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A Surrogate Model Approach for Studying Performance and Cycle Time in Complex System Development

Paper 131

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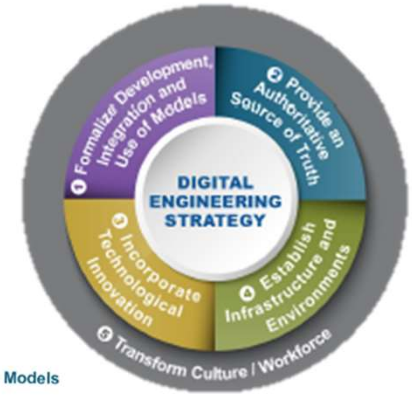
Motivation:

Improve System Performance, Delivery New Capabilities, Faster

- DoD Digital Engineering Strategy [1]
  - Published June 2018
  - Modernize design, development, operation and sustainment
  - Transform acquisition and implementation
  - Improve speed for critical capability delivery to the warfighter
  - Connected data in a digital environment



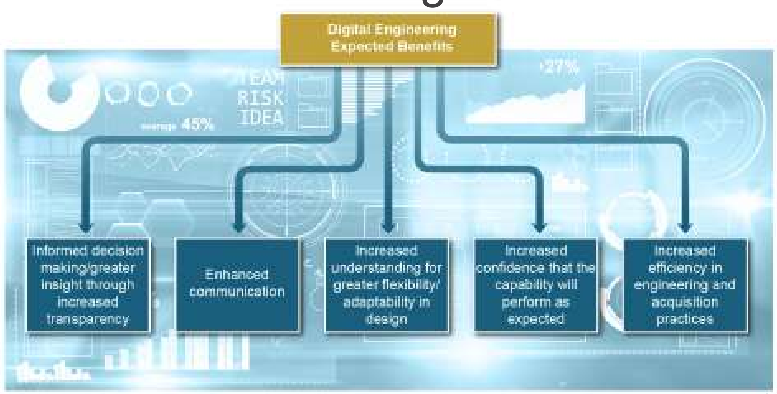


Image credit: DoD Digital Engineering Strategy, June 2018

Problem Description

- Aerospace and defense projects are some of the most complex engineered systems
  - Expensive and long duration design and development
  - Multidisciplinary Design Analysis and Optimization (MDAO) does not capture all emergent behaviors
- Design models do not capture the impact of:
  - Modes of communication in design, development and operation
  - Effects of different communication types
  - Correlation of these to solution performance
  - Other coupling and relationships of design
- Interoperability challenged by desire for retaining intellectual property
- Insufficient knowledge of what data to connect and what decisions to automate

Digital Engineering Impact on System Performance

- Digital Engineering changes organization, processes and interactions in development
- Lack of theory to suggest how this will change solution performance
- We need a way to study complex communications, organization, processes and collaboration in these types of projects to assess the impact on system design performance and cycle time in digital engineering environments

Addressing the Knowledge Gap

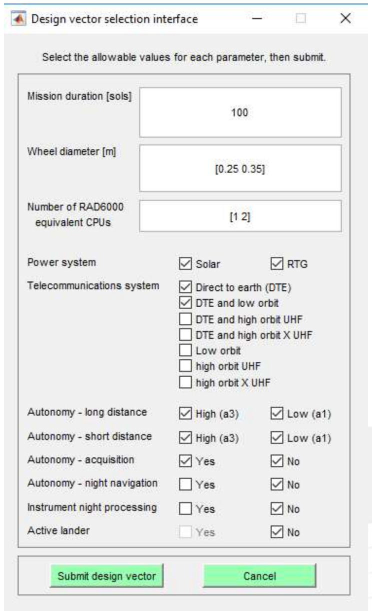
- How can we study how changes in engineering decision-making associated with Digital Engineering impact system performance and cycle time?
  - Without spending the time and money to develop detailed design models and perform human subject testing
  - In a controlled, repeatable experiment that can provide statistically meaningful data for analysis
- Agent-based simulation with surrogate models could be a timely method for studying how changes in engineering decision-making associated with Digital Engineering impact system performance and cycle time
- This approach has been applied in other domains and could be a method for conducting research on the changes that Digital Engineering will have on engineering design decision-making

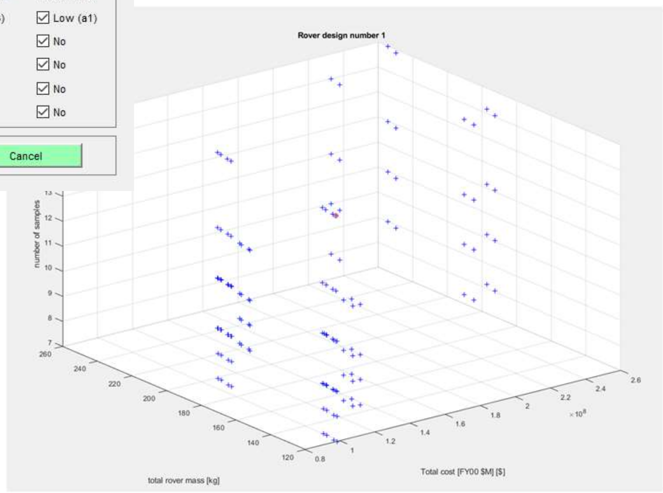
Current Practice: Complex System Design and Analysis

