

An Expert-Level Research Guide to Electronic Homeostasis and Self-Organization in Technological Systems

I. Foundational Principles: Defining the Core Concepts

A. The Concept of Homeostasis in Cyber-Physical Systems

Homeostasis is a fundamental concept in biology, originally formalized by Walter B. Cannon, that describes an organism's ability to maintain a stable internal environment despite a constantly changing external and internal landscape.¹ It is not a static state of stagnation, but rather a dynamic process in which key physiological variables—such as body temperature or blood glucose levels—are kept within a relatively constant range or "set point".¹ This biological principle, in turn, was inspired by Claude Bernard's mid-19th-century concept of the "milieu intérieur," or internal environment, the constancy of which he deemed essential for a free and independent life.³ This foundational understanding provides a powerful conceptual lens for analyzing technological systems.

The principles of homeostasis are directly applicable to engineered systems, particularly to Cyber-Physical Systems (CPS), which integrate computational elements with physical processes.⁴ In a CPS, a homeostatic control system functions to maintain the system's output within tolerable ranges, even when faced with frequent and significant external disturbances.⁶ A classic example is a car's cruise control system, which serves as a compelling analogy for biological homeostasis. The driver sets a desired speed (the set point), and a control algorithm continuously monitors the actual speed via a sensor. If the car's speed deviates due to a change in road grade or wind, the system acts as an "effector," adjusting the throttle to restore the speed to its set point. This constitutes a closed-loop feedback system, which is the cornerstone of homeostatic control.²

The architecture of a CPS mirrors the components of a biological homeostatic system.² Sensors act as receptors, collecting data from the physical environment (e.g., ambient light and sound levels, as in the user's project). Computational nodes serve as the control center, processing the sensor data and making decisions. Finally, actuators act as effectors, carrying out the necessary physical control actions based on the decisions made by the computational nodes.⁴ Most homeostatic systems rely on negative feedback loops to function correctly, as these loops work to counteract any deviation from the set point, returning the system to its normal, stable state.² This is in contrast to positive feedback, which amplifies a stimulus and is less common in physiological homeostasis.²

There is a profound distinction between the robustness of an evolved biological system and the inherent fragility of a human-designed engineered system. Biological systems have evolved over millennia, developing a capacity to adapt to an immense range of external and internal perturbations, including those that were not "designed" for. In contrast, engineered systems are designed with a limited, predefined set of conditions and a specific solution space.⁶ As a result, they can be highly "fragile to unmodeled conditions"—situations for which the system was not explicitly designed. For a multi-agent system, this implies a critical engineering challenge: the system must be able to handle not just expected variations in stimuli but also unforeseen environmental changes to be considered truly homeostatic. The goal is to imbue the system with a capacity for "requisite variety," a cybernetic concept that suggests the controller must possess a complexity that is at least equivalent to the variety of the system it aims to control.³

Furthermore, a failure in a homeostatic system can occur in a more complex way than a simple component breakdown. In medicine, many diseases are now understood as "loopopathies" — a failure of the control system itself rather than of a single organ or component.⁶ This concept translates directly to engineered systems. A technological homeostatic system may not fail because a single agent malfunctions, but because a critical feedback loop breaks down, becomes unstable, or transitions from a stabilizing negative feedback loop to a pathogenic positive one.³ For a system of digital agents, this could manifest as runaway oscillations in behavior or a cascading failure of the overall equilibrium, even if the individual agents appear to be functioning correctly.¹ The risk of a "catastrophic collapse" due to a single sensor failure or an incorrect calculation of a homeostatic variable is a unique consideration in engineered systems, highlighting the need for redundant or "degenerate" methods for evaluating system states.¹

B. The Principles of Self-Organization and Emergence

Self-organization is a process through which a system spontaneously develops order and

structure from the local interactions of its components, without any external direction or central blueprint.⁷ This is a profound departure from traditional engineering, where order is imposed from the outside through explicit commands or a predetermined design. In self-organizing systems, the global "pattern" is not encoded in any single component; instead, it is an "emergent property" that arises from the collective behavior of the system's parts.⁷ Examples of self-organization are found throughout nature and technology, including sand dunes, animal swarms, chemical oscillations, and the formation of crystalline structures.⁷

For self-organization to occur, four basic ingredients must be present ⁸:

1. **Strong dynamical non-linearity:** The system must contain feedback loops, both positive and negative, which can amplify or diminish certain behaviors.
2. **A balance of exploitation and exploration:** The system's components must be able to leverage proven successful behaviors while also having the capacity to explore new states and solutions.
3. **Multiple interactions among components:** The individual parts must be able to interact with one another, using only local information, to collectively influence the system's state.
4. **Availability of energy:** The system must be an open, thermodynamically non-equilibrium system with a continuous input of energy to overcome the natural tendency toward entropy and loss of free energy.⁸

A particularly crucial and non-intuitive aspect of self-organization is the principle of "order from noise," formulated by the cybernetician Heinz von Foerster.⁸ In traditional engineering, noise is a disruptive force to be minimized. However, in self-organizing systems, random perturbations are not an error but a necessary catalyst.⁸ These random fluctuations allow the system to explore a greater variety of states and find novel, stable configurations, which it might not discover if its behavior were perfectly deterministic. For a simulation of digital agents, this suggests that incorporating a degree of randomness into their behavior is not merely a stylistic choice but a fundamental requirement for the system to achieve its emergent equilibrium.

The power of self-organization lies in its decentralized and distributed nature.⁸ Because the global order arises from local interactions, the system as a whole is robust and resilient.⁸ It lacks a single point of failure, meaning it can often survive or self-repair substantial perturbations that would cause a centralized system to fail entirely.⁶ This decentralized resilience is a primary driver for its use in modern systems like swarm robotics and distributed computing.

C. The Nexus: How Self-Organization Achieves Homeostasis

The concepts of homeostasis and self-organization are distinct but deeply interconnected. Homeostasis describes a desired state or goal—a condition of dynamic equilibrium.¹ Self-organization describes a process—a mechanism by which global order emerges from local rules.⁷ The central theoretical framework for a multi-agent system that maintains equilibrium is that its homeostasis is an emergent property of its self-organizing behavior.

The causal relationship is clear: by defining simple, local rules for how digital agents interact with each other and their environment, the system is primed to engage in a self-organizing process.⁷ From this decentralized, bottom-up process, a robust, system-wide state of equilibrium—homeostasis—is expected to emerge.¹

II. Influential Thinkers and Foundational Works

A. The Birth of Cybernetics: Norbert Wiener

The intellectual foundation for electronic homeostasis and self-organization is a field known as cybernetics, a term first introduced and defined publicly by the American mathematician Norbert Wiener in his seminal 1948 book, *Cybernetics: Or Control and Communication in the Animal and the Machine*.¹⁰ Wiener's core thesis was that the problems of communication, control, and statistical mechanics share an "essential unity," whether they are observed in living organisms or in machines.¹¹ This groundbreaking work provided the theoretical underpinnings for servomechanisms, automatic navigation, and artificial intelligence.¹⁰

Wiener's work was not merely technical; it was a profound philosophical inquiry into the nature of control and information. He traced the roots of his ideas back to the philosophy of Leibniz and explored the contrast between the predictable, time-reversible processes of Newtonian mechanics and the time-irreversible processes governed by the Second Law of Thermodynamics.¹⁰ He also introduced a concept now central to both information theory and cybernetics: the relationship between entropy and information.¹⁰ Wiener's book laid out the mathematical treatment of feedback and oscillation, and it drew powerful parallels between the nervous system and computing machines, foreshadowing modern developments in both neuroscience and computer science.¹⁰ This rich, interdisciplinary approach establishes that a project exploring electronic homeostasis is not just a technological exercise but a continuation of a deep inquiry into the fundamental nature of information and control.

B. Complex Adaptive Systems: John H. Holland

John H. Holland is recognized as the founder of the field of **Complex Adaptive Systems** (CAS), which provides a crucial framework for understanding the behavior of multi-agent systems.¹² While Holland is widely known for his invention of **genetic algorithms** (GAs), his work on GAs was merely an offshoot of his broader and more ambitious goal: to develop a general theory of adaptation in complex systems.¹²

