Fat tails, hard limits, thin layers
John Doyle, Caltech

Rethinking fundamentals*
• Parameter estimation and goodness of fit measures for fat tail distributions
• Hard limits on robust, efficient networks integrating comms, controls, energy, materials
• Essentials of layered architectures, naming and address, pub-sub, control, coding, latency, and implications for wireless
• Implications for control over networks
• Try to get you to read some papers you might otherwise not

*really simple so we can move fast
A rant

A series of “obvious” observations (hopefully)
Case studies

• Networking and clean slate architectures
  – wireless end systems
  – info or content centric application layer
  – integrate routing, control, scheduling, coding, caching
  – control of cyber-physical

• Lots from cell biology
  – glycolytic oscillations for hard limits
  – bacterial layering for architecture

• Neuroscience

• PC, OS, VLSI, etc (IT components)

• Earthquakes

• Medical physiology

• Smartgrid, cyber-phys

• Physics: turbulence, stat mech (QM?)

• Wildfire ecology

• Lots of aerospace

Fundamentals!
Existing design frameworks
• Sophisticated components
• Poor integration
• Limited theoretical framework

Fix?
Layered architectures

Cortex
- Slow, Broad scope
- Prediction
- Goals
- Actions

Meta-layers
- Fast, Limited scope
- Actions

Physiology

Interface

Comms
- Remote Sensor
- Sensor
- Actuator

Control

Plant
- Disturbance

Errors
This paper aims to bridge progress in neuroscience involving sophisticated quantitative analysis of behavior, including the use of robust control, with other relevant conceptual and theoretical frameworks from systems engineering, systems biology, and mathematics.

Architecture, constraints, and behavior

John C. Doyle\textsuperscript{a,1} and Marie Csete\textsuperscript{b,1}

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Edited by Donald W. Pfaff, The Rockefeller University, New York, NY, and approved June 10, 2011 (received for review March 3, 2011)

This paper aims to bridge progress in neuroscience involving sophisticated quantitative analysis of behavior, including the use of robust control, with other relevant conceptual and theoretical frameworks from systems engineering, systems biology, and mathematics. Familiar and accessible case studies are used to illustrate concepts of robustness, organization, and architecture (modularity and protocols) that are central to understanding complex networks. These essential organizational features are hidden during normal function of a system but are fundamental for understanding the nature, design, and function of complex biologic and technologic systems.

Doyle and Csete, Proc Nat Acad Sci USA, online JULY 25 2011
Requirements on systems and architectures

accessible accountable accountable accurate adaptable administrable affordable auditible autonomy available credible process capable compatible composable configurable correctness customizable debuggable degradable determinable demonstrable dependable deployable dependable dependable durable effective efficient evolvable extensible failure failure transparent fault-tolerant fidelity flexible inspectable installable Integrity interchangeable interoperable learnable manageable mobile modifiable modular nomadic operable orthogonality portable precision predictable producible provable recoverable relevant reliable repeatable reproducible resilient responsive responsive reusable robust safety scalable seamless self-sustainable serviceable supportable survivable sustainable tailorable testable timely traceable ubiquitous understandable usable
Simplified, minimal requirements

accessible  accountable  accurate  adaptable  administrable  affordable  auditable  autonomy  available  credible  process  capable  compatible  composable  configurable  correctness  customizable  debugable  degradable  determinable  demonstrable  dependable  deployable  discoverable  distributable  durable  effective  efficient  evolvable  extensible  failure  transparent  fault-tolerant  fidelity  flexible  inspectable  installable  Integrity  interchangeable  interoperable  learnable  maintainable  manageable  mobile  modifiable  modular  nomadic  operable  orthogonality  portable  precision  predictable  producible  provable  recoverable  relevant  reliable  repeatable  reproducible  resilient  responsive  reusable  robust  reliable  repeatable  reproducible  resilient  responsive  reusable  robust  safety  scalable  seamless  self-sustainable  serviceable  supportable  serviceable  supportable  securable  sustainable  tailorable  testable  timely  traceable  ubiquitous  understandable  usable
Requirements on systems and architectures

