Pairwise Coordination: Rhythmic Phase Coupling and Dynamic Attractors

Entry 6 - Module 8

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Abstract

This paper describes a method for analyzing the processing of environmental sensor data, with a focus on temperature and power signals. The dynamic nature of the data is explored by constructing phase diagrams, signal localization, Hilbert transform and CPR-based analysis. This study reflects fundamental concepts from complex systems science, in particular coordination, attractor dynamics, and phase synchronization. This paper provides a foundation for further studies of system coordination.

1. Introduction

Understanding how the parts of a system coordinate over time is essential to studying complex systems [1]. We used temperature and power time series data from a single beehive, cleaned, resampled, and normalized, to extract phase features using tools such as Hilbert transforms and CRP (Continuous Relative Phase) analysis to study this synergy. These tools were first applied to fields such as sports science and psychology to study how people move or interact [3], but are now also used by scientists to analyze patterns in environmental data. We can perform the following analyses in this complex systems project: Do temperature changes and power have predictable daily cycles? Are they temporally correlated? Is this temporal relationship stable or does it change over time? Do they gradually "sync up"?

We focus on temperature and power data because they are key to understanding how the system balances energy use and environmental needs. CRP analysis allows us to plot whether these signals are always in sync or whether there is no clear pattern. These answers may help design smarter energy systems that work with natural rhythms rather than against them. The code used for the computations and visualizations in this entry can be found here.

2. Data and Methods

2.1. Dataset Description

The dataset contains time series measurements of temperature and cellular power. To ensure data consistency, we selected a subset corresponding to tag number 202204 for focused analysis. The dataset was preprocessed to prepare for subsequent resampling and difference operations, select variables and clean to ensure that the analysis is consistent with the sensing object and ensure data integrity, resampling plus interpolation to facilitate subsequent spectrum and phase analysis, and use z-scores to normalize both variables, which is suitable for subsequent frequency domain analysis or comparison of relative intensities.

We analyzed the original data, analyzed the temperature and power variables, and confirmed whether there was a long-term trend of slowly rising or falling, which laid the foundation for selecting which period of time could be used as the main analysis window, and then analyzed the autocorrelation of the variables themselves. As shown in the figure, both temperature and power variables have strong autocorrelation, and we need to detrend the data for the subsequent Hilbert phase analysis or CRP analysis. The detrended ACF values are 0.849 for temperature and 0.626 for power, which are in a very suitable range and sufficient to support the use of Hilbert Transform and Continuous Relative Phase (CRP) to analyze the relationship between the two variables.

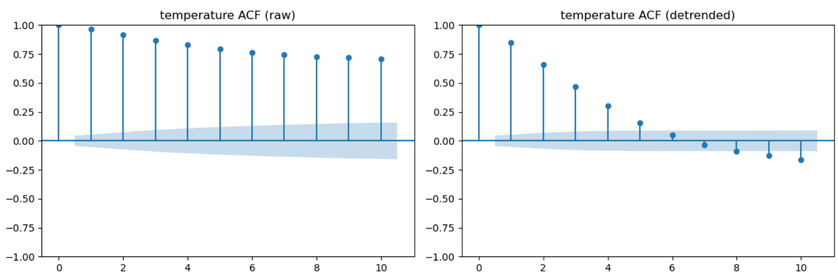

Figure 1: Centered temperature signal

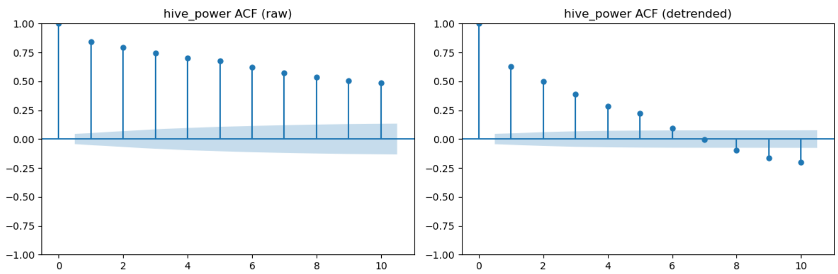

Figure 2: Centered power signal

2.2. Analytical Methods

Signal Centering: To ensure the effectiveness of the transformation and the interpretability of the synchronization indicator, we need careful signal preprocessing. Both signals are centered around zero to ensure the symmetry of the amplitude oscillation. These necessary centering processes are very important for the subsequent Hilbert analysis. A key step is signal centering. We need to subtract the mean from each time series to make it oscillate around zero.