Holland's theory is built on the premise that CAS, such as economies or ecosystems, are composed of a large number of agents that interact, learn, and adapt over time.¹³ He identified key features of these systems, including **parallelism (many simultaneous interactions), conditional action (IF/THEN rules for agents), and a continuous process of adaptation and evolution**.¹³ A crucial finding in Holland's work is that complex adaptive systems "rarely reach equilibrium" and that "optima and steady states are, at best, short-lived".¹³ This appears to contradict the goal of a homeostatic system, but it reveals a more nuanced truth: the desired state of equilibrium is not a fixed point but a dynamic attractor.⁸ A truly resilient homeostatic system must be a complex adaptive system that continuously adjusts to maintain a moving target of stability, rather than seeking a static solution. Holland's work also emphasized the need for a balance between exploiting successful behaviors and exploring new possibilities, which is analogous to how a homeostatic system must adapt to novel challenges.⁸

C. The Principles of Self-Organization: Ashby and von Foerster

Building on Wiener's work, other cyberneticians provided a more formal and abstract understanding of self-organization. William Ross Ashby's 1947 principle of self-organization posits that any deterministic, **dynamic system will automatically evolve toward an equilibrium state, which can be described as an "attractor" in a basin of surrounding states**.⁸ Once the system enters this attractor, its future evolution is constrained to remain within that state.⁸ This provided a rigorous mathematical formalism for a system's ability to find a stable and coordinated state.

Ashby's work was complemented by Heinz von Foerster's principle of "order from noise".⁸ This concept highlights how self-organization is facilitated by random perturbations or "noise".⁸ In this view, noise is not a detrimental force but a beneficial one that allows the system to explore a wide variety of states in its state space. This random exploration is critical for

discovering new and more resilient configurations, and it complements Ashby's concept of an attractor by explaining how the system can find and settle into such a state without a central guiding intelligence.⁸

The combined work of Ashby and von Foerster provides the theoretical scaffolding for the user's project. They offer an explanation for why a decentralized system of agents should be able to find and maintain a stable equilibrium (Ashby's attractors) and how it achieves this without explicit instructions (von Foerster's noise-driven exploration).⁸ This provides the conceptual language necessary to describe and analyze the emergent behavior of the simulation.

Table 1: Foundational Figures and Their Contributions

Figure Name	Key Discipline	Foundational Work/Concept	Core Contribution to the Field
Norbert Wiener	Cybernetics	<i>Cybernetics</i> (1948)	Unified the study of control, communication, and statistical mechanics in animals and machines; introduced the concept of feedback loops as a cornerstone of self-regulating systems.
Claude Bernard	Physiology	<i>Milieu Intérieur</i> (1865)	Introduced the concept of a stable internal environment that is essential for the survival of complex organisms, a precursor to the theory of homeostasis.

Walter B. Cannon	Physiology	Homeostasis (1929)	Coined the term "homeostasis" and formalized the concept of physiological processes that maintain internal stability, providing the biological model for engineered systems.
William Ross Ashby	Cybernetics	Principle of Self-Organization (1947)	Argued that deterministic dynamic systems evolve to a state of equilibrium, described as an attractor, providing a formal, mathematical basis for self-organization.
Heinz von Foerster	Cybernetics	"Order from Noise" (1960)	Proposed that self-organization is facilitated by random perturbations that allow a system to explore its state space and find stable states.
John H. Holland	Complex Systems	Complex Adaptive Systems (CAS) theory	Developed a general theory of adaptation in systems with many interacting agents; viewed genetic

			algorithms as a tool for exploring these dynamics.
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III. Intersecting Academic Disciplines

The user's project lies at the intersection of several distinct academic fields, each providing a unique perspective and set of tools for understanding the phenomena of electronic homeostasis and self-organization.

A. Cybernetics and Control Theory

Cybernetics is the foundational field for the study of communication and control in both living and artificial systems.¹⁴ It provides the conceptual and mathematical tools for analyzing feedback, regulation, and information flow within a system.¹⁴ Control theory, a more specialized branch of engineering, focuses on the design of systems that can maintain a desired output despite external disturbances.⁶ Together, these disciplines provide the framework for understanding how the user's agents can be designed to maintain a state of equilibrium. The report on a computational model of homeostatic regulation in cortical circuits uses a mathematical formalism based on time-constants and integrators, which are core concepts in control theory, to analyze the stability of the system's feedback loops.¹⁵

A compelling distinction within the field is between "first-order cybernetics" and "second-order cybernetics".¹⁴ First-order cybernetics studies the observed system, while second-order cybernetics includes the observer as part of the system.¹⁴ A project of this nature, where the user defines the rules and parameters for the agents, embodies second-order cybernetics. The user is not a passive observer but an active participant in the cybernetic loop, designing the conditions under which the system can achieve its homeostatic goal. This shifts the project from a simple simulation to a deeper inquiry into the relationship between the system's designer and its emergent behavior.

