

Engineering determinants of cost trends in energy systems

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MIT LGO Operating Committee

Trancik Lab: Energy Systems

research areas:

- technology assessment
 - dynamics of change and influence of engineering characteristics
- technology design
 - for rapid improvement and scaling

domains:

- electricity (e.g. solar, coal, wind)
- transportation (e.g. fuels, electrification)
- materials design

methods:

- statistical analysis of large datasets
- theory and modeling
 - device physics
 - networks
 - optimization
 - ...

goal: accelerate the discovery and scaling of clean energy technologies.

Outline

technology assessment

- **coal-fired electricity**

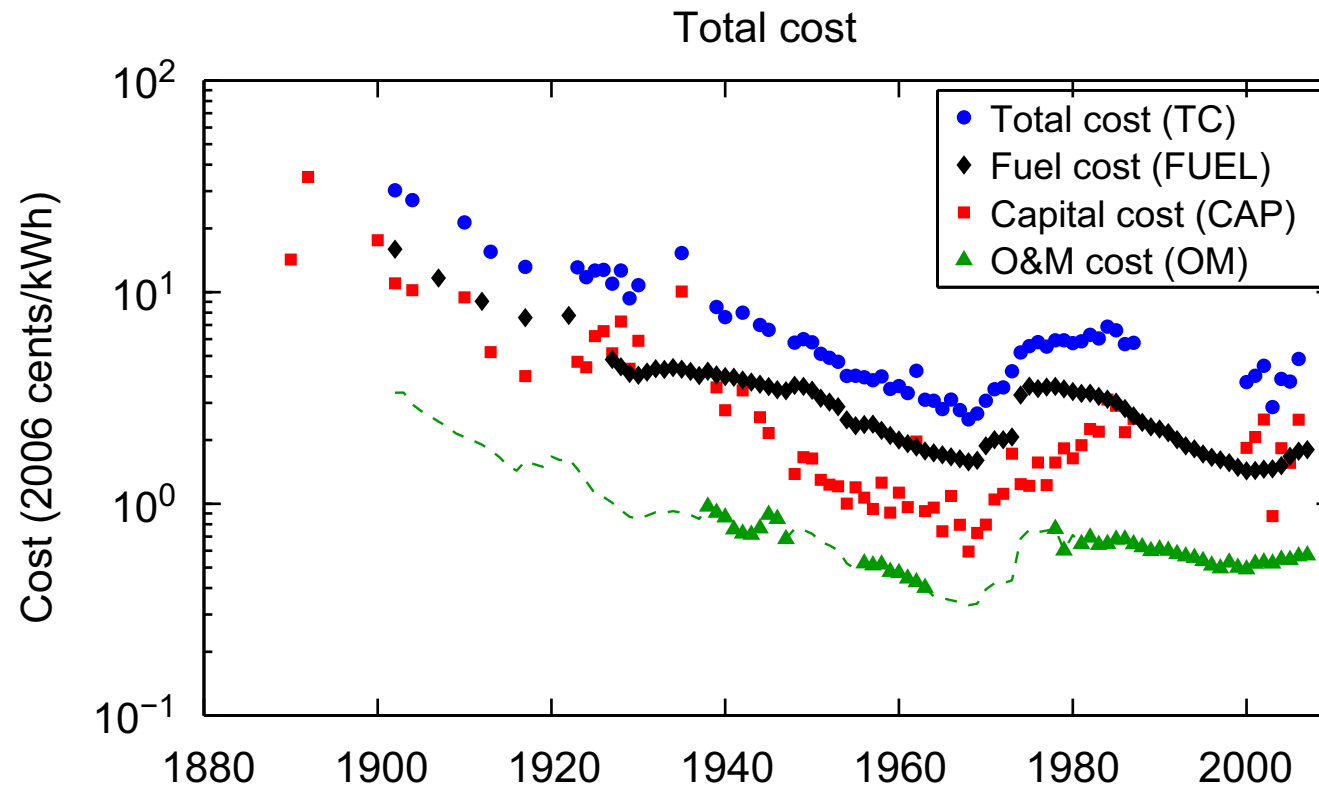
technology/system design

- **role of design complexity in rate of improvement**

Historical costs of coal-fired electricity and implications for the future

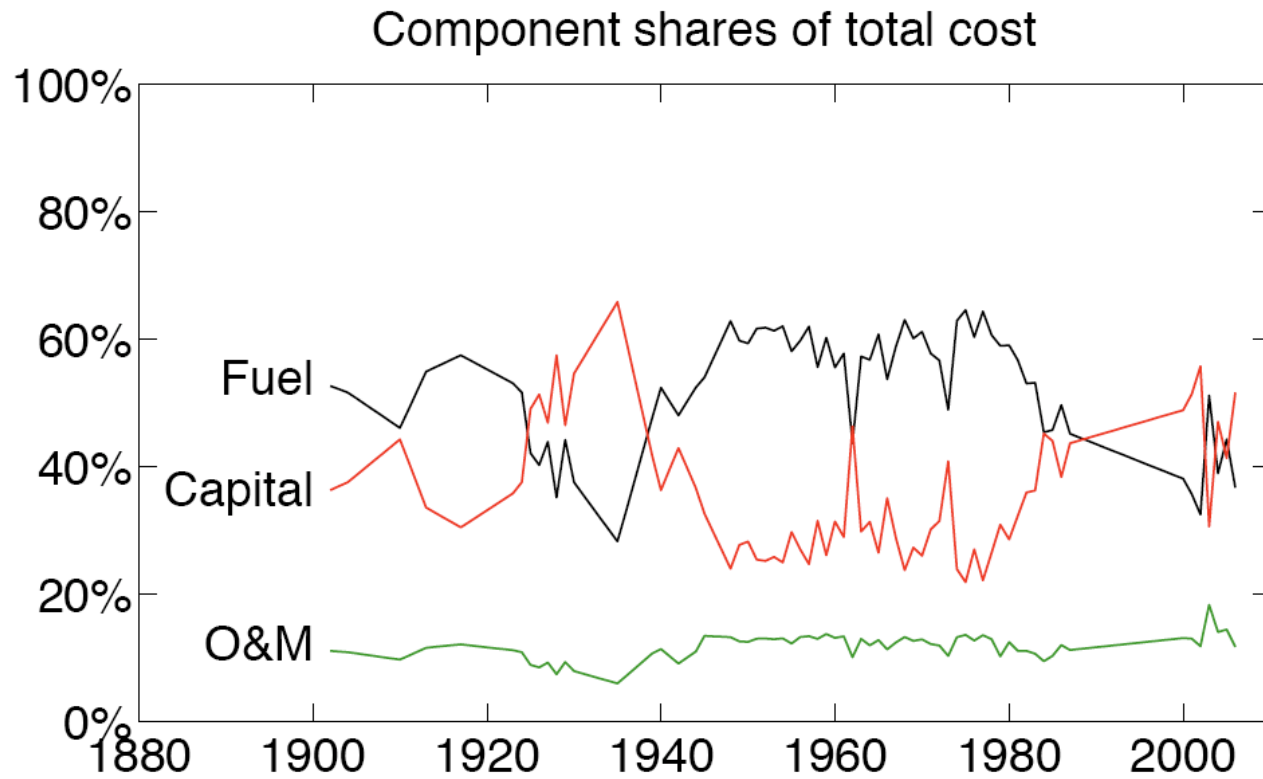
- why study coal?
 - basis of comparison for new technologies
- why a historical perspective (rather than make projections)?
 - valuable information on dynamics (as compared to static estimate of future best performance)
- why focus on decomposed costs?
 - cost determines adoption of energy technologies
 - different cost components may evolve differently

US coal-fired electricity: the last 125 years...