- Accessible
- Accountable
- Accurate
- Adaptable
- Administrable
- Affordable
- Auditable
- Autonomy
- Available
- Credible
- Process
- Capable
- Compatible
- Composable
- Configurable
- Correctness
- Customizable
- Debugable
- Degradable
- Determinable
- Demonstrable
- Dependable
- Deployable
- Discoverable
- Distributable
- Durable
- Effective
- Efficient
- Evolvable
- Extensible
- Failure
- Transparent
- Fault-tolerant
- Fidelity
- Flexible
- Inspectable
- Installable
- Integrity
- Interchangeable
- Interoperable
- Learnable
- Maintainable
- Manageable
- Mobile
- Modifiable
- Modular
- Nomadic
- Operable
- Orthogonality
- Portable
- Precision
- Predictable
- Producible
- Provable
- Recoverable
- Relevant
- Reliable
- Repeatable
- Reproducible
- Resilient
- Responsive
- Reusable
- Robust
- Safety
- Scalable
- Seamless
- Self-sustainable
- Serviceable
- Supportable
- Securable
- Simple
- Stable
- Standards
- Compliant
- Survivable
- Sustainable
- Tailorable
- Testable
- Timely
- Traceable
- Ubiquitous
- Understandable
- Upgradable
- Usable
Robust to uncertainty in environment and components
Efficient in use of real physical resources

Want robust efficiency
2.5d space of systems and architectures
Want to understand the space of systems/architectures

- Case studies?
- Strategies?
- Architectures?

Hard limits on robust efficiency?

Want robust and efficient systems and architectures
Control, OR Comms

Bode

Pontryagin

Kalman

Shannon

Nash

Von Neumann

Turing

Gödel

Heisenberg

Einstein

Carnot

Boltzmann

Physics

Compute

Theory?

Deep, but fragmented, incoherent, incomplete
• Each theory ≈ one dimension
• Tradeoffs across dimensions
• Assume architectures a priori
• Progress is encouraging, but…
At best we get one
Often neither
Bad theory? Bad architectures?

Robust theory? Efficient wasteful

Fragile gap?
Conservation “laws”?

- Fragile
- Wasteful

Sharpen hard bounds

Case studies

Hard limit
\[ \int \log |S| d\omega = \int \log |E| d\omega - \int \log |D| d\omega = h(e) - h(d) \]

Sensitivity \quad \approx \text{Bode}

Circa 1950?

Entropy \quad \approx \text{Shannon}

Assume “favorable” delays
\[ h(e) - h(d) \geq -C_S \]

\[ \int \log |E|d\omega - \int \log |D|d\omega = h(e) - h(d) \]

Assume “favorable” delays
\[ e = d - u \]

\[ \approx \text{Bode} \]

\[ \int \log |S| \, d\omega \geq p \]

unstable pole \( p \)

\[ \int \log |S| \, d\omega = \int \log |E| \, d\omega - \int \log |D| \, d\omega \]

Sensitivity

Simplified and dropped constants, slight differences between cont and disc time
Control

\[ e = d - u \]

\[ d \]

Plant

\[ u \]

Control

\[ u \]

Comms

\[ e = d - u \]

\[ d \]

Decode

\[ u \]

Disturbance

\[ u \]

Capacity \( C \)

Sense/Encode

\[ \int \log |S| d\omega = \int \log |E| d\omega - \int \log |D| d\omega = h(e) - h(d) \]

\[ \int \log |S| d\omega \geq p \]

Circa 1950? \( h(e) - h(d) \geq -C_s \)

So, anything happened since?
Layered architectures

Diverse applications

TCP
IP

MAC
Switch

MAC
Pt to Pt

MAC
Pt to Pt

Physical
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Doyle and Csete, \textit{Proc Nat Acad Sci USA}, online JULY 25 2011
Layering as Optimization Decomposition: A Mathematical Theory of Network Architectures

There are various ways that network functionalities can be allocated to different layers and to different network elements, some being more desirable than others. The intellectual goal of the research surveyed by this article is to provide a theoretical foundation for these architectural decisions in networking.

By Mung Chiang, Member IEEE, Steven H. Low, Senior Member IEEE, A. Robert Calderbank, Fellow IEEE, and John C. Doyle

Chang, Low, Calderbank, and Doyle
Too clever?

Diverse applications

TCP
IP

Diverse

Physical
Layered architectures

Deconstrained (Applications)

TCP IP

Constrained

Deconstrained (Hardware)

“constraints that deconstrain” (Gerhart and Kirschner)
Original design challenge?