B. Complex Systems Theory and Systems Science

While cybernetics focuses on control loops, complex systems theory is the discipline that studies the behavior of systems with many interacting components, from which emergent, non-linear, and often surprising properties arise.¹⁴ It provides the language to describe and understand the phenomena of self-organization and emergence, which are central to the user's project.¹⁶

A major challenge in this field, as highlighted in current research, is the "lack of proper metrics" to quantify and measure the degree of emergence and self-organization.¹⁶ This is not a simple problem, as the emergent properties are often qualitative or difficult to define a priori. For the user's project, this means that merely observing the system's behavior is insufficient; the user will need to define explicit, quantitative metrics to measure the system's overall state of equilibrium. This methodological consideration is crucial for moving the project from a qualitative exploration to a rigorous scientific study.¹⁶

C. Agent-Based Modeling (ABM) and Artificial Life (ALife)

Agent-Based Modeling (ABM) is the core computational method for simulating and exploring complex systems from the bottom up.¹⁷ It is the ideal tool for the user's project, as it allows for the construction of a system where a global state emerges from the local, conditional actions of individual agents.¹³ As one researcher has noted, ABM embodies the "generative social science motto: 'If you didn't grow it, you didn't explain its emergence'".¹⁷ This principle validates the user's approach as a genuine scientific endeavor: it is not enough to simply observe a phenomenon; one must be able to construct it from first principles.

Artificial Life (ALife) is a related field that uses computational models to explore life-like phenomena, including self-organization.¹⁸ It provides a conceptual home for the user's project, as it seeks to understand how biological behaviors and structures, such as homeostasis, can be replicated in artificial systems.¹⁸

D. Systems Biology and Bio-Inspired Computing

Systems biology analyzes biological processes as interconnected dynamical systems with intricate feedback and internal control mechanisms.¹⁹ This field provides the direct inspiration for the user's project, as it studies how living organisms achieve robust homeostasis and

adaptation.⁹

However, the process of transferring biological principles to engineering systems, known as biomimicry, is fraught with challenges.²⁰ Biological systems have evolved over millions of years and operate within a restricted set of constraints (e.g., avoiding high temperatures or pressures).²⁰ In contrast, technical systems are intentionally designed to solve problems and often do so by consuming energy and matter, whereas nature often solves problems with "structure and information".²⁰ The languages of biology and engineering are often incompatible, and a direct, one-to-one translation of biological forms or functions often fails.²¹ A successful approach to bio-inspired computing requires a deep understanding of the abstract, underlying principles, rather than a simplistic attempt to replicate a biological system's appearance or behavior.²⁰

Table 2: Interdisciplinary Contributions to the Project

Discipline	Core Concepts	Application to the Project
Cybernetics & Control Theory	Feedback, communication, control loops, stability analysis, servomechanisms, integrators.	Provides the mathematical and conceptual foundation for designing and analyzing the homeostatic feedback loops within the system.
Complex Systems Theory	Emergence, non-linearity, local interactions, collective behavior, attractors, self-organization.	Provides the theoretical framework for understanding how the system-wide homeostasis arises from the local interactions of the agents.
Agent-Based Modeling (ABM) & Artificial Life (ALife)	Agent, environment, local rules, simulation, generative science, constructivist approach.	Offers the specific computational methodology for building and simulating the multi-agent system.
Systems Biology & Bio-Inspired Computing	Homeostasis, adaptation, feedback mechanisms, resilience, biomimicry.	Provides the core conceptual inspiration for the project, drawing parallels between the stability of living organisms

		and the desired behavior of the artificial system.
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IV. Existing Projects and Case Studies

A. Homeostatic Regulation in Neural Networks

The principles of homeostasis are not just theoretical; they have been successfully modeled in computational neuroscience to understand how brain circuits maintain stability.²² Researchers have used computational models to demonstrate how mechanisms like synaptic scaling and intrinsic plasticity operate to homeostatically regulate network activity.²²

A specific computational framework has been developed to model this behavior, using a system of equations that describe neuronal firing rates and the integration of homeostatic signals.¹⁵ A key finding from this research is that to prevent instability, the homeostatic feedback mechanism must operate on a slower timescale within a network of neurons than it would for a single, isolated neuron.¹⁵ This is a critical design consideration for a multi-agent system: the sensitivity of the agents' homeostatic responses must be carefully calibrated to avoid a runaway, oscillating, or chaotic system.¹⁵ The model suggests that the system's "sensitivity" parameters are not arbitrary but are a direct function of the network's internal dynamics.