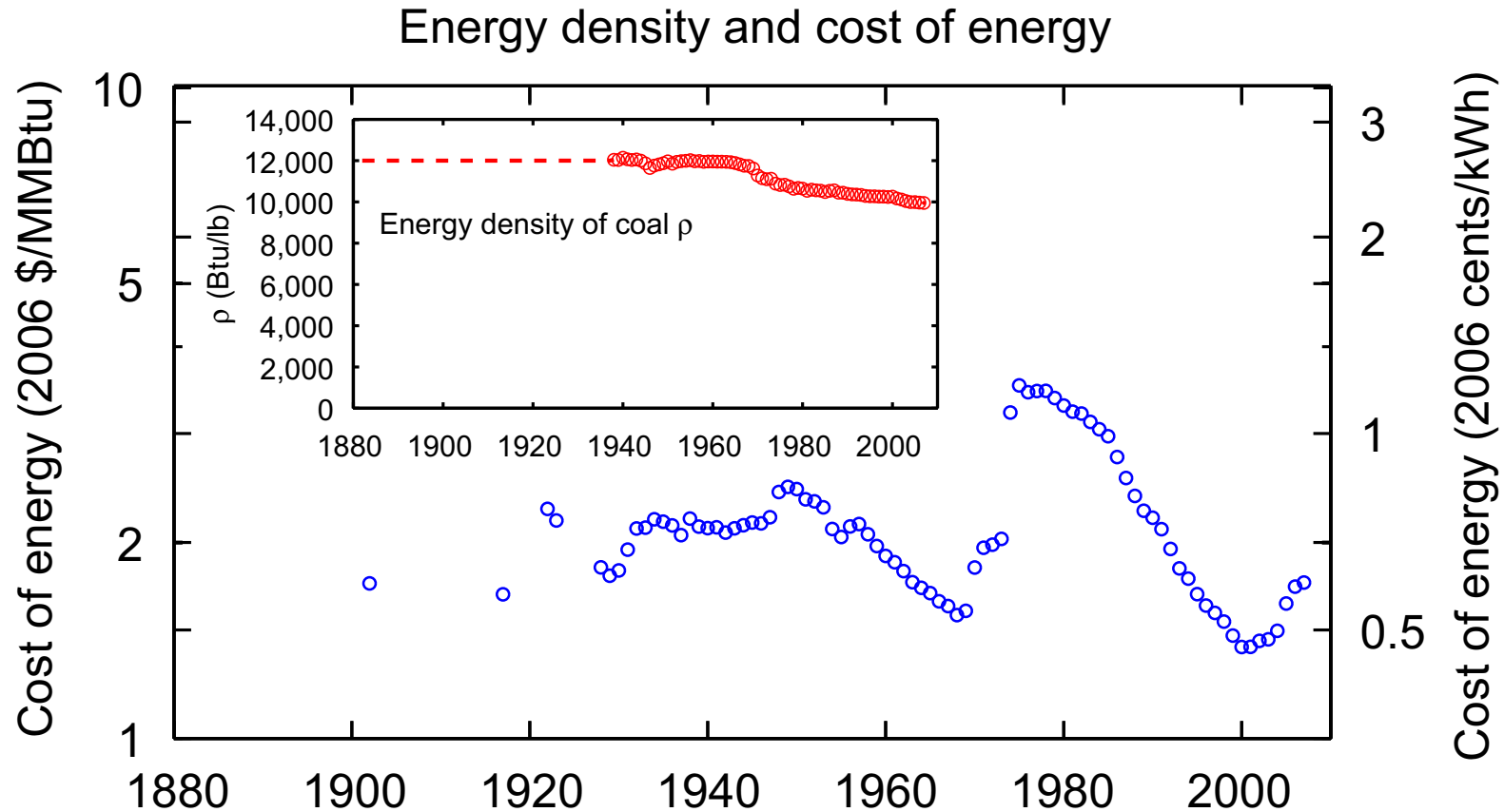


$$\begin{aligned} TC_t &= OM_t + FUEL_t + CAP_t \\ &= OM_t + \frac{COAL_t + TRANS_t}{\rho_t \eta_t} + \frac{SC_t \times CRF(r_t, n)}{CF_t \times 8760 \text{ h}}. \end{aligned} \quad (1)$$

