

Impact of Cognitive Linearity on Epistemic Modeling

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Evidence from

Timekeeping and Control Systems

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Abstract

This study investigates the epistemological tension between human linear constructs and natural nonlinearity. Drawing on Mach’s principle of the “economy of science,” we argue that linearity serves as a “pragmatic abstraction”—a necessary cognitive and technical simplification that enables coordination and control. However, through the Reification Fallacy, these abstractions are frequently mistaken for ontological reality. We examine two case studies: the historical standardization of time, where solar nonlinearity was replaced by the linear “mean time,” and control engineering, where linearization techniques tame nonlinear dynamics. Using computational simulations, we quantify the “cognitive cost” of linear heuristics ($C \approx 242.49$) and the “reification gap” in temporal measurement. We conclude that while linearity is an essential tool, its uncritical reification leads to “ontological silence” regarding the complexity of the systems we govern. We propose a framework of “Adaptive Pragmatism” and specific protocols for de-reification to navigate the “Anthroposeen.”

Keywords

Linearity, Epistemic Modeling, Reification Fallacy, Timekeeping, Control Theory, Anthroposeen, Pragmatic Abstraction

1.0 Introduction: The

Linear-Nonlinear Tension

1.1 Contextualizing the

Problem

The natural world is inherently nonlinear, characterized by complex feedback loops, chaotic dynamics, and ecological entanglements that resist simple quantification (Bourriaud, 2025). Yet, human cognition and social governance rely heavily on the imposition of linear constructs—grids, timelines, and regular intervals—to render this complexity manageable. This imposition fosters an anthropocentric worldview where the environment is viewed through the lens of human control rather than its intrinsic ecological reality (Lepenes, 2018). While metaphorical abstraction is a necessary tool for scientific inquiry (Carrillo & Martínez, 2023), a fundamental epistemic tension arises when these linear models are mistaken for the nonlinear territory they are meant to represent. The friction between the “wild” nonlinearity of nature and the “tame” linearity of human constructs forms the core of a pervasive, yet often unexamined, epistemic crisis.

1.2 Historical Trajectory of

Linearity

The dominance of linear thinking is not merely a cognitive default but a historical product of the scientific drive for efficiency. Following Ernst Mach's principle of the "economy of science," abstraction serves to save cognitive energy, allowing complex phenomena to be manipulated with minimal mental effort (Banks, 2021). This drive is exemplified in the history of measurement, particularly timekeeping, where the variable flow of solar time was replaced by the rigid, standardized linearity of mean time to facilitate social coordination (Tal, 2016). Over centuries, these pragmatic simplifications have hardened into unquestioned infrastructure, obscuring their origins as convenient fictions and presenting themselves as objective descriptions of reality.

1.3 The Reification Fallacy

Defined

This hardening process leads to the fallacy of reification, defined as the treatment of an abstract concept or model as if it were a concrete, real entity. In the context of modeling, reification occurs when the formal structure of a mathematical model is mismapped onto the target phenomenon, leading practitioners to believe that the model's properties (such as linearity) are inherent properties of the system itself (Kiverstein, 2022). This error is not harmless; as seen in biological allometry, misinterpreting scaling exponents as concrete physical laws rather than statistical artifacts can derail scientific understanding (Sileshi, 2015). The danger lies in the "misplaced concreteness" that blinds us to the limits of our linear tools.

1.4 Research Questions

To investigate the mechanics and consequences of this tension, this study posits three primary research questions. First, what are the cognitive mechanisms that predispose human reasoning toward linear bias, and how can this bias be quantified (Melnik-Leroy et al., 2023)? Second, how does the reification of idealization manifest in technical fields, specifically leading to "ontological silence" regarding the limitations of models (Czerniak, 2020)? Third, can a synthesis of philosophical pragmatism and engineering control theory offer a framework for using linearity without succumbing to its epistemic pitfalls?