TCP/IP

- Trusted end systems
- Unreliable hardware

Facilitated wild evolution

Created

- whole new ecosystem
- complete opposite

Deconstrained (Applications)

Constrained

Deconstrained (Hardware)

Networked OS
Layered architectures

Deconstrained (Applications)

Constrained

OS

Deconstrained (Hardware)

Control, share, virtualize, and manage resources

Processing
Memory
I/O

Few global variables

Don’t cross layers

Essentials
Layered architectures

Deconstrained (diverse) Environments

Bacterial biosphere

Architecture = Constraints that Deconstrain

Deconstrained (diverse) Genomes

Shared protocols
Inside every cell

Almost

Building Blocks
Catabolism
Precursors

AA

RNA

DNA

Repl.

transc.

transl.

Proteins

Ribosome

RNAp

DNAp

Gene

xRNA

Enzymes

ATP

ATP

Enzymes

Macro-layers

Crosslayer autocatalysis
What makes the bacterial biosphere so adaptable?

- Deconstrained genome
- Deconstrained phenotype
- Core conserved constraints facilitate tradeoffs
- Active control of the genome (facilitated variation)

Layered architecture
Layered architectures

Deconstrained (Applications)

Few global variables

Don’t cross layers

Constrained

Direct access to physical memory?

Deconstrained (Hardware)

Processing
Memory
I/O
Deconstrained (diverse) Environments

Few global variables

Shared protocols

Don’t cross layers

Deconstrained (diverse) Genomes

Bacterial biosphere

Architecture = Constraints that deconstrain few global variables that don’t cross layers.
Problems with *leaky* layering

Modularity benefits are lost
- Global variables?  @$%*&!^%@@
- Poor portability of applications
- Insecurity of physical address space
- Fragile to application crashes
- No scalability of virtual/real addressing

- Limits optimization/control by duality?
Fragilities of layering/virtualization

• Hijacking, parasitism, predation
  – Universals are vulnerable
  – Universals are valuable
• Breakdowns/failures/unintended/… not transparent
• Hyper-evolvable but with frozen core
**Original design challenge?**

- **TCP/IP**
  - Constrained
    - Trusted end systems
    - Unreliable hardware
  - Facilitated wild evolution
  - Created
    - whole new ecosystem
    - complete opposite

- **Deconstrained (Applications)**
- **Deconstrained (Hardware)**

**Networked OS**
Layered architectures

Deconstrained (Applications)

Few global variables?
Don’t cross layers?

TCP/IP

Constrained
Control, share, virtualize, and manage resources

Deconstrained (Hardware)

I/O
Comms
Latency?
Storage?
Processing?
Robust?
- Secure
- Scalable
- Verifiable
- Evolvable
- Maintainable
- Designable
- …

Global and direct access to physical address!

IP addresses interfaces (not nodes)
Naming and addressing need to be
• resolved within layer
• translated between layers
• not exposed outside of layer

Related “issues”
• VPNs
• NATS
• Firewalls
• Multihoming
• Mobility
• Routing table size
• Overlays
• …
Next layered architectures

Deconstrained (Applications)

Constrained

Deconstrained (Hardware)

Control, share, virtualize, and manage resources

Comms
Memory, storage
Latency
Processing
Cyber-physical

Few global variables
Don’t cross layers
Persistent errors and confusion ("network science")

Every layer has different diverse graphs.

Architecture is least graph topology.

Architecture facilitates arbitrary graphs.
What happened to this picture?

\[ e = d - \hat{d} \]

1. Hard limits
2. Achievability
3. Decomposition/Layering

Source coding

Source

\[ \Delta d \rightarrow \infty \]

Decode

Code

Channel coding

Decode

Channel

Code
Under certain assumptions

- Decoupled
- Hides details
- Virtualizes channel

**Channel coding**

- Decode
- Rcv
- Channel
- Xmit
- Code

Physical layer
$e = d - \hat{d}$

- Decoupled
- Hides details
- Virtualizes source

Under certain assumptions
Hard tradeoffs

Rate distortion (backwards)

error

gap?

Architecture = separation + coding

data rate

$R$
Rate distortion (backwards)

error

gap?
delay?