Phase Plot: For phase map-based analysis, signals were biased to zero. This normalization is necessary to make symmetric distribution of amplitude oscillations such that a Hilbert Transform can be applied.

Hilbert Transform: To analyze the temperature and power signals, we use an analytical signal representation. (Rosenblum et al., 1996) This method allows us to compute two important values: continuous relative phase (CRP) and instantaneous phase. This allows us to study two things: (1) how the frequency and phase of the signals change over time; and (2) how the two signals interact. We assume that the result is that one signal is constantly "leading" or "lagging" the other, indicating a dynamic relationship between temperature and humidity. We then use a phase plot to visualize the phase difference and show how the signal behavior changes over time.

CRP: We will use this method to focus on the temporal relationship between temperature and power and use a tool to compute the difference between the instantaneous phase of temperature and power. We scale the data to the range [-180°, +180°], which tells us whether the two signals are in sync or out of sync, and whether they are leading or lagging each other. If the CRP stays close to 0°, the signals are highly in sync. If the CRP fluctuates between -180° and +180°, the signals are out of sync. This analysis clearly reveals how temperature and humidity interact in real-world environments.

Visualization: CRP curves, histograms, and phase portraits were used to explore synchronization and attractor-like dynamics.

3. Results and Analysis

3.1. Signal Centering

Centralization principle: Signal centralization is a key step in phase analysis. Its core principle is to meet the basic assumptions of the Hilbert transform: the input signal should be narrow-band and symmetrically oscillate around the zero point. Raw sensor data often has DC offsets, such as long-term high temperatures, which will destroy the symmetry of the signal and cause discontinuities or systematic deviations in phase estimation [4]. The essence of centralization processing is "data zeroing" - by subtracting the overall mean, eliminating sensor calibration errors and environmental baseline drift, so that the signal only retains the real dynamic fluctuations. Just like shielding the background noise to hear the content of the conversation, the centralized signal can reveal the synchronization relationship between temperature and power, making the subsequent phase calculation and CRP analysis more accurate and reliable. For example, a signal with a temperature fluctuation between $-3°C$ and $+3°C$ and a mean of 28°C will become a symmetrical signal fluctuating between $-3°C$ and $+3°C$. This transformation emphasizes the relative dynamic characteristics, which is crucial for detecting synchronization patterns. Without proper centering, continuous relative phase (CRP) analysis can be confounded by inconsistent signal baselines, creating spurious phase shifts that make it look like the two signals are out of sync when they are just starting from different points. The purpose of centering is to pull the two signals back to the same starting line, ensuring that their comparison in phase space is fair.

Normalization involves centering, but also scaling by the standard deviation. For Hilbert analysis, centering is required, but normalization is optional. If the noise is dominant in the high-frequency range, filtering should be performed first to avoid biasing the mean estimate due to transients or outliers. To illustrate the effect of centering, Figure 3 shows the removal of baseline shifts by comparing the original temperature signal and the centered temperature signal with a horizontal zero line. Figure 4 shows the complex plane representation of the Hilbert transformed signal, where the real axis reflects the centered signal and the imaginary axis reflects the orthogonal components, showing the circular or elliptical shapes required for phase continuity.

In the analysis, centering improves CRP estimates by accurately extracting the instantaneous phase in the temperature and power signals. This preprocessing step makes the synchronization patterns we observe clearer and thus less likely to be misleading.

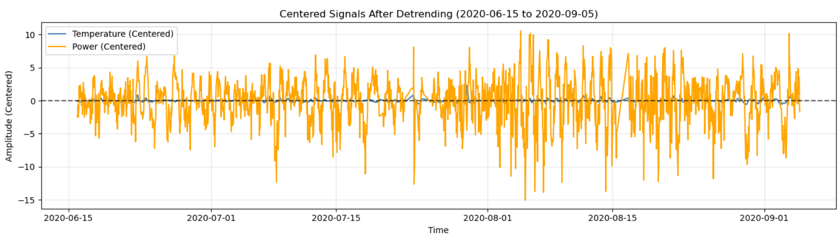

Figure 3: Centered Signals After Detrending

3.2. Phase Portraits

phase plot of the temperature signal reveals a clear attractor-centered dynamical structure. The phase plot of the detrended temperature signal reveals a stable, center-centered dynamical structure. Most of the data points are concentrated near the origin (0, 0), where the detrended temperature is close to zero and the rate of change is minimal. Occasional deviations from this center, reflected in scattered points far from the origin,