Shares of total cost: fuel and capital dominate

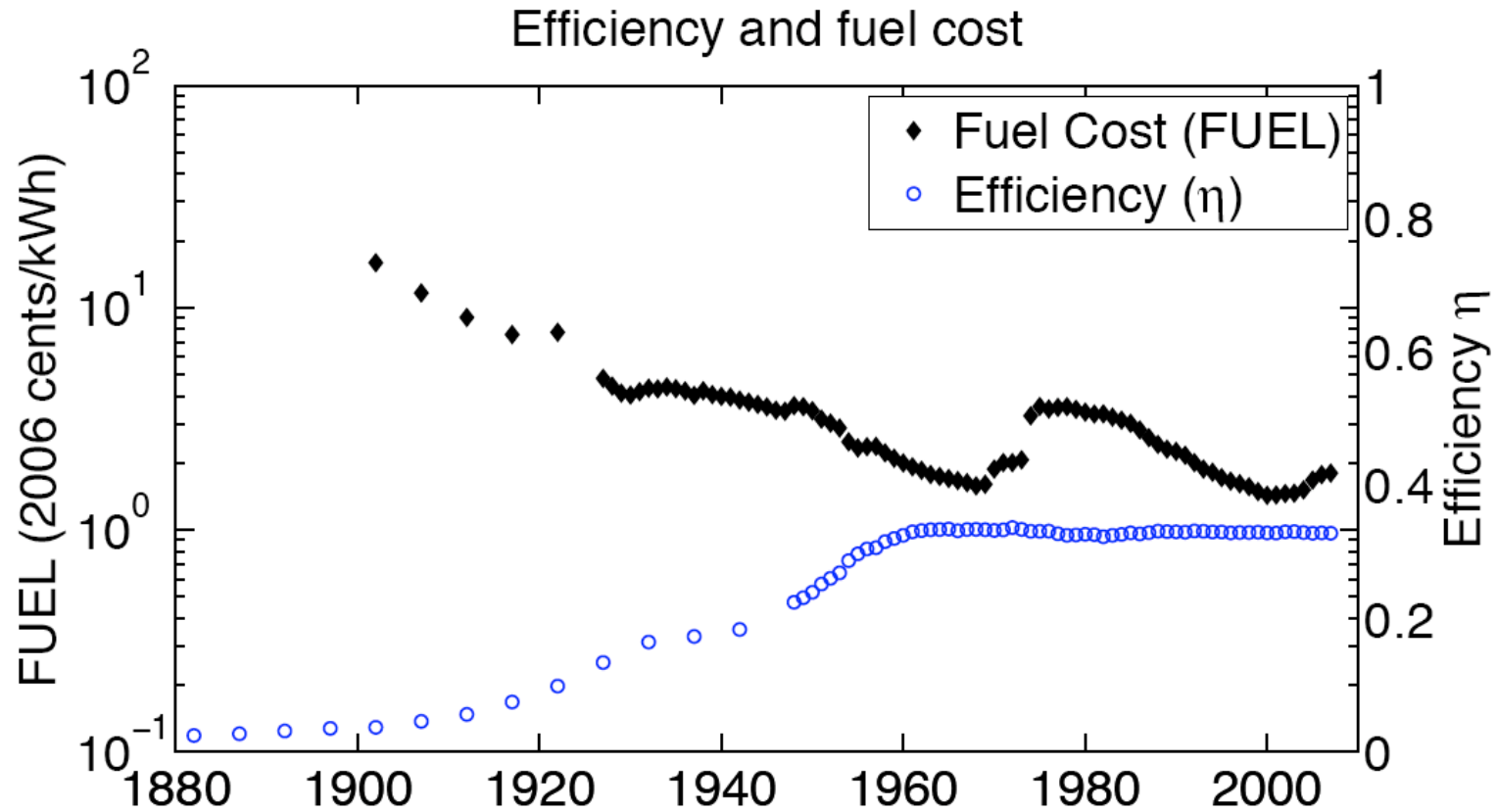


Cost of coal-stored energy



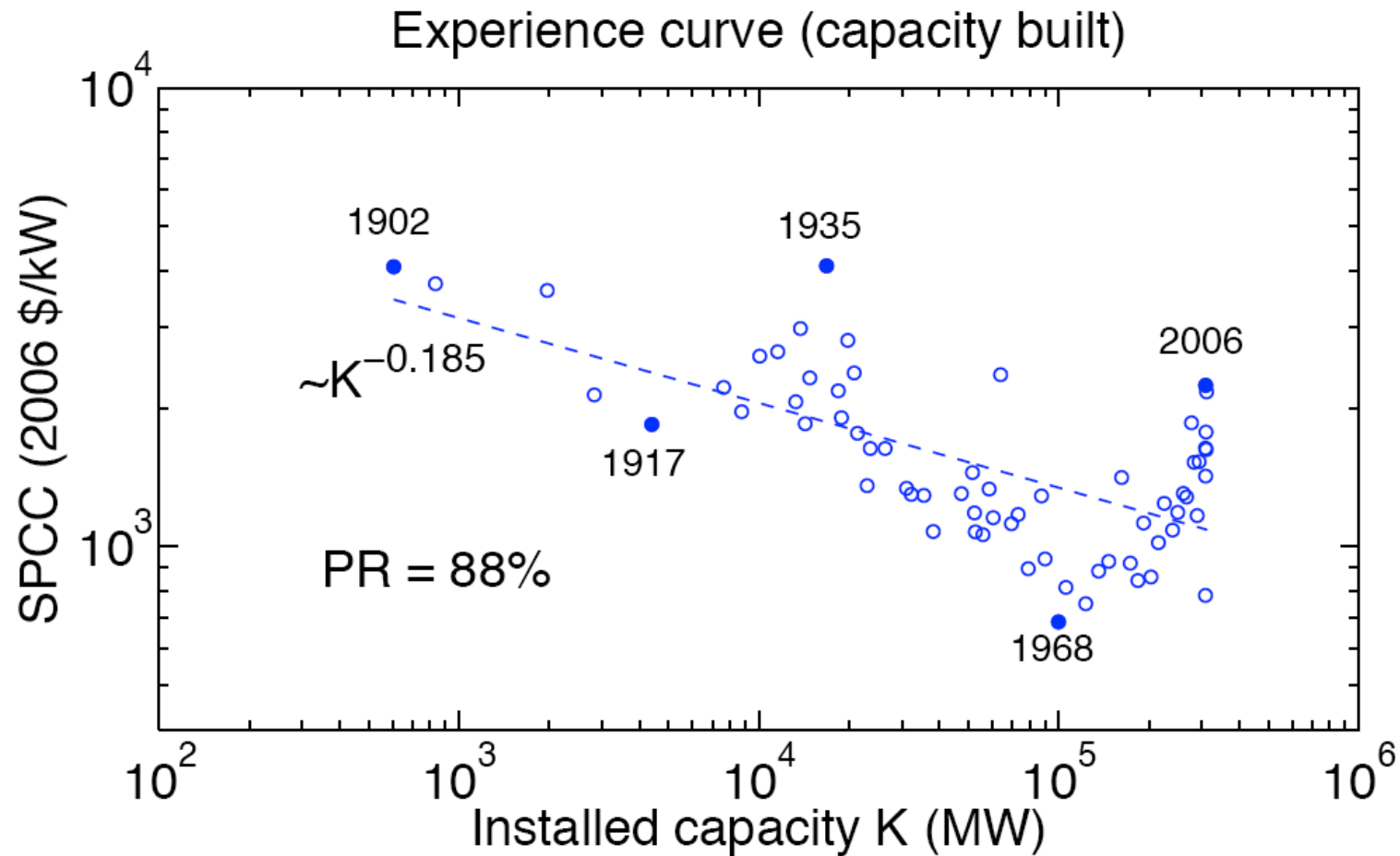
- Coal prices have fluctuated and shown no overall trend up or down
- We cannot rule out a random walk model
- This is consistent with expected behavior of a traded commodity (should not be possible to make easy arbitrage profits by trading it)

Fuel cost



$$\begin{aligned} TC_t &= OM_t + FUEL_t + CAP_t \\ &= OM_t + \frac{COAL_t + TRANS_t}{\rho_t \eta_t} + \frac{SC_t \times CRF(r_t, n)}{CF_t \times 8760 \text{ h}}. \end{aligned} \quad (1)$$

Construction costs



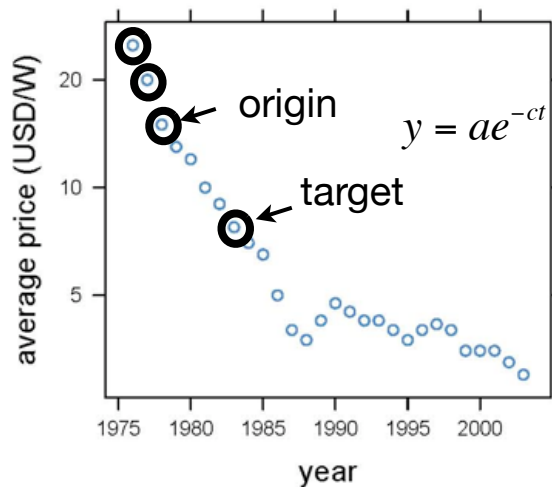
- Plant construction costs follow long term trends (with noise)
- Decreasing until 1970
- Turning point in 1970 (in part due to pollution controls)

Historical costs of coal-fired electricity and implications for the future: conclusions

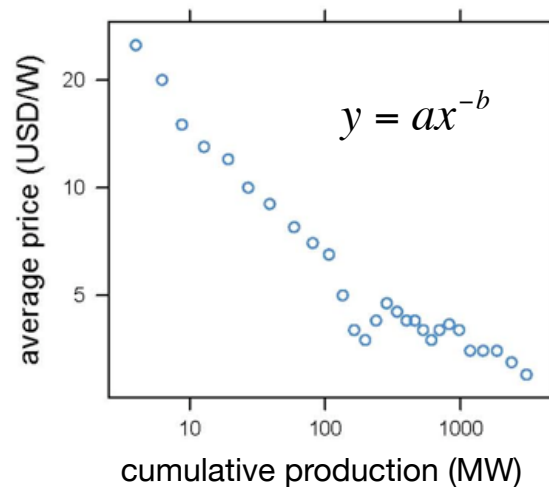
- fuel cost imposes a fluctuating floor on total cost of coal electricity
 - greater variability in total costs over time
- qualitatively different behavior between coal (and other fossil fuels) and other energy technologies
 - should be considered in integrated assessment models
- technology versus commodity: effect on innovation dynamics