Hard tradeoffs

Architecture
= separation + coding

data rate

$R$
$e = d - \hat{d}$

**Compress**

**Decomp**

Data compression

**Source**

**Internet = Distributed OS**

**Layered architecture**

**Control theory**
Control/optimization theory needed for

- Routing
- Congestion control
- Scheduling
- Caching?
- Distributed control of cyber-physical

Still incomplete, needs more integration, with

- OS, languages
- Info theory, particularly for wireless
\[
\int \log |S| d\omega = \int \log |E| d\omega - \int \log |D| d\omega = h(e) - h(d)
\]

Sensitivity  Circa 1950?  Entropy

What next?
\[ S(\omega) = \frac{E(\omega)}{D(\omega)} \]

\[ e = d - u \]

\[ \approx \text{Bode} \]

\[ \int \log |S| \, d\omega \geq -\int \log |S| \, d\omega + p \]

\[ \text{benefits} \quad \text{causality} \quad \text{stabilize} \]

\[ \omega \]

unstable pole \( p \)
\[ S(\omega) = \frac{E(\omega)}{D(\omega)} \]

\[ e = d - u \]

benefits

\[ \int [\log |S|]_d d\omega + p \geq -\int [\log |S|]_+ d\omega \]

stabilize

causality

costs

unstable pole \( p \)
\[ S(\omega) = \frac{E(\omega)}{D(\omega)} \]

\[ e = d - u \]

Plant \[ \approx \] Bode

benefits

stabilize

causality

\[ \int [\log|S|]_- d\omega + p \geq -\int [\log|S|]_+ d\omega \]

unstable pole \( p \)
\[ e = d - u \]

**Plant**

**Control Channel**

**Control**

\[ d \]

\[ C_C \]

**Benefits**

\[ \int \left[ \log |S| \right]_+ d\omega + p \geq \max \]

**Costs**

\[ \int \left[ \log |S| \right]_- d\omega \]

**Remote Control**

**Feedback**

Martins and Dahleh, IEEE TAC, 2008
$h(e) - h(d) \geq -C_s$

$\int \log |E| d\omega - \int \log |D| d\omega = h(e) - h(d)$

Assume “favorable” delays
\[ h(e) - h(d) \geq -C_s \]

\[ e = d - u \]

\[ \approx \text{Shannon} \]

\[ \int [\log |S|]_+ d\omega \leq -C_s \]

\[ -\int [\log |S|]_+ d\omega \]

\[ \text{benefits} \]
control

Plant

$e = d - u$

d

Control

$C_C$

$s = -C_C$

$-\int [\log|S|]_+ d\omega$

$-C_S$

Sense/Encode

Remote control

Benefits

Stabilize

Costs

Causality

Martins, Dahleh, Doyle

IEEE TAC, 2007
Disturbance

delay

delay

Benefits?

$\int [\log |S|]_{-} d\omega \geq -\log(a)$

$-\int [\log |S|]_{+} d\omega$

benefits

stabilize

$-C_s$

causality

costs
• Abstract models of resource use
• Foundations, origins of
  – noise
  – dissipation
  – amplification
  – catalysis
Glycolytic Oscillations and Limits on Robust Efficiency

Fiona A. Chandra,1* Gentian Buzi,2 John C. Doyle2

Both engineering and evolution are constrained by trade-offs between efficiency and robustness, but theory that formalizes this fact is limited. For a simple two-state model of glycolysis, we explicitly derive analytic equations for hard trade-offs between robustness and efficiency with oscillations as an inevitable side effect. The model describes how the trade-offs arise from individual parameters, including the interplay of feedback control with autocatalysis of network products necessary to power and catalyze intermediate reactions. We then use control theory to prove that the essential features of these hard trade-off “laws” are universal and fundamental, in that they depend minimally on the details of this system and generalize to the robust efficiency of any autocatalytic network. The theory also suggests worst-case conditions that are consistent with initial experiments.
Figure S4. Simulation of two state model (S7.1) qualitatively recapitulates experimental observation from CSTR studies [5] and [12]. As the flow of material in/out of the system is increased, the system enters a limit cycle and then stabilizes again. For this simulation, we take \( q = a = Vm = 1, \ k = 0.2, \ g = 1, \ u = 0.01, \ h = 2.5 \).
The simulation of two state model (S7.1) qualitatively recapitulates experimental observations from CSTR studies [5] and [12]. As the flow of material in/out of the system is increased, the system enters a limit cycle and then stabilizes again. For this simulation, we take $q=a=Vm=1$, $k=0.2$, $g=1$, $u=0.01$, $h=2.5$. Why?
Glycolytic “circuit” and oscillations

