C (Recovery):** Prioritize breaks and low-stress tasks (high w_{impact} restorative, low w_{urg}).

Selecting a path updates downstream parameters in the optimization engine (e.g., modifying Auto(i) and subsequent weighting of Willpower / energetic impact), giving the user tangible control over the schedule.

5.1.2 Competence: Visualizing the Energy Manifold

Competence is supported through feedback:

- **Dashboard:** Visualizes the Energy Vector $\vec{E}(t)$, including "Focus Battery" and "Willpower Reserves," alongside the schedule.

- **Effect:** Users can see the physiological and energetic consequences of their choices. For instance, a low Focus value due to circadian dips explains temporary underperformance, helping to separate Performance from Self-Worth.

  Ego depletion effects on mathematics performance in primary school students: Why take the hard road? `https://www.researchgate.net/publication/233010046_Ego_depletion_effects_on_mathematics_performance_in_primary_school_students_Why_take_the_hard_road`

5.1.3 Relatedness: Social Prioritization

To support social needs, the system monitors for extended isolation:

- If a schedule contains > 4 hours of solitary deep work, the Heuristic Mask prioritizes a "Heart/Fire" window (11:00-13:00) for social tasks.
- Tasks tagged "Communication" or breaks with peers are preferentially scheduled to maintain social connectivity.

5.2 Polyvagal Theory: The "Vagal Brake"

The system models the Autonomic Nervous System (ANS) to ensure the user remains in an operable state for goal-directed work.

Safety Control Loop:

1. **Monitor:** Compute ΔW over a sliding 30-minute window.
2. **Detect:** Identify high-stress or shutdown states if $\Delta W > \text{Threshold}_{\text{panic}}$ or repeated task rejection occurs.
3. **Infer:** Determine shift from Ventral Vagal (Safe) to Sympathetic (Mobilization) or Dorsal Vagal (Immobilization).
4. **Intervene (Circuit Breaker):**
   - **HALT:** Suspend scheduling.
   - **Regulate:** Insert a "State Break" task (e.g., physiological sigh, cold water splash, walk), bypassing optimization logic.
   - **Reason:** In dysregulated states, executive function is impaired, making further optimization futile ($E \to 0$ in TMT terms).

Summary: By combining weighted objectives, Pareto-front breadth of choice, real-time energy feedback, and ANS-informed safety control, the Psychological Control Envelope preserves autonomy, competence, and relatedness while ensuring schedules remain achievable and psychologically safe.

6 Technical Implementation & Architecture

6.1 Hybrid Discrete-Continuous Architecture

- **Continuous Layer (Integrator):** RK4 integration of JFK Pacemaker (x, x_c, n), Homeostat S, and Energy Vector (W, F, M) at $\Delta t = 1\,\text{min}$.
- **Discrete Layer (Scheduler):** GA operates on 15-minute time slots.

- **Interface:** The Continuous layer computes chronobiological cost matrices; the Discrete layer generates schedules; predictions feed back to the Continuous layer.

Hybrid Discrete-Continuous Optimization for the Frequency Assignment Problem in Satellite Communication System `https://www.researchgate.net/publication/268590156_Hybrid_Discrete-Continuous_Optimization_for_the_Frequency_Assignment_Problem_in_Satellite_Communication_System`
Symbiotic Simulation System `https://figshare.com/ndownloader/files/56778035`

6.2 The Kalman Filter for State Estimation

Observation model from *A Mathematical Approach to Circadian Medicine*: `https://www.siam.org/publications/siam-news/articles/a-mathematical-approach-to-circadian-medicine/`

$$y_k = H(x_k) + v_k$$

User feedback updates the latent phase ϕ, oscillator stiffness μ, and other chronobiological parameters. If the user repeatedly reports high energy at night, the system will shift the inferred circadian phase accordingly.

6.3 Statistical Pipeline for Continuous Self-Correction

To ensure long-term accuracy, the system maintains a multi-layered **statistical feedback pipeline**:

1. **Random Forest Incremental Retraining** Each observed outcome (success, dropout, delay, mood shift) becomes a new training datapoint:

$$\mathcal{D}_{t+1} = \mathcal{D}_t \cup \{(\text{features}, \text{label})\}$$

2. **Kalman Filtering for Latent Physiological States** A Level-Set Kalman Filter continuously refines the hidden ODE parameters (phase ϕ, damping μ, homeostat stiffness, etc.).

3. **Schedule Re-Estimation** After any update (new RF parameters, new Kalman state, new duration priors), the GA is re-run on the moving horizon.

4. **Model Drift Control** A small "forgetting factor" prevents over-fitting a single anomalous day, ensuring:

$$\theta_{t+1} = (1 - \lambda)\theta_t + \lambda\hat{\theta}_t$$

Thus the engine is not static; it is a continuously updating *statistical organism* that learns the user's rhythms, behaviors, and cognitive friction points.

Conclusion

The Bio-Semantics Scheduler represents a rethinking of productivity software. By merging chronobiological ODEs, ancient semantic timing systems, machine learning prediction, and multi-objective optimization, it forms an *Exoskeleton for Volition.* Rather than forcing users to push through friction, it constructs schedules that *flow with* their physiology and psychology, enabling sustainable and autonomous high performance.