Comparison of (predictive ability) of functional forms for performance curves

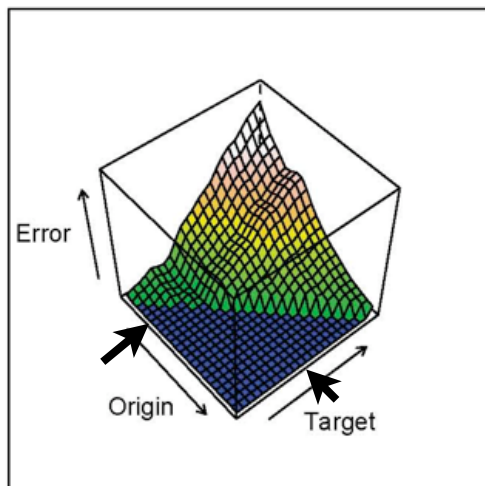
Moore's yearly price history



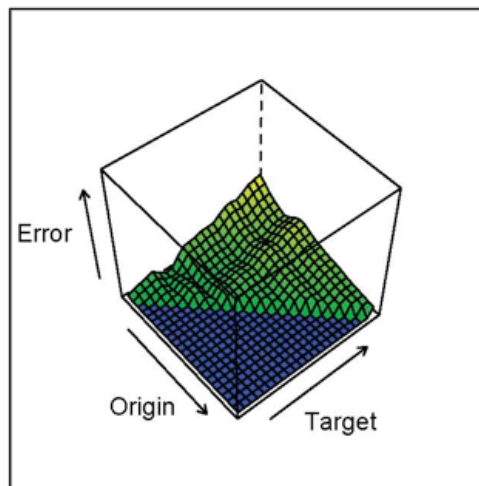
Wright's experience curve



Moore's prediction errors



Wright's prediction errors

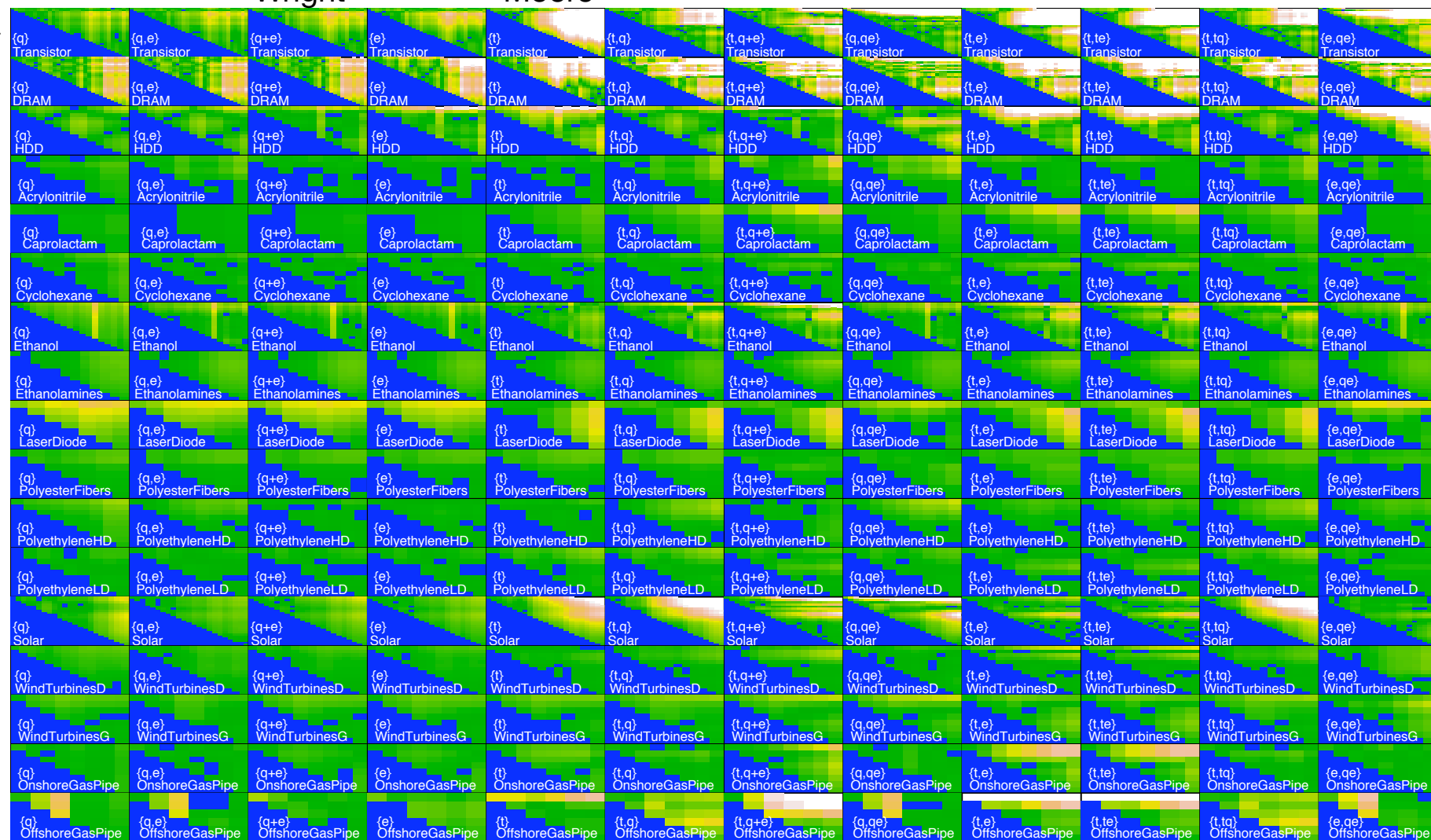


- prediction is uncomfortable but sometimes necessary
 - e.g. cost of mitigating climate change
- many proposals for predicting the future evolution of technologies
- which one performs best? how can we capture uncertainty?
- ~60 datasets (from energy and hardware to beer and chemicals)
- ~15 fcn forms, compared using a mixed effects statistical model...
- **main conclusion:** a tie between Moore and Wright (the two are indistinguishable because of exponential growth)

different data-sets

Wright

Moore



different functional forms

performance curve database: pcdb.santafe.edu

Outline

technology assessment

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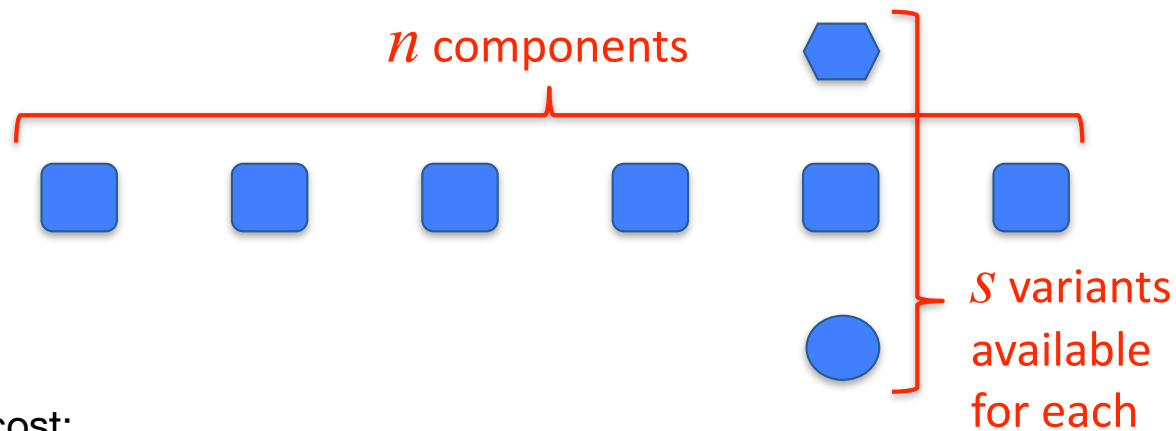
technology/system design

- **role of design complexity in rate of improvement**

Role of design complexity in technology improvement

- simple model of innovation process
- incorporate effect of engineering design characteristics