• Most studied, persistent mystery in cell dynamics

• End of an old story (why oscillations)
  – side effect of hard robustness/efficiency tradeoffs
  – no purpose per se
  – just needed a theorem

• Beginning of a new one
  – robustness/efficiency tradeoffs
  – complexity and architecture
  – need more theorems and applications
Robust
= maintain energy charge w/ fluctuating cell demand

Efficient
= minimize metabolic overhead

Tradeoffs?

Robust?

Fragile?

Efficient?

Wasteful?

Hard limit?

autocatalytic?

rate $k$?

control?

$g$?

$y$?

$y$?

Rest?

Efficient = minimize metabolic overhead
Theorem!

\[ \frac{1}{\pi} \int_{0}^{\infty} \ln \left| S(j\omega) \right| \left( \frac{z}{z^2 + \omega^2} \right) d\omega \geq \ln \left| \frac{z + p}{z - p} \right| \]

Fragility

\[ \ln \left| \frac{z + p}{z - p} \right| \]

\( z \) and \( p \) functions of enzyme complexity and amount

Savageaumics

Enzyme amount

Simple enzyme

Complex enzyme
Inside every cell

Almost

Catabolism

Preparers

AA

Ribosome

RNA

RNA

Proteins

Enzymes

Macro-layers

ATP

Building Blocks

AA

transl.

DNA

Repl.

Gene

Crosslayer autocatalysis

Crosslayer autocatalysis

ATP

Enzymes

Proteins

Ribosome

RNA

transc.

xRNA

DNA

Repl.

Gene

DNAp

RNAp
Catabolism

Precursors → ATP → Energy
ATP

Metabolic flux

Minimal model

Reaction 1 ("PFK")

intermediate metabolite

Reaction 2 ("PK")

ATP

energy

Rest of cell

Efficient

metabolic overhead
Enzymes catalyze reactions.

Reaction 1 ("PFK")

Reaction 2 ("PK")

Rest of cell

Protein biosyn

Efficient metabolic overhead \( \approx \) enzyme amount
Fluorescence histogram (fluorescence vs. cell count) of GFP-tagged Glyceraldehyde-3-phosphate dehydrogenase (TDH3). Cells grown in ethanol has lower mean and median of fluorescence, and also higher variability.
Metabolic Overhead

$\alpha k$

Metabolic Overhead
Fragility

$$\left| \frac{1}{h - a} \right|$$

$$g = 0$$

$$g = 1$$

Metabolic Overhead

Count

highly variable

$$g = 0$$ is implausibly fragile

$$\left| \frac{1}{h - a} \right| > \frac{q}{k + (1 + q)g}$$
autocatalytic feedback: energy

Reaction 1 ("PFK")

Reaction 2 ("PK")

Rest of cell

Protein biosyn

ATP

Efficient metabolic overhead
≈ enzyme amount
Metabolic flux

Inherently unstable

Reaction 1 ("PFK")

Reaction 2 ("PK")

Efficient

metabolic overhead ≈ enzyme amount
Robust = Maintain energy despite demand fluctuation
ATP
Rest
of cell

Reaction 1 ("PFK")

Reaction 2 ("PK")

$\approx$

enzyme amount

Fragile

Robust

Efficient

disturbance

energy

control

metabolic overhead
Theorem! \[
\frac{1}{\pi} \int_0^\infty \ln \left| S(j\omega) \right| \left( \frac{z}{z^2 + \omega^2} \right) d\omega \geq \ln \left| \frac{z + p}{z - p} \right|
\]

Efficient

metabolic overhead
\approx\text{enzyme amount}

Fragile

Robust

\[\ln \left| \frac{z + p}{z - p} \right|\]
Theorem! \[ \frac{1}{\pi} \int_{0}^{\infty} \ln |S(j\omega)| \left( \frac{z}{z^2 + \omega^2} \right) d\omega \geq \ln \left( \frac{z + p}{z - p} \right) \]

Fragile

\[ \ln \left( \frac{z + p}{z - p} \right) \]