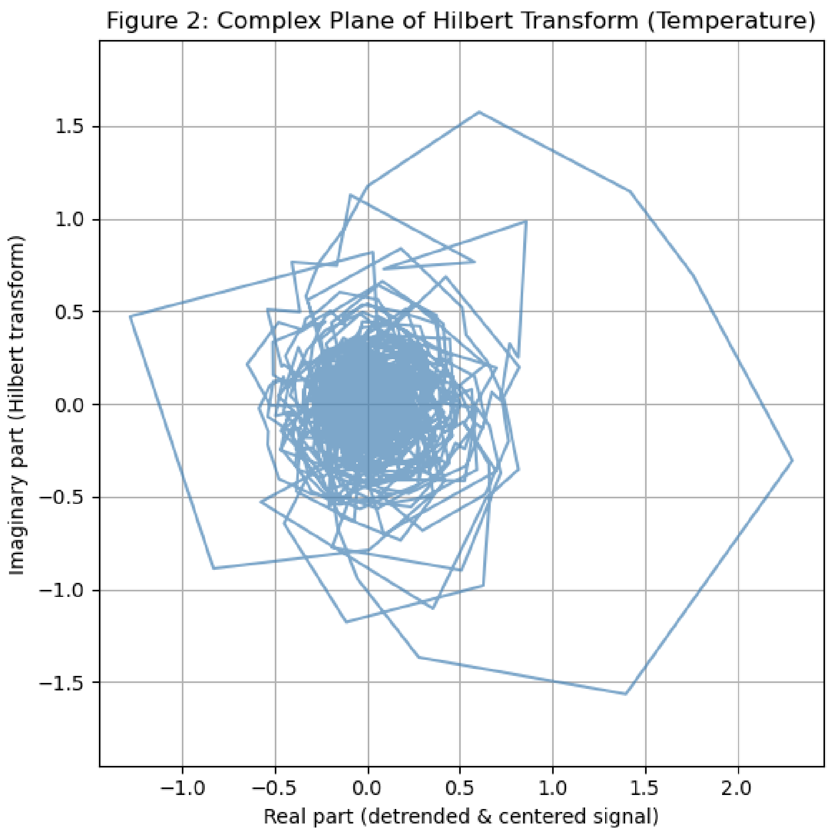

Figure 4: Complex Plane of Hilbert Transform (Temperature)

indicate transient transitions or perturbations, perhaps driven by environmental fluctuations or active regulatory events. Unlike ideal oscillating systems that produce closed elliptical trajectories, the lack of strong periodic or rotational structures in the phase diagram suggests that the temperature dynamics are quasi-steady-state and based primarily on fluctuations rather than intrinsic oscillations. Figure 5 shows that the system is primarily stable but responsive, with a clear regulatory target.

The phase diagram of the detrended honeycomb power signal shown in Figure 6 shows a compact elliptical cluster centered at the origin, with a structure similar to the temperature signal in Figure 4, but with a significantly wider distribution of amplitudes and rates of change. Unlike a purely periodic system with thin elliptical rings, the density and thickness of the clusters indicate a quasi-oscillatory but noisy behavior—possibly driven by internal switching mechanisms rather than smooth harmonic rhythms. The central concentration near zero still implies a steady-state equilibrium, but the wider dynamic range indicates that the system is more responsive and more actively regulated than the temperature system.