Simple model of design or production



Total cost:

$$C = C_1 + C_2 + C_3 + C_4 + C_5 + C_6$$

Simplification:

$$S \rightarrow \infty$$

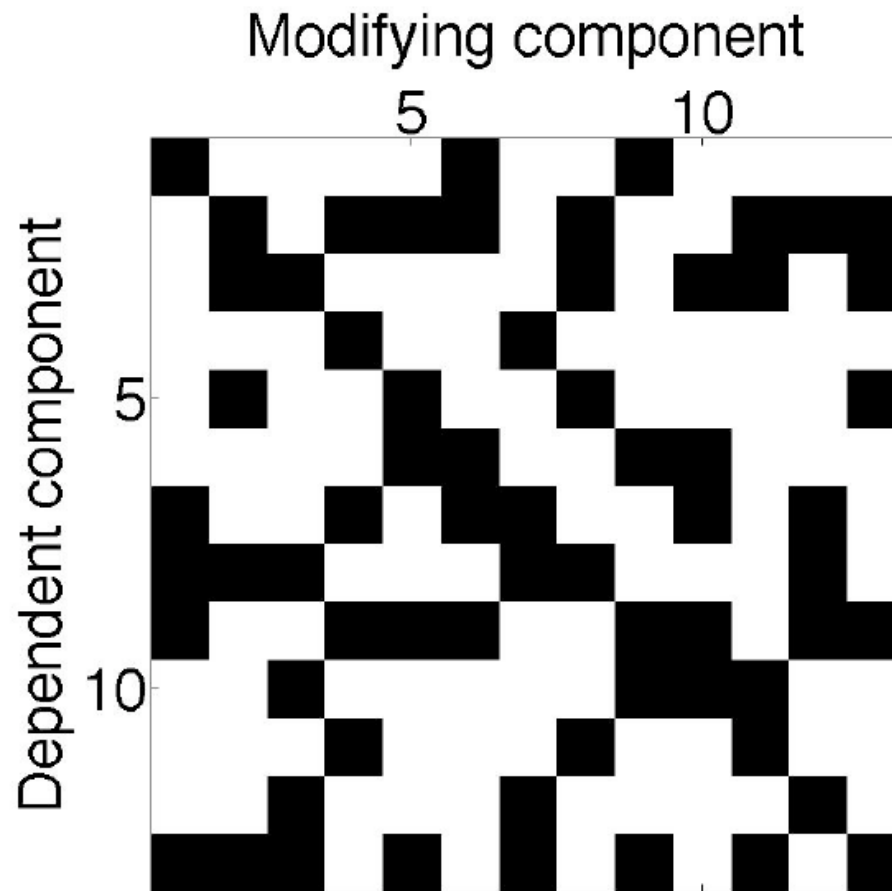
In addition, components depend on one another...

Inspiration from Muth, 1986 and Auerswald et al., 2000

McNerney, Farmer, Redner, Trancik, *PNAS*, 2011

Design structure matrix: fixed out-degree

d dependencies per component



Simulations

1. Pick a random component i .
2. Use the DSM to identify the set of components $\mathcal{A}_i = \{j\}$ whose costs depend on i (the outset of i).
3. Determine a new cost c'_j for each component $j \in \mathcal{A}_i$ from a fixed probability distribution f .
4. If the sum of the new costs, $a'_i = \sum_{j \in \mathcal{A}_i} c'_j$, is less than the current sum, a_i , then each c_j is changed to c'_j . Otherwise, the new cost set is rejected.

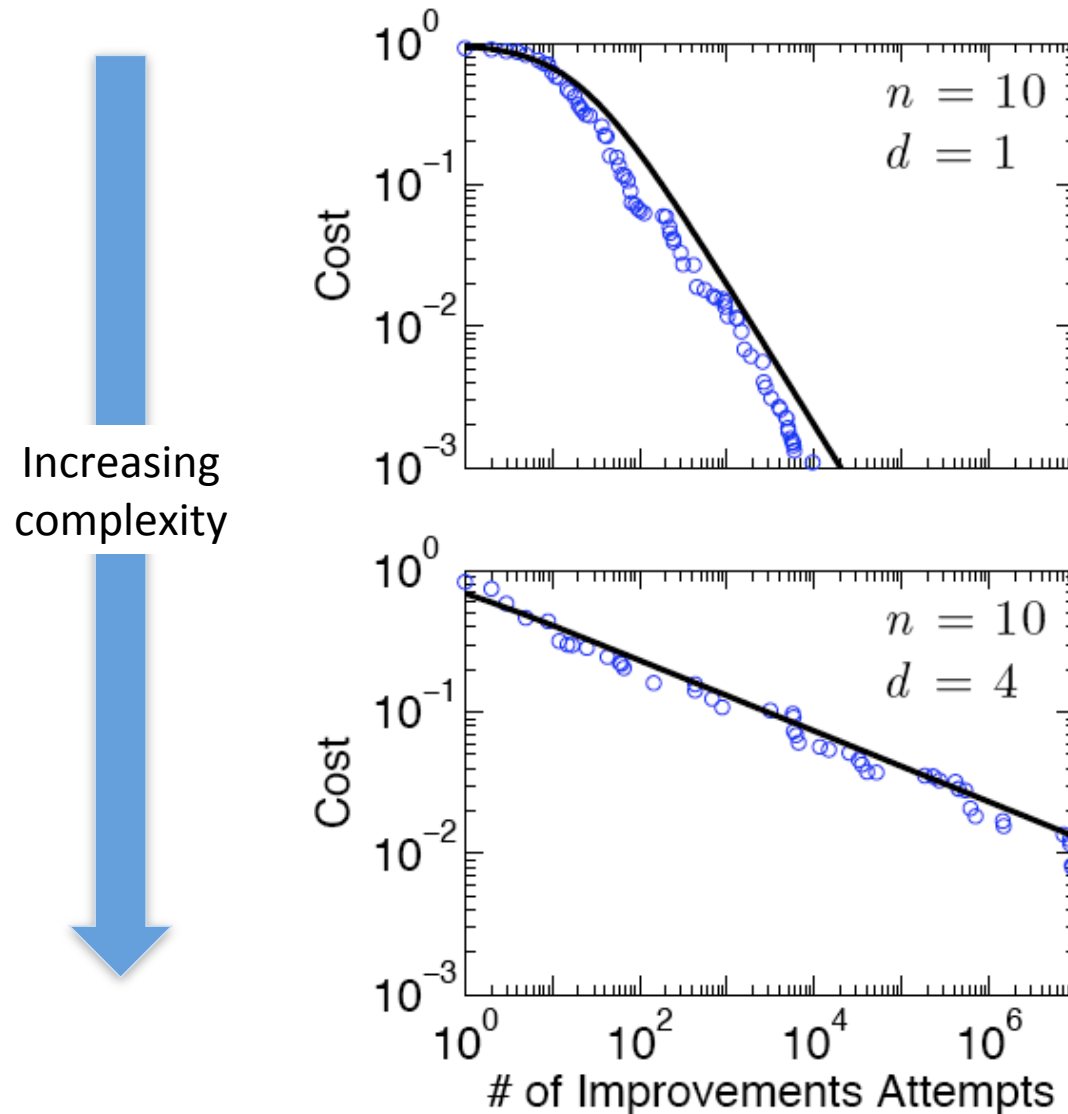
$$c = c_1 + c_2 + c_3 + c_4 + c_5 + c_6$$