1.5 Methodological Approach

This research employs a hybrid methodological approach, integrating theoretical synthesis with computational verification. Drawing on the enactive approach to science, which views scientific knowledge as a product of "doing" rather than passive representation (Manca, 2024), we combine qualitative text analysis of philosophical and engineering literature with quantitative Python simulations. By contrasting the epistemological frameworks of pragmatism (Kaushik, 2019) with mathematical simulations of linearization error and cognitive bias, we aim to bridge the gap between abstract critique and technical practice.

1.6 Scope and Limitations

The scope of this investigation is limited to two primary case studies: the historical construction of standardized time (Tal, 2016) and the application of linearization techniques in control engineering. While the implications of linear bias extend into economics, sociology, and artificial intelligence, this study focuses on these domains to provide concrete examples of the "metaphor-to-abstraction" pipeline (Carrillo & Martínez, 2023). We acknowledge that linearity is often a functional necessity; our critique is directed not at the use of linear models, but at the epistemic unawareness of their limitations.

1.7 Thesis Statement

We argue that while linearity is a necessary “pragmatic abstraction” for human coordination and technical control, it becomes an ontological danger when reified. By tracing the “economy of thought” (Banks, 2021) from cognitive heuristics to engineering protocols, this study demonstrates that the stability of our technological world rests on a “useful lie”—a linear overlay on a nonlinear reality—that requires constant, conscious maintenance to prevent epistemic collapse.

2.0 Cognitive Foundations of

Linearity

2.1 The Cognitive Bias for

Regularity

The human cognitive architecture exhibits a profound and persistent preference for regularity, a tendency that fundamentally shapes our interaction with a chaotic world. This “cognitive bias” is not merely a cultural artifact but appears to be a biological imperative to conserve processing energy. Research indicates that the human brain struggles significantly with nonlinear concepts, specifically exhibiting an “exponential bias” where individuals systematically underestimate exponential growth, intuitively mapping it onto linear progressions instead (Melnik-Leroy et al., 2023). This inability to intuitively grasp nonlinearity forces the mind to impose linear patterns—straight lines, constant rates, and predictable intervals—onto data that is inherently dynamic.

2.2 Heuristics and

Simplification

To manage the computational load of an information-rich environment, the brain relies on heuristics—mental shortcuts that simplify complex decision-making processes. While pragmatic, these heuristics are prone to systematic error. Dror (2020) identifies eight distinct sources of bias in expert decision-making, noting that the brain’s reliance on “bottom-up” data processing is frequently overridden by “top-down” cognitive expectations (Dror, 2020). In the context of linearity, this manifests as a “smoothing” function: data points that deviate from a predicted line are often dismissed as noise rather than recognized as signal. This simplification is not a passive failure but an active reconstruction of reality.

2.3 Visual Abstraction

Mechanisms

This linearizing tendency extends into our fundamental sensory processing. The act of seeing itself is an act of abstraction. Fan (2019) demonstrates that visual communication relies on “pragmatic inference,” where visual details are stripped away to convey essential meaning (Fan, 2019). This visual abstraction acts as a form of lossy compression; just as a JPEG algorithm discards “unnecessary” color data, our visual cortex discards nonlinear irregularities to create coherent, stable objects. While this enables efficient communication and recognition, it reinforces a worldview composed of discrete, bounded, and stable entities—a “block universe”—rather than the fluid, continuous processes that characterize ecological reality.

2.4 Language as a Linearizing

Force

Language further calcifies these cognitive tendencies by forcing fluid processes into static grammatical structures. The very structure of subject-verb-object syntax encourages a linear view of causality, where an agent acts upon a patient in a discrete timeframe. This leads to linguistic “logical fallacies,” where abstract concepts like “intelligence” or “addiction” are treated as concrete, physical properties—a process known as reification (Strickland et al., 2022). By naming a nonlinear trend (e.g., “climate change”), language treats it as a singular object, obscuring the complex feedback loops and exponential accelerations that define it. Thus, language acts as a “linearizing force,” trapping nonlinear phenomena in linear semantic cages.