B. Self-Organizing Swarms and Multi-Agent Systems

The field of swarm robotics is a prime example of self-organization in a technological context.⁸ In these systems, a collection of simple robots, each following a set of local rules, can achieve complex, emergent global behaviors such as collective foraging, pattern formation, or object manipulation.⁸ This research demonstrates the power of the user's proposed approach, showing that intricate, purposeful behavior can arise without a central command structure.

Beyond robotics, the concept of self-organization extends to abstract socio-technical systems. The idea of "algorithmic self-governance" shows how computational and social systems can be designed to achieve a state of "planned emergence".²³ In this approach, a desired collective property—such as social stability or the fair distribution of resources—is not imposed but rather emerges from the carefully engineered conventional rules followed by the individual software agents.²³ This is a vital conceptual tool for the user's project, as it frames the design process not as one of specifying the final state, but as one of crafting the underlying rules that will make the desired homeostatic outcome likely to emerge.

C. Cyber-Physical System Applications

Homeostatic principles are not confined to academic models; they are essential for the security and resilience of real-world Cyber-Physical Systems. In critical infrastructure like smart grids, autonomous vehicles, and smart pipelines, control loops are used to maintain stability and adapt to changing conditions.⁴ For example, research into smart grids has explored how statistical models can be used to detect and counter false data injection attacks, which disrupt the homeostatic balance of the power system.⁵ This provides a compelling real-world context for the user's project, demonstrating that homeostasis is not a luxury for these systems but a fundamental imperative for their survival and reliable operation in a hostile and uncertain environment.

D. Research on Differentiable Self-Organizing Systems

The leading edge of research into self-organizing systems is now exploring a new paradigm that combines traditional principles with modern machine learning techniques.²⁴ Projects from Google Research and others have focused on "differentiable models" and "neural cellular automata," which are self-organizing systems where the local rules are not explicitly hand-coded by a designer but are learned through a training process.²⁴ The system learns its own rules for how to achieve a desired emergent property.²⁴ This represents a significant evolution from the traditional, rule-based approach to a data-driven, learning-based approach. While the user's project is based on a more traditional, rule-based design, this research points to a key future direction for the field.

V. Conclusions

The research reveals that the project to model electronic homeostasis in a technological system is a sophisticated and highly relevant endeavor that sits at the nexus of several academic disciplines. The user's vision—of a system of digital agents that exhibits homeostatic behavior in response to environmental stimuli—is a direct exploration of how a complex, system-level property (homeostasis) can emerge from simple, local interactions (self-organization).

This report has provided the foundational theoretical and historical context for this project. It has shown that homeostasis is not a static state but a dynamic, self-regulating process, and that its electronic analogue must be robust to "unmodeled conditions." It has also shown that self-organization is a decentralized process where global order arises from local interactions, and that random perturbations are a necessary element for a system to discover novel, stable states. The core causal relationship is that the system's homeostasis is the emergent property of its self-organizing behavior.

The work of Norbert Wiener provides the philosophical and technical origin of the field, linking control in machines to that in living systems. John H. Holland's theory of complex adaptive systems further refines this view, highlighting that a system's equilibrium is not a fixed point but a dynamic attractor that it is perpetually hunting. The work of Ashby and von Foerster offers the mathematical formalism for these concepts.

While the user's project is a simulation, the principles explored have profound real-world implications, from the resilience of smart grids to the behavior of swarm robotics. The challenges of a project of this nature are not trivial and include the methodological problem of defining proper metrics to measure emergence and the conceptual challenge of moving from a simple, rule-based system to one that can learn its own rules for adaptation.

Ultimately, the most advanced understanding of homeostasis moves beyond the idea of a fixed "set point" to a more nuanced concept known as allostasis, which is the process of achieving stability through change by dynamically shifting the set point in response to prolonged stress.³ This is a more accurate biological model for the user to consider and represents the next frontier for electronic homeostasis. The user's project stands as a fundamental step toward building truly resilient, adaptive, and autonomous cyber-physical systems.

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