$$c' = c'_1 + c_2 + c'_3 + c'_4 + c_5 + c_6$$

$c' < c \rightarrow$ accept changes

$c' > c \rightarrow$ keep old recipe

Design complexity and rate of improvement

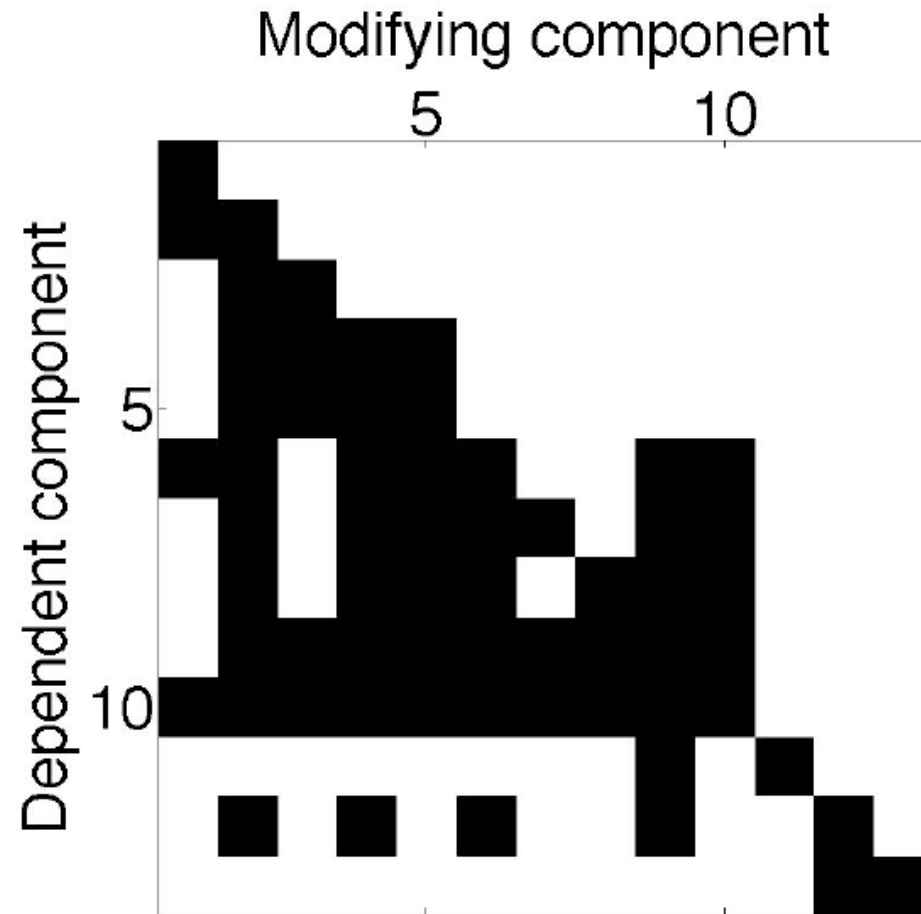


$$c(x) \sim x^{-\alpha}$$

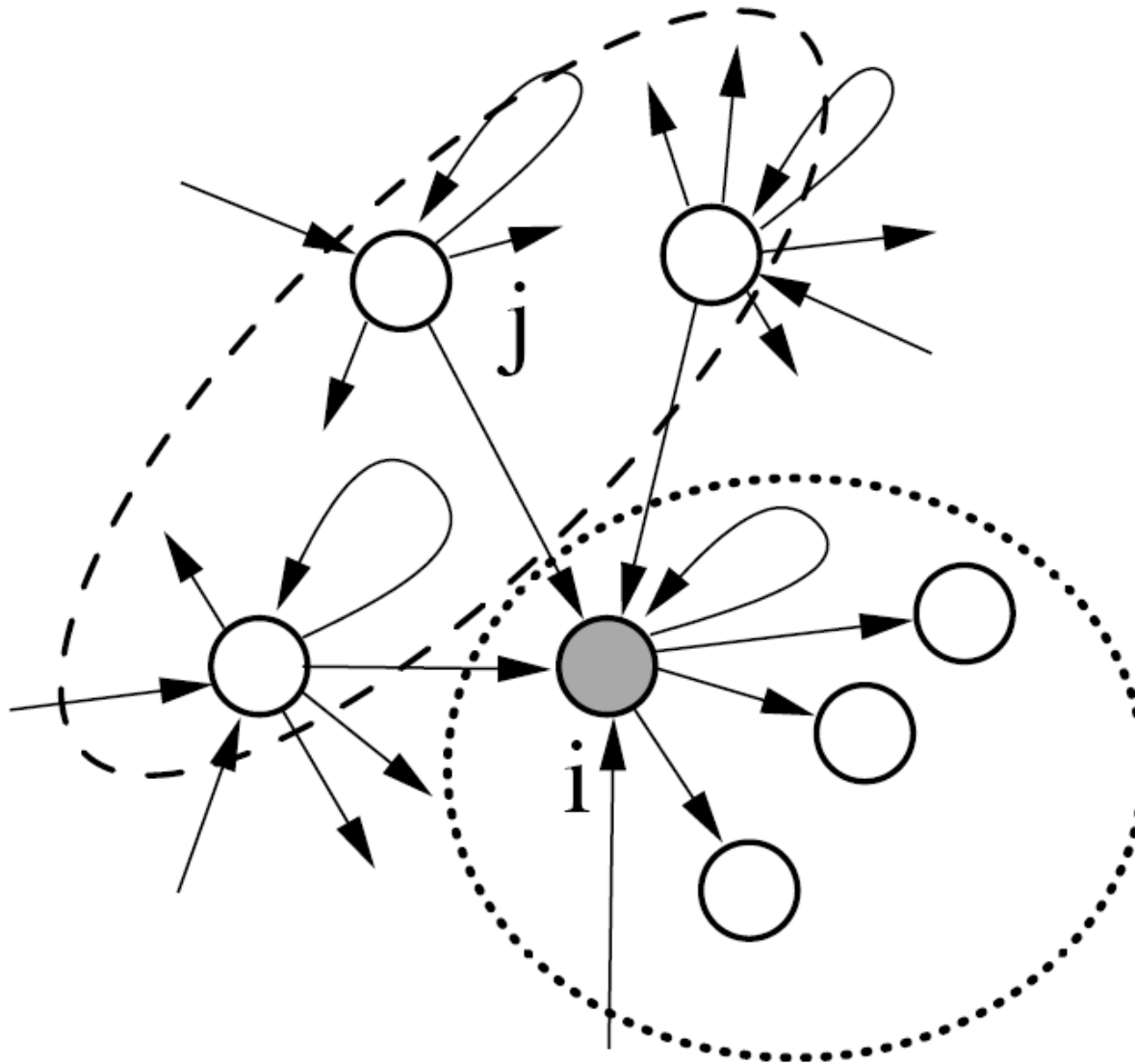
$$\alpha \sim \frac{1}{d}$$

Design structure matrix: variable out-degree

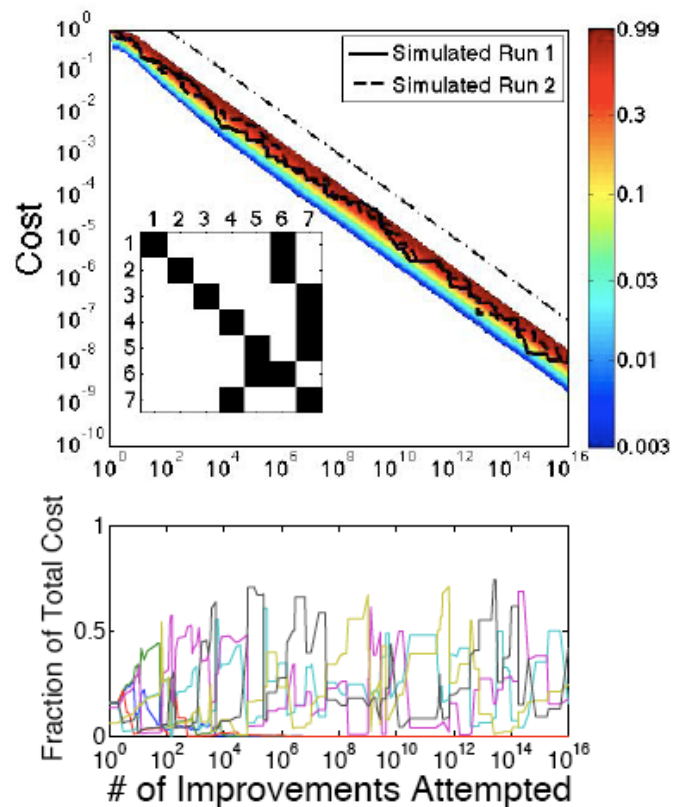
d - average number of dependencies per component