2.5 Quantifying the Linear

Bias

While the existence of this bias is well-documented, quantifying the specific epistemic error it introduces is critical. We modeled the divergence between a linear heuristic and a nonlinear reality using a computational simulation. The simulation contrasted an exponential growth function ($y = e^{0.5x}$) representing a natural phenomenon, against a linear heuristic derived from the initial 20% of the timeline ($t = 0$ to $t = 2$).

The analysis revealed a catastrophic failure of the linear model. While the heuristic remained predictive within the “local” operating range, the error grew exponentially beyond the divergence point at $t=3.13$ (where the error exceeded 1.0). By $t = 10$, the cumulative cognitive cost—representing the total magnitude of error between the mental model and reality—reached **242.49**.

$$\text{Cost} = \int_0^{10} |y_{\text{reality}}(t) - y_{\text{heuristic}}(t)| dt \approx 242.49$$

This quantification demonstrates that linear bias is a dynamic error; the cost of maintaining a linear worldview in a nonlinear environment accelerates over time. It is important to note that this simulation employs a static heuristic; while human cognition is adaptive and capable of learning, the persistence of the “exponential bias” in subjects (Melnik-Leroy et al., 2023) suggests a fundamental lag in recalibration that mirrors the static model’s failure.

2.6 Neuro-Correlates of

Simplification

The persistence of such high-cost biases suggests they must offer a significant evolutionary advantage. Connecting back to Mach’s “economy of science,” we can infer that this simplification is neuro-biologically “profitable” in the short term. The brain operates under strict metabolic constraints; calculating a linear projection requires significantly fewer neural resources than computing a differential equation (Banks, 2021). Therefore, linearity is an “efficiency hack.” The brain trades long-term accuracy (ontology) for short-term processing speed (pragmatism). This neuro-economic trade-off explains why linear models persist even when they are demonstrably false: they are cheap to run.

2.7 Section Summary

In summary, the linear worldview is supported by a robust interlocking structure of cognitive bias, heuristic efficiency, sensory abstraction, and linguistic reification. From the “exponential bias” that blinds us to growth rates, to the “visual compression” that stabilizes our perception, our cognitive architecture is designed to linearize. As the simulation evidence confirms, this strategy works efficiently within narrow local bounds but accrues massive epistemic debt over time.

3.0

Philosophical Frameworks: Pragmatism vs. Reification

3.1 Mach's Economy of Science

The philosophical justification for linearity finds its most robust articulation in Ernst Mach's principle of the "economy of science." Mach argued that the primary function of science is not to uncover the metaphysical "essence" of reality, but to organize human experience in the most efficient manner possible. According to Mach, scientific laws, concepts, and mathematical formulas are "compendious expressions"—shorthand summaries that allow us to reconstruct facts in thought without the burden of re-experiencing them directly (Banks, 2021). In this view, linearity is the ultimate economic tool: it compresses the messy, nonlinear data of the world into clean, predictive vectors.

3.2 Pragmatism as a Research

Paradigm

Expanding on Mach's foundation, modern pragmatism reframes the validity of a model based on its consequences rather than its correspondence to an objective ontology. As a research paradigm, pragmatism asserts that "truth" is found in what works—concepts are tools to solve problems, and their value lies in their actionable outcomes (Kaushik, 2019). This aligns with the "enactive approach" to science, which posits that knowledge is generated through the active engagement of the scientist with their environment (Manca, 2024). Within this framework, a linear model is "true" insofar as it enables successful control or prediction of a system. The danger arises when this pragmatic validity is mistaken for ontological truth; a linear control system may stabilize a chemical plant, but that does not mean the chemical reactions themselves are linear.

3.3 The Mechanism of

Reification

The transition from pragmatic tool to ontological fallacy occurs through the mechanism of reification. Reification (or hypostatization) is the cognitive error of treating an abstraction as a concrete reality. Kiverstein (2022) describes this as a "mismatching" of formal structure onto target phenomena: we create a mathematical model to describe a behavior, and then, finding the model successful, we attribute the mathematical properties (such as smoothness, continuity, or linearity) to the physical entity itself (Kiverstein, 2022). This allows the abstraction to "usurp" the place of the phenomenon in our understanding. We stop studying the river and start studying the flow-rate equation.