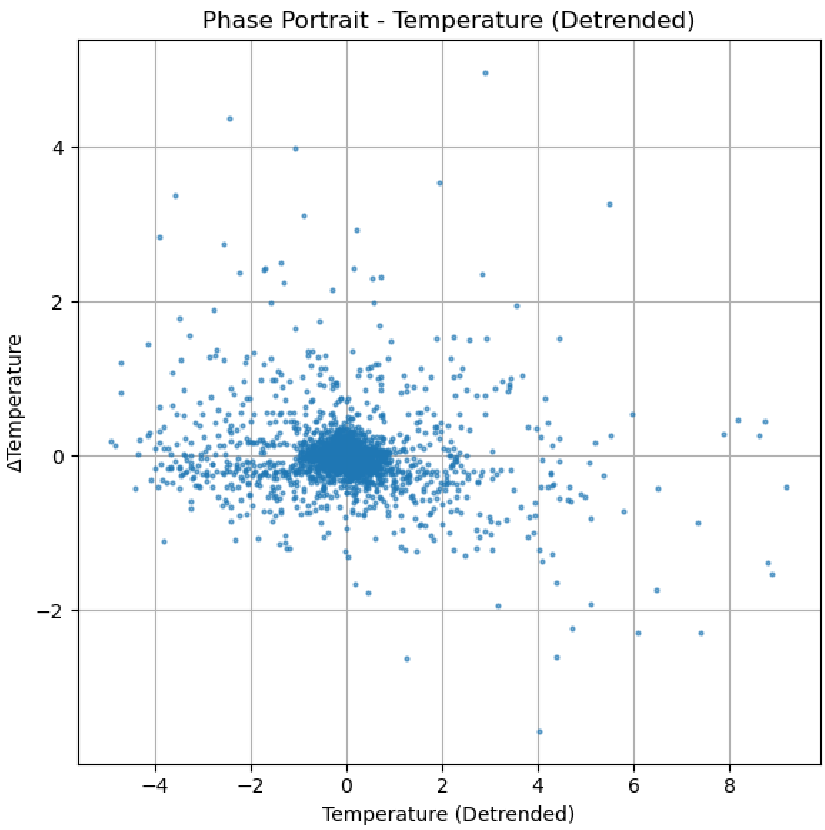

Figure 5: Phase Portrait - Temperature (Detrended)

3.3. Hilbert Analysis

To investigate the temporal patterns of the instantaneous frequency and phase of the signals, we applied the Hilbert transform to the temperature and power signals. This transform converts each real-valued signal into a complex analytic signal, from which the instantaneous phase and frequency can be derived. The instantaneous phase reflects the position of the signal oscillation at each instant and captures transient dynamics that may be missed by traditional amplitude-based analysis. The instantaneous frequency, derived from the time derivative of the phase, reveals how fast the signal phase changes, thus providing insight into the periodicity of thermal and energy dynamics. We performed this step of the analysis so that we could track the local temporal properties of the temperature and power modulations, such as how often they oscillate, when the mutations occur, and whether their timing is consistent. By using concentrated signals, we ensure that the assumptions of the Hilbert transform are met, making the extracted phase information more accurate and easier to interpret.

3.4. CRP and Coordination

To analyze the dynamic coordination between the temperature and power signals, we calculated the continuous relative phase (CRP) by subtracting the instantaneous phase