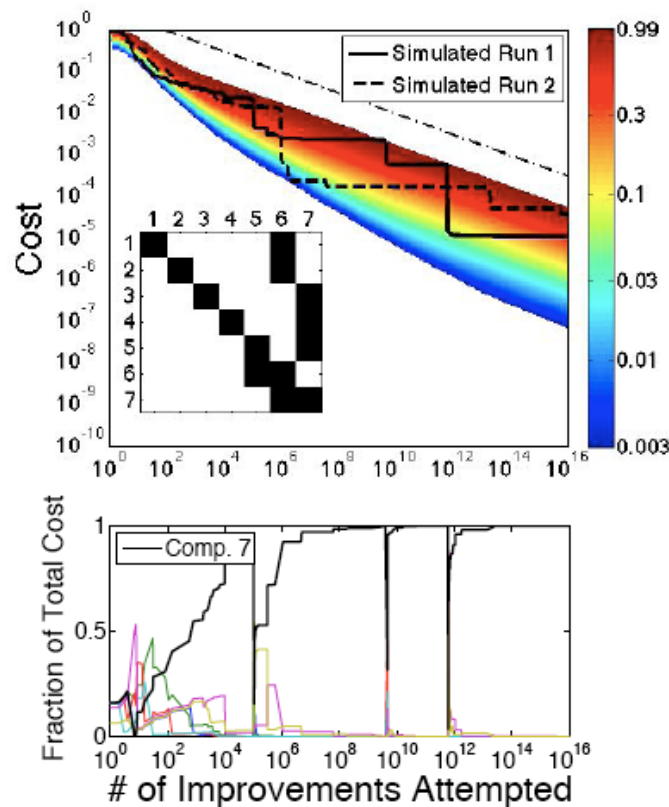
Bottlenecks form - $d_i^{\min}$



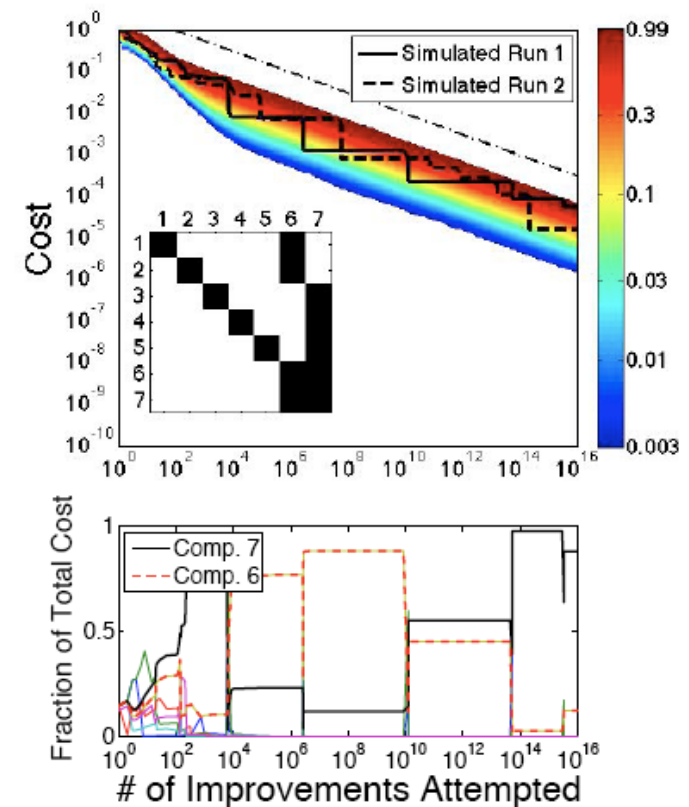
Bottlenecks determine rate of improvement



component i	1	2	3	4	5	6	7
out-degree of i	1	1	1	2	2	3	4
$d_i^{\min}$	1	1	1	2	2	2	2



component i	1	2	3	4	5	6	7
out-degree of i	1	1	1	1	2	4	4
$d_i^{\min}$	1	1	1	1	2	2	4



component i	1	2	3	4	5	6	7
out-degree of i	1	1	1	1	1	4	5
$d_i^{\min}$	1	1	1	1	1	4	4