3.4 Idealization in Economic

Models

A potent example of this fallacy is found in economic research, where the "reification of idealization" has become methodological dogma. Economics relies heavily on "idealized" models—highly simplified representations of markets that assume rational actors, perfect information, and linear equilibrium states. While intended as heuristic devices, these models are frequently treated as accurate descriptions of social reality (Czerniak, 2020). This leads to a dangerous feedback loop: policies are designed for the "idealized" market, and when the real, nonlinear market fails to conform, it is treated as an anomaly rather than a disproof of the model.

3.5 The Allometry Exponent

Debate

The reification fallacy also pervades the natural sciences, as illustrated by the debate over allometry exponents in biology. Allometry describes the relationship between body size and shape, often expressed through power laws. However, researchers frequently succumb to the “fallacy of reification” by interpreting statistical exponents as concrete biological constants or physical laws (Silesi, 2015). When a data set is fitted to a linear regression on a log-log plot, the resulting straight line is an artifact of the mathematical transformation, not necessarily a feature of the organism’s growth.

3.6 Metaphor to Abstraction

The pathway to reification often begins with metaphor. Scientific inquiry frequently starts with metaphorical reasoning—mapping a known domain onto an unknown one—to generate hypotheses. As these metaphors solidify into formal abstractions, their metaphorical roots are forgotten (Carrillo & Martínez, 2023). We begin by saying “time is *like* a river” (a metaphor for flow) and end by measuring “time’s current” as a precise linear vector. This “metaphor-to-abstraction” pipeline is necessary for the formalization of knowledge, but it strips away the context and nuance of the original comparison.

3.7 Section Summary

In synthesizing these frameworks, a clear epistemic trajectory emerges: from Mach’s “economy” and pragmatic utility, through the “metaphor-to-abstraction” pipeline, and finally into the trap of reification. Linearity is revealed not as a fundamental property of nature, but as a “pragmatic fiction”—a highly efficient cognitive and scientific tool. The error lies not in using the tool, but in forgetting its nature.

4.0 Case Study I: Temporal

Constructs

4.1 Epistemology of

Measurement

The measurement of time serves as the primary historical example of a “pragmatic abstraction” achieving total reification. Tal (2016) argues that the success of time standardization—the move from local solar time to Coordinated Universal Time (UTC)—depends not on its fidelity to the natural rotation of the Earth, but on its ability to facilitate social coordination. The epistemic objective shifted from *representing* the natural flow of days to *constructing* a stable temporal grid that enables global synchronization (Tal, 2016). In this transition, “accuracy” was redefined: a clock is no longer accurate if it matches the sun (which is irregular), but if it matches the ensemble average of atomic clocks (which is linear).

4.2 Historical Hardening of

Time

This reification was not instantaneous but the result of a centuries-long process of “epistemic hardening.” Just as linearization techniques in engineering have evolved over sixty years to become standard tools (Elishakoff, 2016), the linear construct of time has calcified through layers of technological reinforcement—from the mechanical escapement to the atomic second. This longitudinal drift represents a progressive alienation from the original nonlinear source. Over time, the pragmatic origins of these measurements were forgotten, leaving behind a rigid ontological structure. We no longer treat the clock as a tool for coordination; we treat it as the “flow of time” itself.

4.3 Solar vs. Mean Time

The divergence between the linear construct and the nonlinear reality is not merely philosophical; it is quantifiable. Addressing the empirical gap, we utilized the Python simulation to calculate the “Equation of Time”—the discrepancy between “Mean Solar Time” (our linear clock) and “Apparent Solar Time” (the actual sun). The analysis reveals that the assumption of a 24-hour day is a mathematical abstraction. The sun is “fast” or “slow” compared to the clock by significant margins throughout the year:

Maximum Deviation (Ahead): +16.45 minutes (early November)

Maximum Deviation (Behind): -14.60 minutes (mid-February)

Mean Deviation: ~7.25 minutes

Equation of Time (Minutes deviation from Linear Mean)

This 30-minute oscillation range demonstrates that the “steady ticking” of our daily lives is a linearized framework. We inhabit a constructed model, detached from the primary astronomical reality by a cumulative “reification gap” that fluctuates daily.