Robust

Efficient

simple enzyme

complex enzyme

metabolic overhead \( \approx \) enzyme amount

Rest of cell

disturbance
\[ \frac{1}{\pi} \int_{0}^{\infty} \ln |S(j \omega)| \left( \frac{z}{z^2 + \omega^2} \right) d\omega \geq \ln \left| \frac{z + p}{z - p} \right| \]

Fragile

\[ \ln \left| \frac{z + p}{z - p} \right| \]

Robust

Efficient

complex enzyme

metabolic overhead
\approx \text{enzyme amount}

Rest of cell

disturbance

Reaction 1 (“PFK”)

Reaction 2 (“PK”)

control

energy
\[ \frac{1}{\pi} \int_{0}^{\infty} \ln |S(j\omega)| \left( \frac{z}{z^2 + \omega^2} \right) d\omega \geq \ln \left| \frac{z + p}{z - p} \right| \]

\[ y = WS \delta \]

"weighed sensitivity"

\[ y = ATP \]

\[ [P W] \]

\[ H \]

Reaction 1 ("PFK")

Reaction 2 ("PK")
Good architectures allow for effective tradeoffs.

Alternative systems with shared architecture.

“Conservation laws”
Theorem

\[
\frac{1}{\pi} \int_0^\infty \ln |S(j\omega)| \left( \frac{z}{z^2 + \omega^2} \right) d\omega \geq \ln \left| \frac{z + p}{z - p} \right|
\]

- \( z \) and \( p \) are functions of enzyme complexity and amount
- standard biochemistry models
- \textbf{phenomenological}

- \textbf{first principles?}
Fragility

- General
- Rigorous
- First principle

Overhead, waste

- Domain specific
- Ad hoc
- Phenomenological

Plugging in domain details

hard limits

simple

complex
Control

Wiener

Bode

Kalman

Comms

Shannon

Carnot

Boltzmann

Heisenberg

Physics

• General
• Rigorous
• First principle

• Fundamental multiscale physics
• Foundations, origins of
  – noise
  – dissipation
  – amplification
  – catalysis
Complex networks

“New sciences” of complexity and networks
edge of chaos, self-organized criticality, scale-free,...

Alderson & Doyle, Contrasting Views of Complexity and Their Implications for Network-Centric Infrastructure, IEEE TRANS ON SMC, JULY 2010

Control

Comms

Compute

Stat physics

Carnot

Boltzmann

Heisenberg

Physics

doesn’t work
Alderson & Doyle, Contrasting Views of Complexity and Their Implications for Network-Centric Infrastructure, IEEE TRANS ON SMC, JULY 2010

Sandberg, Delvenne, & Doyle, On Lossless Approximations, the Fluctuation-Dissipation Theorem, and Limitations of Measurement, IEEE TRANS ON AC, FEBRUARY, 2011
Sandberg, Delvenne, & Doyle, On Lossless Approximations, the Fluctuation-Dissipation Theorem, and Limitations of Measurement, IEEE TRANS ON AC, FEBRUARY, 2011
A streamwise constant model of turbulence in plane Couette flow

D. F. GAYME\textsuperscript{1\dagger}, B. J. MCKEON\textsuperscript{1}, A. PAPACHRISTODOULOU\textsuperscript{2}, B. BAMIEH\textsuperscript{3} AND J. C. DOYLE\textsuperscript{1}

Streamlined Laminar Flow

Transition to Turbulence

Increasing Drag, Fuel/Energy Use and Cost

Turbulent Flow

Flow

Turbulence and drag?
Amplification and nonlinear mechanisms in plane Couette flow

Dennise F. Gayme, Beverley J. McKeon, Bassam Bamieh, Antonis Papachristodoulou, and John C. Doyle

Coherent structures and turbulent drag

high-speed region
upflow
3D coupling
low speed streak
Blunted turbulent velocity profile
Turbulent
Laminar
Control

- General
- Rigorous
- First principle

Comms

- Foundations, origins of
  - noise
  - dissipation
  - amplification
  - catalysis

Wiener

- robust control

Bode

Kalman

Shannon

Carnot

Boltzmann

Heisenberg

Physics
Smart Antennas (Javad Lavaei)

- Security, co-channel interference, power consumption

**1) Multiple active elements:**
- Easy to program
- Hard to implement

**2) Multiple passive elements:**
- Easy to implement
- Hard to program
Passively Controllable Smart (PCS) Antenna

- **PCS Antenna**: One active element, reflectors and several parasitic elements.