$$d^* = \max(d_i^{\min})$$

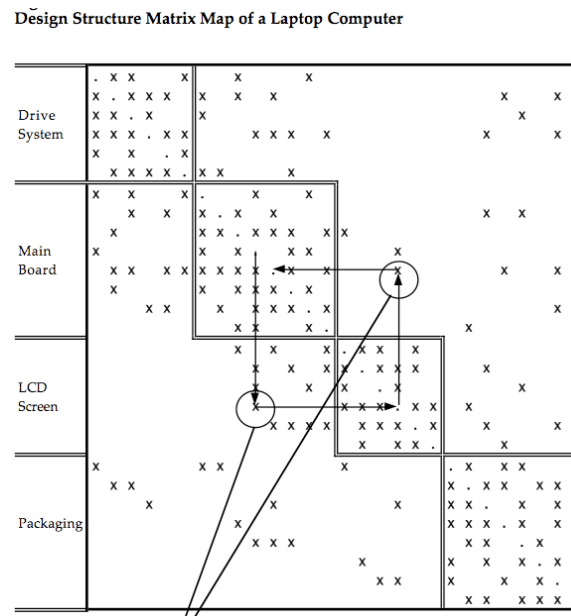
Next step - empirical relationships

$$c(x) \sim x^{-\alpha} \quad \alpha \sim \frac{1}{d^*}$$

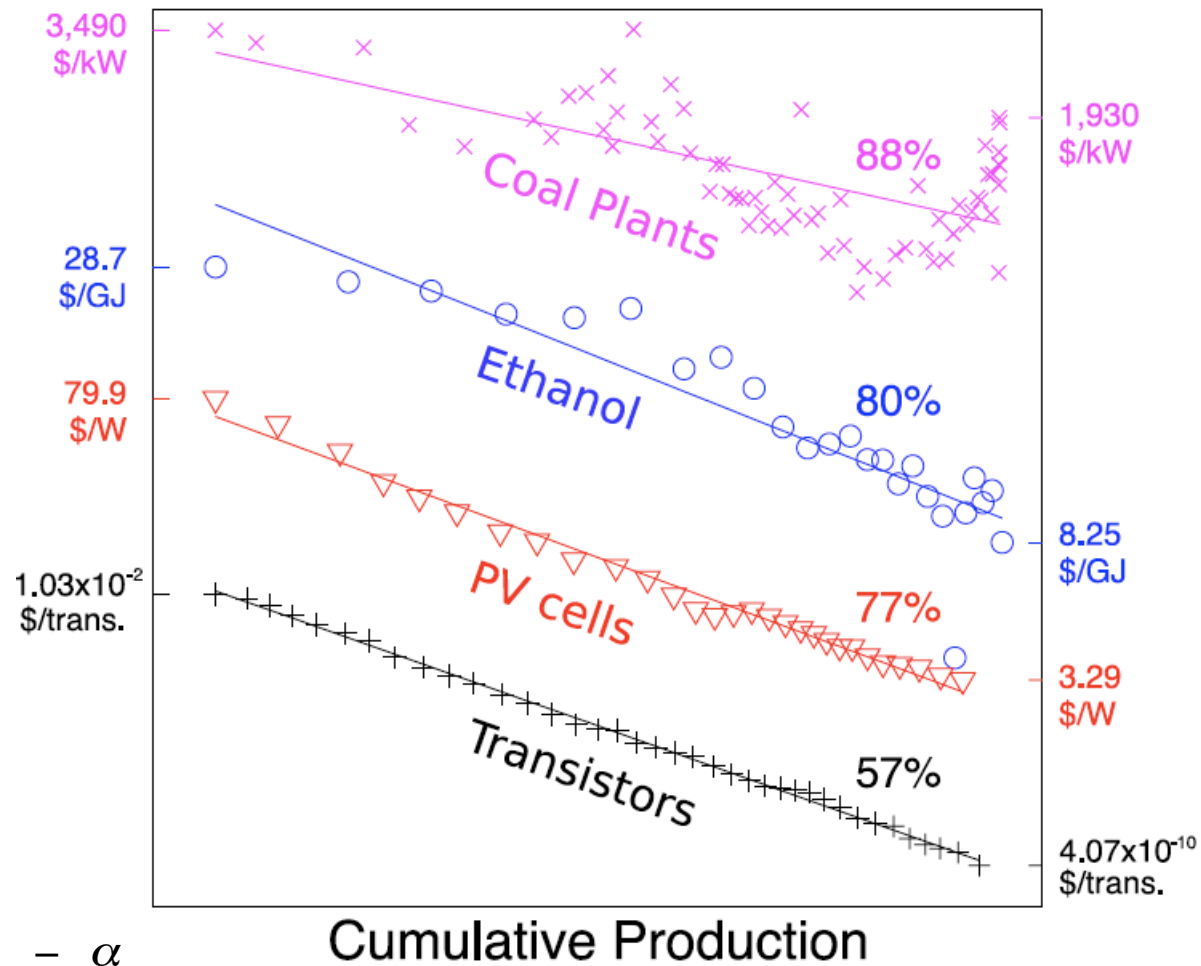
- Testable prediction:
Component decoupling → faster cost reduction
- Design structure matrices (DSM)

d	Progress Ratio 2 [^] (-1/d*)
1	50.0%
2	70.7%
3	79.4%
4	84.1%
5	87.1%
10	93.3%
20	96.6%
40	98.3%

DSM of a
laptop computer:



Performance curves



$$c(x) \sim x^{-\alpha}$$

$$PR = 2^{-\alpha}$$

Series	Years	Range
Coal plants	1902–2006	$6.1 \times 10^5 - 3.1 \times 10^8$ kW
Ethanol	1980–2004	$3.4 \times 10^6 - 2.7 \times 10^8$ m ³
PV cells	1975–2003	$5.4 \times 10^2 - 2.2 \times 10^6$ kW
Transistors	1968–2005	$2.0 \times 10^9 - 1.1 \times 10^{19}$

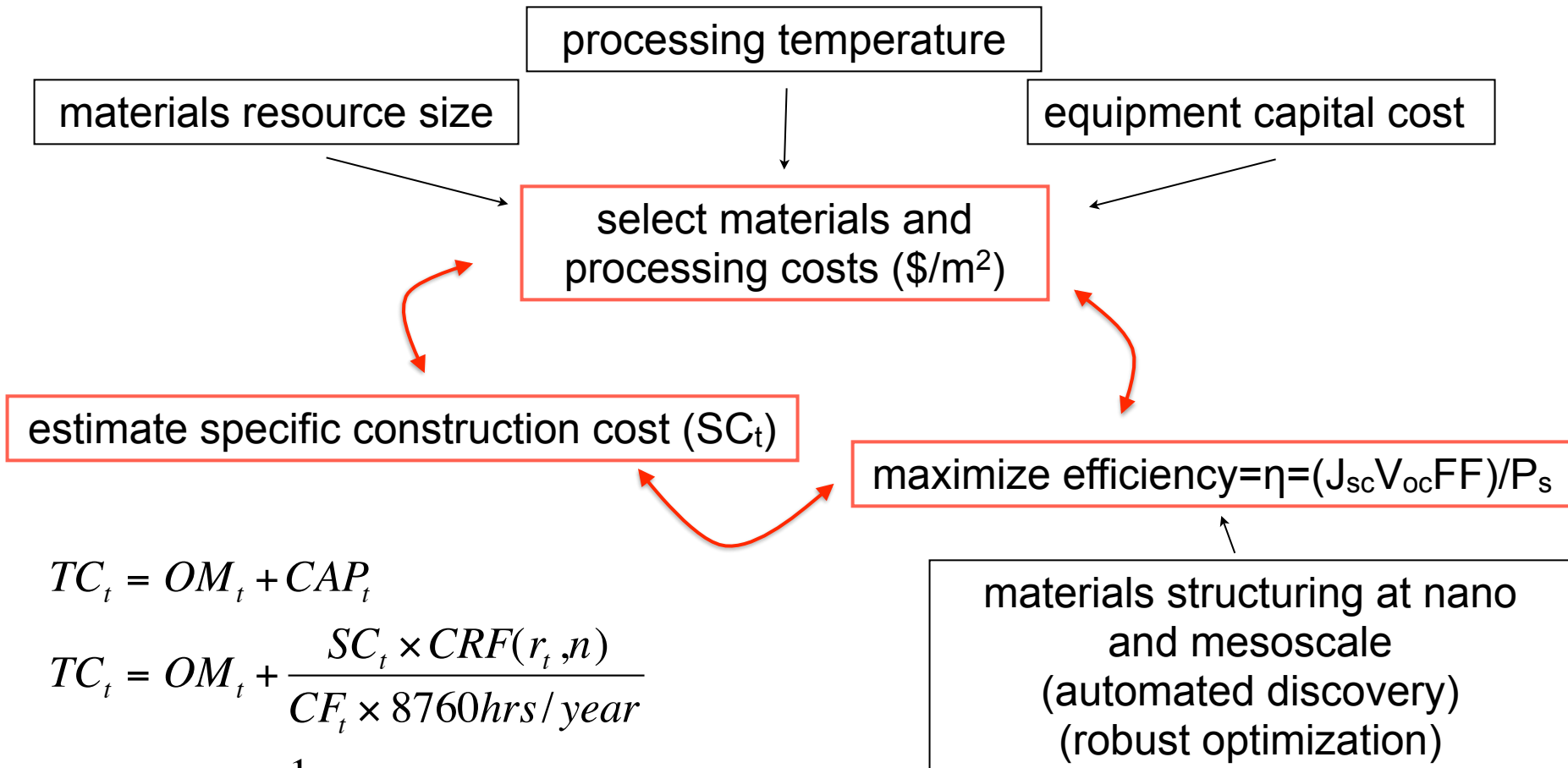
Conclusions

- we can reproduce power function performance curve with a simple model
- relationships between components greatly affect rate of improvement
- bottlenecks can form, determining whether progress is steady

Interpretation of theory and future directions

- what does the theory tell us?
 - an effort-based model gives rise to an empirically observed regularity
 - lessons for technology investment
 - lessons for technology and engineering system design
- future developments applications?
 - design technologies for rapid *future* development
 - materials selection and design
 - model of networks of networks
 - infrastructure
 - supply chains

Materials optimization map: example photovoltaics



$$TC_t = OM_t + CAP_t$$

$$TC_t = OM_t + \frac{SC_t \times CRF(r_t, n)}{CF_t \times 8760 \text{ hrs/year}}$$

$$SC_t (\$/W) = \frac{1}{\eta} \times (\$/m^2) \times (m^2/W)$$

Trancik, Barton, Hone, *Nano Letters*, 2008
 Trancik and Hone, US Patent App. 2008
 Trancik, in preparation

future extensions:

- consider device lifetime: $SC_t \times CRF(r, n)$
- design complexity: design for rapid innovation
- other performance metrics
- other devices

Students and postdocs

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