4.4 Empirical Impact of

Standardized Time

The imposition of this linear grid has profound empirical consequences for human cognition and social organization. While standardization allows for the precise coordination of global systems—banking, transport, telecommunications—it creates a fundamental “alienation” from the environment. Tal (2016) suggests that the success of standardization requires the suppression of local, contextual, and sensory cues in favor of universal, abstract standards (Tal, 2016). This aligns with the “anthroposeen” critique, suggesting that our cognitive distress—the feeling of being “out of time”—may stem from the friction between our biological rhythms (which are evolved for nonlinear solar cues) and the relentless linearity of the industrial clock (Lepenies, 2018).

4.5 Anthropocentric

Perspective

The invention of linear time parallels the invention of linear perspective in art; both are mechanisms that place the human subject at the center of a controlled, measurable universe. The “Anthroposeen” framework argues that linear perspective was a decisive moment in the emergence of the geological age of mankind, fostering a worldview where nature is a static backdrop arranged for the human viewer (Lepenies, 2018). Similarly, linear time arranges temporal events into a predictable sequence, creating the illusion that the future is a straight extrapolation of the past.

4.6 Ecological Negotiations

In contrast to the dominance of linear time, ecological thinking requires a “negotiation” with nonlinearity. Recent analyses in media studies, such as the examination of “cozy games,” suggest emerging cultural forms that attempt to negotiate with, rather than conquer, environmental rhythms (Pinder, 2024). Furthermore, contemporary art theory asserts that “nothing can be linear anymore,” arguing that ecological awareness forces an abandonment of the singular, progressive timeline in favor of multiple, entangled temporalities (Bourriaud, 2025).

4.7 Section Summary

The case of timekeeping perfectly illustrates the trajectory of reification. What began as a pragmatic tool for railway coordination has hardened into a metaphysical prison. The quantified deviation of the Equation of Time—up to 16 minutes of “error” that we collectively agree to ignore—serves as a testament to the power of the linear model. We have successfully replaced the territory (the sun) with the map (the clock).

5.0 Case Study II:

Engineering Linearization

5.1 Stochastic

Linearization Techniques

The history of control engineering is largely defined by the relentless pursuit of mathematical tractability, a goal achieved primarily through the application of linearization techniques to fundamentally nonlinear dynamic systems. This trajectory is exemplified by the stochastic linearization technique, which, over the past sixty years, has evolved into a cornerstone method for solving nonlinear stochastic boundary value problems (Elishakoff, 2016). Rather than attempting to map the full chaotic geometry of a nonlinear system, stochastic linearization replaces the nonlinear terms with equivalent linear elements that minimize the mean-square error. This approach has proven so successful that novel adaptations continue to be developed (Asadpour et al., 2023). However, the epistemological shift here is profound: the engineer abandons the search for the exact physical reality in favor of a statistically “good enough” shadow.

5.2 Feedback Linearization

While stochastic methods approximate linearity, feedback linearization takes a more active approach: it forcefully imposes linearity onto the system through control inputs. In complex biomedical applications, such as computer-controlled medication design, nonlinear physiological responses to drug dosage pose a significant danger (Padhi, 2006). Feedback linearization control theory calculates the exact nonlinearities inherent in the patient’s biological system and injects counteracting control signals to cancel them out, leaving a pure, predictable linear system in the loop. The mechanism represents an aggressive form of “epistemic mastery.” The controller does not just describe the world as linear; it actively reconstructs the local environment so that it behaves linearly.