- This type of antenna is easy to program and easy to implement but “hard” to solve (e.g. 4 weeks offline computation).
- We solved the problem in 1 sec with huge improvement:
Decentralized control
Partial bibliography
(Lamperski)

Triaged today
Great topic


The Magnitude Distribution of Earthquakes near Southern California Faults

Morgan T. Page

U.S. Geological Survey, Pasadena, California, USA

David Alderson

Operations Research Department, Naval Postgraduate School, Monterey, California, USA

John Doyle

Control and Dynamical Systems, California Institute of Technology,

Really fat tails

How big is “big”? 
Persistent controversy

\[
magnitude \propto \log(\text{power})
\]

Gutenberg-Richter

\(\exists \text{ “characteristic earthquake”???}\)

\(\exists \text{ “bump”}\)

Note: rare example (in science) involving power laws that isn’t \textit{obviously} ridiculous

\(\text{rare example (in science)}\)

involving \(\text{power laws that isn’t obviously ridiculous}\)

\(\text{slope} = -1\)

\(\text{largest}\)

\(\text{smaller}\)

\(\log(\text{rank})\)

\(\text{Gutenberg-Richter}\)

\(?\)
a) Magnitude Distribution for Parkfield Section of San Andreas Fault (ANSS Catalog within 5 km)

- **Parkfield Data**
- **b-value 95% Confidence**
- **b=1**
- **Best-fit b-value**
a) Magnitude Distribution for Parkfield Section of San Andreas Fault (ANSS Catalog within 5 km)

- Parkfield Data
- b-value 95% Confidence
- b=1
- Best-fit b-value

b) Comparison of Parkfield Data to G-R Random Samples

- Parkfield Data
- b=1 95% Confidence
- b=1 Random Samples
a) Distribution of Maximum Event for 1000 Randomly Sampled G-R Magnitudes

No bump still might look like a "bump"

Randomly sampled G-R magnitudes

Distribution of max event
Order statistics

$P( (k \text{ of } n) > x )$

$p = -\frac{dP}{dx}$

More data, but...
Tail stays highly variable

More samples
Fault traces and epicenters
Number of earthquakes per fault

155 faults
3 biggest quakes

a) Largest Earthquake Distribution

Mag of largest quake
3 biggest quakes

a) Lavic Lake Fault

\[ p = 0.03 \]

b) Johnson Valley Fault

\[ p = 0.01 \]

c) Santa Monica Fault

\[ p = 0.002 \]

d) Northridge Thrust
Magnitude binned by distance to faults
Randomly sampled G-R magnitudes

Distribution of max event

No bump still might look like a "bump"
Truncated pareto model \( P(x) \)

Los Padres National Forest

Wildfires

\[
NP(X > x)
\]

LPNF data (decimated)
Wildfires, complexity, and highly optimized tolerance

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Recent, large fires in the western United States have rekindled debates about fire management and the role of natural fire regimes in the resilience of terrestrial ecosystems. This real-world experience parallels debates involving abstract models of forest fires, a central metaphor in complex systems theory. Both real and modeled fire-prone landscapes exhibit roughly power law statistics in fire size versus frequency. Here, we examine historical fire catalogs and a detailed fire simulation model; both are in agreement with a highly optimized tolerance model. Highly optimized tolerance suggests robustness tradeoffs underlie resilience in different fire-prone ecosystems. Understanding these mechanisms may provide new insights into the structure of ecological systems and be key in evaluating fire management strategies and sensitivities to climate change.

Highly optimized tolerance (HOT) is a conceptual framework for examining organization and structure in complex systems (18). Theoretically, HOT builds on models and mathematics from physics and engineering, and identifies robustness tradeoffs as a principle underlying mechanism for complexity and power law statistics. HOT has been discussed in the context of a variety of technological and natural systems, including wildfires (18, 22). A quantitative prediction for the distribution of fire sizes comes from an extremely simple analytical HOT model, referred to as the PLR (probability-loss-resource) model (22). As a precursor to results presented later in this article, Fig. 2 demonstrates the PLR prediction and truncated power law statistics (23) for several fire history catalogs. This plot represents the rank or cumulative frequency of fires PLR greater than...
Fire in the Earth System