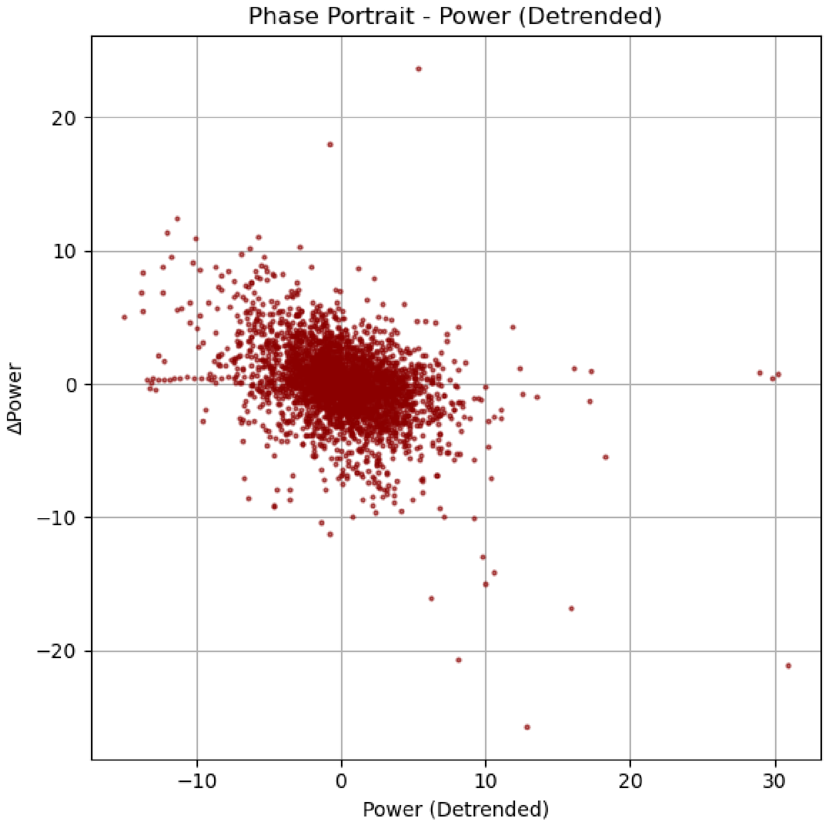

Figure 6: Phase Portrait - Power (Detrended)

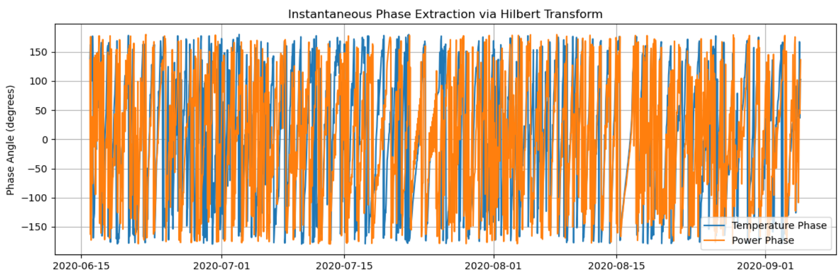

Figure 7: Instantaneous Phase Extraction via Hilbert Transform

of the power signal from the temperature signal. This allows us to observe how the two signals synchronize over time. By observing the temporal evolution of the instantaneous phase, we first confirm that both signals exhibit rhythmicity: temperature follows quasi-periodic environmental cycles, while power exhibits faster, often threshold-triggered phase shifts. These underlying rhythmic structures make the CRP estimates meaningful. During stable time intervals, CRP values are close to zero or $\pm 180°$, indicating a consistent pattern of coordination. The periodicity of CRP fluctuations reflects unstable coupling or environmental perturbations.

To further quantify the pattern of coordination between the temperature and power signals, we computed several phase-based metrics. The vector strength of the CRP distribution is 0.578, indicating a moderate degree of phase locking, the signals show clear synchronization, although not always perfectly aligned. The kurtosis of the CRP distribution is relatively low (0.80), indicating that the relative phase values are highly dispersed rather than narrowly concentrated around one value. This dispersion reflects adaptive coupling rather than strict entrainment.

We observe that the temperature signal leads the power signal in about 60.82 percent of the time samples and lags the power signal in 39.18 percent of the time samples. This asymmetry suggests that changes in temperature dynamics tend to drive subsequent changes in power, supporting the interpretation that the system responds to thermal fluctuations by delaying energetic regulation. Together, these findings suggest a goal-directed yet flexible coordination mechanism: the system remains partially synchronized to maintain homeostasis but allows for temporal changes to adapt to environmental and internal changes.