5.3 Ontological Silence in

Engineering

Despite the ubiquity of these methods, the engineering literature is characterized by a notable “ontological silence” regarding the philosophical implications of their use. In the discourse surrounding power amplifiers and medical controllers, linearization is treated purely as a technical tool for mitigating distortion (Haider Al-kanan, 2020) or optimizing drug delivery (Padhi, 2006). It is crucial to acknowledge that advanced engineering fields, such as Robust Control and Adaptive Control, explicitly deal with model uncertainty and parameter variance. However, they typically treat these nonlinearities as “noise” or “disturbance” to be bounded, rather than as ontological features to be engaged. The gap in the literature is epistemic: even when uncertainty is modeled, the goal remains the imposition of linear predictability. By failing to acknowledge the “lossy compression” of their equations as a philosophical stance, the discipline risks a form of technological hubris, where the limits of the model are mistaken for the limits of the world itself.

5.4 Power Efficiency and

Distortion

This epistemic hubris faces a hard collision with physical reality in the domain of wireless communications. Haider Al-kanan (2020) demonstrates that power amplifiers must be driven into their saturation regions to achieve maximum energy efficiency, which inherently introduces severe nonlinear distortion (Haider Al-kanan, 2020). To correct this, nonlinear behavioral models are used, but their implementation often relies on linearized approximations that fail under stress. Furthermore, as Kundur Subramaniyan (2023) notes, the measured improvement in linearity in physical silicon is frequently much lower than the expectations generated by computational simulations (Kundur Subramaniyan, 2023). This discrepancy between the clean, linearized simulation and the “noisy” thermal reality of the physical chip is the Reification Fallacy made manifest.

5.5 Quantifying Linearization

Error

To formally visualize the cost of this reification, we must quantify how linearization error grows as a system deviates from its intended operating point. Using a Python simulation, we analyzed the classic small-angle approximation—a fundamental engineering linearization where a nonlinear function, $\sin(x)$, is replaced by its first-order Taylor expansion, x .

As detailed in the formal derivations (Appendix A), the Taylor expansion reveals that the error term is governed by cubic growth:

$$f(x) \approx x - \frac{x^3}{6}$$

Residual Error Plot (Abs(sin(x) - x))

The simulation data shows that while the Mean Squared Error (MSE) remains low near the origin, the maximum error reaches **3.14** at the boundaries. Crucially, the “operating range limit”—the point at which the error exceeds a safe threshold of 0.1—is restricted to a narrow band of ± 0.5 radians. Within this band, the linear model successfully masks reality. Outside this band, the approximation collapses.

5.6 Wideband vs. Narrowband

Assumptions

The fragility of this local validity is further exposed when moving from narrowband to wideband systems. In traditional narrowband control systems, variables change slowly, allowing the operating point to remain fixed near the origin. However, wideband software-defined radio receivers operate across vast frequency spectrums, forcing the system state to change rapidly and widely (Kundur Subramaniyan, 2023). Under these conditions, the fundamental assumptions of the linearization model break down; the system escapes the ± 0.5 radian “safe zone.” Here, the linear model ceases to be a pragmatic tool and becomes a liability.

5.7 Section Summary

Engineering provides the ultimate proving ground for the critique of linearity. Through stochastic methods and feedback loops, engineers have successfully tamed nonlinear dynamics. However, the simulation of the Taylor series error and the discrepancies found in physical silicon demonstrate the hard limits of this approach. Engineering

succeeds by explicitly ignoring the ontology of the system—by actively silencing the nonlinear reality. While this is necessary for building devices, its unchecked expansion into the broader governance of ecological and social systems poses a significant danger.

6.0

Synthesis: The Anthropocene and Algorithmic Governance

6.1 The Anthropocene Concept

The imposition of linearity is not merely a cognitive or technical habit; it is a geological force. This study identifies a critical link between the “Anthropocene”—a term describing the age where human perspective reconstructs the physical world—and algorithmic governance. The invention of linear perspective in the Renaissance fostered an anthropocentric worldview where nature was viewed as a static backdrop arranged for the human eye (Lepénies, 2018). Today, this “linear gaze” has been automated. Algorithmic governance systems act as the new vanishing points, projecting linear metrics (GDP, efficiency, engagement) onto complex social and ecological terrains. The “Anthropocene” suggests that our environmental crisis is fundamentally a crisis of representation: we are attempting to manage a nonlinear biosphere with a linear control grid.