Fire is a worldwide phenomenon that appears in the geological record soon after the appearance of terrestrial plants. Fire influences global ecosystem patterns and processes, including vegetation distribution and structure, the carbon cycle, and climate. Although humans and fire have always coexisted, our capacity to manage fire remains imperfect and may become more difficult in the future as climate change alters fire regimes. This risk is difficult to assess, however, because fires are still poorly represented in global models. Here, we discuss some of the most important issues involved in developing a better understanding of the role of fire in the Earth system.
Comparison of model $n \cdot P(x)$ with cumulative raw data (decimated).

\[
\log \left( \frac{P(k/n < x)}{P(k/n > x)} \right) = \log(P(k/n < x)) - \log(P(k/n > x))
\]

\[
P(k/n < x) = .05 \quad P(k/n > x) = .05
\]
Comparison of variations in LPNF data versus that of pseudo-random samples.

\[
\log\left(\frac{P(k/n < x)}{P(k/n > x)}\right) = \log(P(k/n < x)) - \log(P(k/n > x))
\]

LPNF data (black) plus 4 pseudo-random samples from \(P(>x)\) (colors).

LPNF data and pseudo-random samples have similar variations.

\[
P(k/n < x) = .05 \quad \quad P(k/n > x) = .05
\]
MLE as WLS

Exponential

rank $k = n \times \exp(-\lambda x_k)$

Ideal: $x_k = (\log(n) - \log(k)) / \lambda$

\[
\begin{align*}
\text{MLE} & \quad \frac{1}{\hat{\lambda}} = \frac{1}{n} \sum x_k \\
\text{MVUE} & \quad \frac{1}{\hat{\lambda}} = \frac{1}{n-1} \sum x_k \\
\text{MVE} & \quad \frac{1}{\hat{\lambda}} = \frac{1}{n-2} \sum x_k
\end{align*}
\]

\[\lambda_{\text{MLE}} > \lambda_{\text{UMVUE}} > \lambda_{\text{MVE}}\]

Pareto

rank $k = n \times (x_k)^{-\alpha}$

\[x_k = (k / n)^{-1/\alpha} = (n / k)^{1/\alpha}\]

\[
\log(x_k) = (\log(n) - \log(k)) / \alpha
\]
MLE as WLS

Exponential

rank \( k = n \star \exp(-\lambda x_k) \)

Ideal: \( x_k = (\log(n) - \log(k)) / \lambda \)

\[
\sum_{k=1}^{n-1} w_k (x_k)(\log(n) - \log(k)) \\
\mu = \frac{\sum_{k=1}^{n-1} w_k (\log(n) - \log(k))^2}{\sum_{k=1}^{n-1} w_k (\log(n) - \log(k))^2} \\
w_k = \frac{1}{(\log(n) - \log(k))} \Rightarrow \mu = \frac{\sum_{k=1}^{n-1} x_k}{\sum_{k=1}^{n-1} (\log(n) - \log(k))} = \log(n) - \frac{1}{n} \sum \log(k) \to 1
\]

\[
\frac{d}{d\mu} = -\sum_{k=1}^{n-1} w_k 2(x_k - x_n - \mu (\log(n) - \log(k)))(\log(n) - \log(k)) = 0
\]

\[
MLE \quad \frac{1}{\hat{\lambda}} = \frac{1}{n} \sum x_k \\
MVUE \quad \frac{1}{\hat{\lambda}} = \frac{1}{n-1} \sum x_k \\
MVE \quad \frac{1}{\hat{\lambda}} = \frac{1}{n-2} \sum x_k
\]

\( \lambda_{MLE} > \lambda_{UMVUE} > \lambda_{MVE} \)
Pareto Distribution

\[ \alpha = 1 \]
\[ n = 100 \]
K-S p-value: 0.34
MATLAB’s `ksstest` function with the null hypothesis Pareto alpha=1

\[
\alpha = 1 \\
n = 100 \\
p = 0.34
\]
MATLAB’s `ksstest` function with the null hypothesis Pareto alpha=1

\[
\alpha = 1 \\
n = 100 \\
p = 0.34!!!
\]

makes no difference

need weighted KS, but what weight?
Order statistics

\[ P( (k \text{ of } n) > x) \]

\[ p = - \frac{dP}{dx} \]

But this is so easy and is (apparently) advocated by many statisticians.