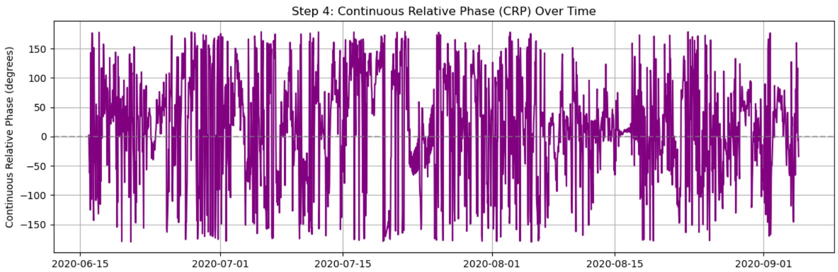

Figure 8: Continuous Relative Phase (CRP) Over Time

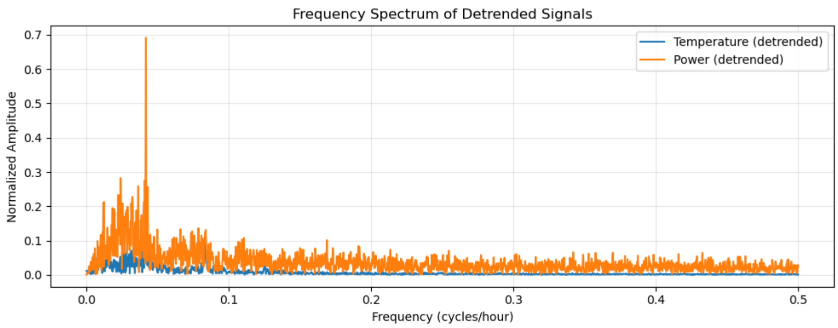

Figure 9: Frequency Spectrum of Detrended Signals

4. Discussion

This study uses a phase-based analytical perspective to explore five core questions about coordination. The interaction between temperature and power reveals a rhythmic coupling pattern. Specifically, the observed coordination model based on continuous relative phase (CRP) is dominated by in-phase dynamics, with occasional brief divergences. These findings are consistent with Kelso's model of coordination dynamics [2]. In this study,

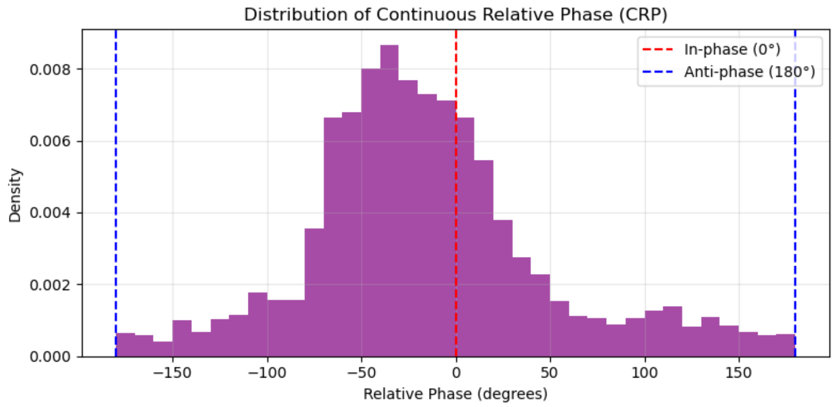

Figure 10: Distribution of Continuous Relative Phase (CRP)

we describe in-phase and anti phase states such that environmental or behavioral perturbations appear to induce changes around a central attractor, reflecting a flexible and goal-directed thermoregulatory strategy.

The moderate vector strength (0.578) indicates that the phase coupling is non random and highly adaptive, while the relatively low CRP kurtosis (0.80) reflects phase dispersion, indicating that the system does not operate under strict entrainment but is dynamically flexible. In addition, in 60.82 percent of the observations, temperature leads power, supporting a reactive regulatory mechanism that adaptively adjusts energy output based on thermal signals.

These results confirm the CRP analysis recommendations of Lamb and Stöckl (2014)[3], in particular regarding signal centering, Hilbert-based instantaneous phase extraction, and temporal filtering. In this context, the behavioral coordination of temperature and power reflects the adaptive intelligence of natural systems (e.g., honey bee colonies) and provides a theoretical basis for the design of robust and efficient environmental control systems..

Our results support Lamb and Stöckl's (2014)[3] suggestions for CRP analysis in practical systems, including appropriate centralization, Hilbert transform, and filtering. The results of this study explain the environmental regulation wisdom of the bee colony, which also provides a theoretical reference for many optimization designs. In the future, our research can further explore the system coordination mechanism under multi-parameter coupling and external disturbances.

5. Conclusion

This paper demonstrates the utility of CRP and Hilbert transform in analyzing the coordination between environmental (temperature) and functional (power) signals. Our results show that both signals show intrinsic rhythmicity and are mostly in phase, reflecting a high degree of temporal synchronization. The CRP dynamics show the changes in attractor behavior over time. Its coordination is consistent with the principles of coordination dynamics theory. These tools provide new insights into the dynamic behavior of environmental systems and pave the way for future research in multivariable synchronization and control.

Through systematic research results, dynamic visualizations show that simple methods in complex system science - especially the treatment of phase partners in synchronization phase analysis, signal concentration and development phases - can be successfully applied to national-level data. These methods reveal the underlying dynamic structure and constitute an effective means to monitor the stability, switching and coordination of complex natural and engineered systems.

References

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