6.2 Nothing Can Be Linear

Anytime

This linear imposition faces a hard limit in the ecological reality of the twenty-first century. As Bourriaud (2025) argues, “nothing can be linear anymore.” The interconnected crises of the Anthropocene—climate feedback loops, viral transmission vectors, and supply chain fragility—demonstrate that the “progress” narrative of modernity is an illusion sustained by ignoring externalities (Bourriaud, 2025). Ecological systems function through circularity, decay, and regeneration, dynamics that are invisible to linear models until they reach catastrophic tipping points.

6.3 Scientific Inquiry

vs. Metaphor

The root of this disconnect lies in the forgotten metaphorical nature of our scientific tools. Abstraction in scientific inquiry begins as metaphor—a way to map the familiar onto the unknown (Carrillo & Martínez, 2023). When we model an ecosystem as a “machine,” we are using a powerful metaphor that allows us to apply linear control theory. However, as the abstraction hardens, the metaphorical “as if” is lost. We stop treating the ecosystem *as if* it were a machine and start treating it *as* a machine.

6.4 Enactive Approach to

Science

To escape this trap, we must pivot from a representational view of science to an enactive one. The enactive approach posits that scientific knowledge is not a passive mirror of nature but a result of “doing science”—an active, embodied negotiation with the world (Manca, 2024). In this view, a model is not a picture of truth but a tool for interaction. This reframing aligns with the pragmatic foundations of Mach and James; it validates the use of linear models as instruments of action while explicitly denying them the status of ontological truth.

6.5 Integrating Pragmatism

and Feedback

This synthesis allows us to close the integration gap by fusing philosophical pragmatism with engineering feedback control. We propose a unified strategy where “Feedback Linearization” serves as a model for epistemic humility. Just as a control engineer continuously measures the nonlinearity of a system to inject a correcting signal (Padhi, 2006), the pragmatic thinker must continuously measure the “reification error” of their models. By integrating Banks’ (2021) analysis of Mach’s economy with modern control theory, we arrive at a concept of ***“Adaptive Pragmatism.”*** In this framework, linearity is not a static truth to be defended, but a dynamic equilibrium to be maintained.

6.6 Negotiating Ecologies

Practical applications of this “Adaptive Pragmatism” are emerging in cultural spheres that model negotiation rather than domination. The genre of “cozy games” offers a surprising but relevant case study, where gameplay mechanics prioritize the negotiation of anthropocentrism and ecology over extraction and conquest (Pinder, 2024). These systems model a relationship where the human actor must adapt to the cyclical rhythms of the environment, rather than forcing the environment to conform to a linear production schedule.

6.7 Section Summary

The synthesis of these diverse fields—geology, art, engineering, and philosophy—points toward a singular conclusion: the “Anthroposeen” is a crisis of reified linearity. By forgetting that our linear grids are metaphors, we have created a governance structure that is blind to the nonlinear vitality of the planet. The solution is not to abandon linearity—which remains our most potent tool for coordination—but to adopt an enactive, adaptive stance.

7.0 Conclusion and Future Work

7.1 Summary of Findings

This investigation has traced the trajectory of linearity from its biological roots to its geological consequences. We have demonstrated that the human preference for linear models is not a reflection of objective reality, but a “cognitive bias” for regularity—an efficiency hack encoded in our neural architecture. Through the case study of standardized time, we revealed how this bias hardened into a reified social infrastructure. In the engineering domain, we observed this same logic raised to a method of physical control. The recurring theme is one of “pragmatic abstraction” mutating into “ontological delusion”: linearity is an indispensable tool for human coordination, but it becomes a source of epistemic blindness when the tool is mistaken for the truth.

7.2 Theoretical Implications

Theoretically, these findings confirm the omnipresence of the Reification Fallacy across disciplines. Whether in the “structure mismapping” of cognitive science or the “operational reification” of control theory, the error remains constant: the properties of the model are illicitly projected onto the phenomenon. This suggests that the “Anthroposeen” is fundamentally an age of “Linear Colonialism,” where we attempt to govern a chaotic, entangled biosphere using the simplified geometry of the machine.

7.3 Practical

Implications for Engineering

For the engineering community, this study offers a crucial corrective. We do not advocate for the abandonment of linear tools; as demonstrated, stochastic and feedback linearization are miracles of modern control. However, we argue for a shift in “epistemic stance.” Engineers must recognize that every linear model functions within a “reality

budget”—a limited range of validity defined by the cubic error terms we quantified. Operating outside this budget without awareness leads to catastrophic “tail risk” failures.

7.4 Protocols for

De-Reification

To operationalize this awareness, we propose the following **Protocol for De-Reification**: 1. **Explicit Assumption Mapping**: Every technical model must be accompanied by a “metadata layer” that explicitly lists the nonlinearities suppressed by the model. 2. **Boundary Testing**: Define the “Operating Range Limit” (as calculated in Section 5.5) where the linearization error exceeds 5%. Systems operating near this boundary must trigger an “Epistemic Alarm.” 3. **Re-Ontologization of Outputs**: System outputs should be labeled as “Model States” rather than “Real States.” 4. **Feedback Loop Sensitivity**: Implement “watchdog” algorithms designed to detect nonlinear feedback signatures that the primary linear controller is blind to (Kiverstein, 2022).

7.5 Limitations

We acknowledge that this study is limited by its focus on two specific domains: timekeeping and control engineering. Furthermore, our quantitative simulations of cognitive bias and linearization error are, by definition, simplified abstractions themselves. We are using linear tools to critique linearity, a recursive limitation inherent to all rational inquiry.

7.6 Future Research Directions

Future research should expand this framework to the domain of Artificial Intelligence and Machine Learning. Deep Learning models, while often nonlinear, are frequently deployed within linear bureaucratic structures that demand explainability and predictability. Investigating how AI “reifies” social biases into rigid algorithmic outputs is an urgent necessity.

7.7 Final Conclusion

Ultimately, the line is not the world. The straight line is a human invention—a brilliant, fragile thread of order spun over a chaotic abyss. It allows us to build bridges, coordinate trains, and stabilize power grids. But when we believe the world itself is straight, we lose the capacity to navigate the curves. The task of the twenty-first century is not to discard our lines, but to remember that we drew them.

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Appendices

Appendix A: Formal

Derivations

Taylor Series Expansion of Linearization Error The Taylor expansion of $f(x) = \sin(x)$ around $x = 0$ is given by:

$$f(x) = x - \frac{x^3}{3!} + \frac{x^5}{5!} - \dots$$

The linearization approximation uses only the first term: $L(x) = x$. The error term $\epsilon(x) = |f(x) - L(x)|$ is dominated by the first omitted term:

$$\epsilon(x) \approx \left| -\frac{x^3}{6} \right|$$

This confirms cubic error growth relative to the deviation from the operating point.

Appendix B:

Computational Assets (Summary)

This study utilized Python scripts to perform three key simulations:

1. **Cognitive Bias Simulation:** Calculated the integral

of the difference between $y = e^{0.5x}$ and a linear heuristic derived from $t \in [0, 2]$. 2. **Equation of Time Calculation:** Implemented the astronomical approximation formula $E = 9.87 \sin(2B) - 7.53 \cos(B) - 1.5 \sin(B)$ to visualize solar vs. mean time. 3. **Taylor Series Error Analysis:** Computed residuals of $\sin(x)$ vs x over the domain $[-\pi, \pi]$ to determine the ± 0.5 radian operating limit.

Appendix C: Data

Tables and Visualizations

Equation of Time (Minutes deviation)

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Linearization Residuals

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