- Multidimensional and Multidisciplinary problem spaces [2]; Example: Mars Rover
  - Trade space development and subjective evaluation
  - Priorities of budget, schedule, performance parameters
  - Quantification of utility/performance parameters:

$$u(x_1,x_2,x_3)= ax_1+bx_2+cx_3$$
$$u(x_1,x_2)=ax_1{}^2+bx_2{}^2$$

- Limitations of these techniques
  - Dependent model variables limit coupled or emergent behavior analysis
  - Does not account for impacts of team or contract organization, task structure, data accessibility, subject matter expert availability [3]
  - Decision making authority dependent
  - Time to create versus decision need date





Using a Mathematical Analog to Study DE Influences on Solution Performance and Cycle Time

- Mathematical models as a surrogate for detailed design models
  - An enabler to study impact of DE on system performance
  - Have been used to analyze adaptive evolution in immune response [4] [8] and organizational performance [5]
- Mathematical models exist to evaluate the approach
  - NK model and variants – Rugged Fitness Landscapes
  - Can be tuned to align to the model space it is intended to represent
    - A system has N variables, each variable can take on A possible values
    - The model assigns a “fitness contribution” to each variable (w_i)
    - K defines the number of coupled variables influencing (w_i)
      - K = 0: contributions are independent of all other variables
      - K = N-1: contributions are entirely dependent on the values of all other variables
    - The total fitness (W) of a system is an average of the fitness contributions of each variable

$$W = \frac{1}{N}\sum_{i=1}^{N} w_i$$

Specific Research Objective

- Define the surrogate model to study complex decision-making in a Digital Engineering environment to determine the impact on solution performance
  - Utilize the NK model as a surrogate for the trade space to be explored, mapping model elements to the real-world elements
  - Define agents and their state variables to represent design engineers
  - Describe a metric for evaluating the feasibility of the surrogate model
  - Compare the suggested evaluation metric utilizing an existing trade space generated from detailed design models [6]
- Assess the results and implications of the approach
- Describe the future work that will be incorporated in the research proposal

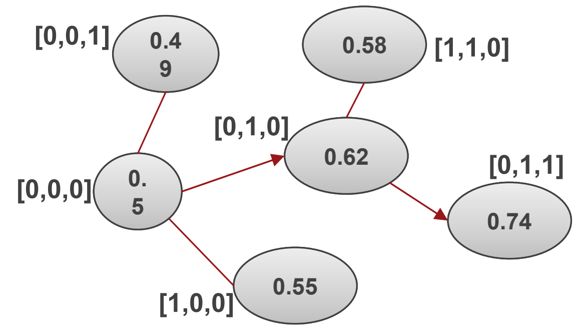
Align the Detailed Design Model to the NK Model

- N represents the Design Variables
  - Design Variables can have different options (values of "A")
  - These contribute different value (w_i) to the system performance (W)
  - In the Mars Rover detailed design model, N = 7

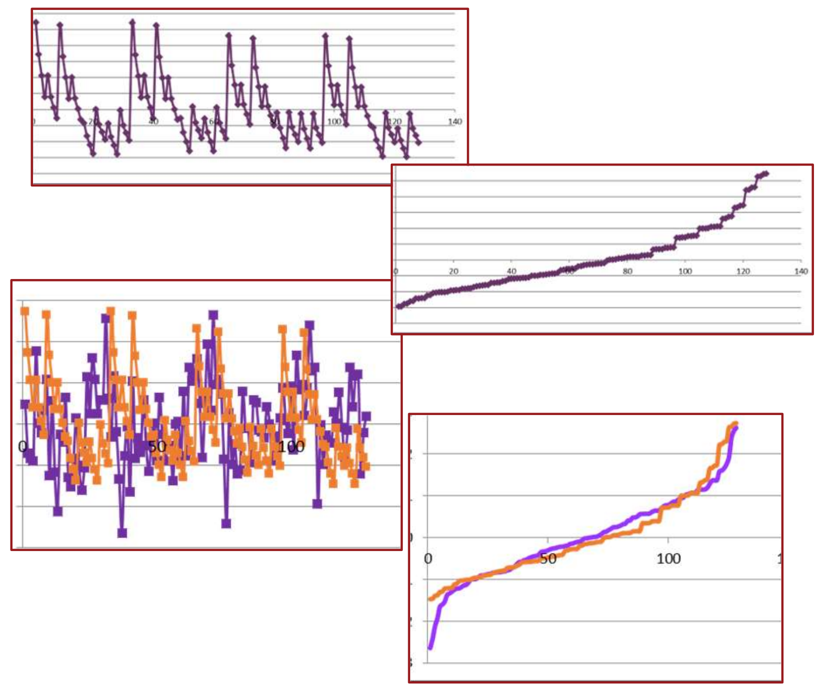
Design Variable	Option 1 (A = 0)	Option 2 (A = 1)
Wheel Diameter (m)	0.25	0.35
# of Central Processing Units (CPUs)	1	2
Power System	Solar	Radioisotope Thermoelectric Generator (RTG)
Telecomm System	Direct to Earth (DTE)	DTE plus Low Orbit Relay
Long Distance Autonomy	High	Low
Short Distance Autonomy	High	Low
Acquisition Autonomy	Yes	No

- K represents interrelatedness
  - Vary K through the simulation to evaluate what value of K best aligns with the Mars Rover detailed design model landscape for walking the landscape

Defining the Agent

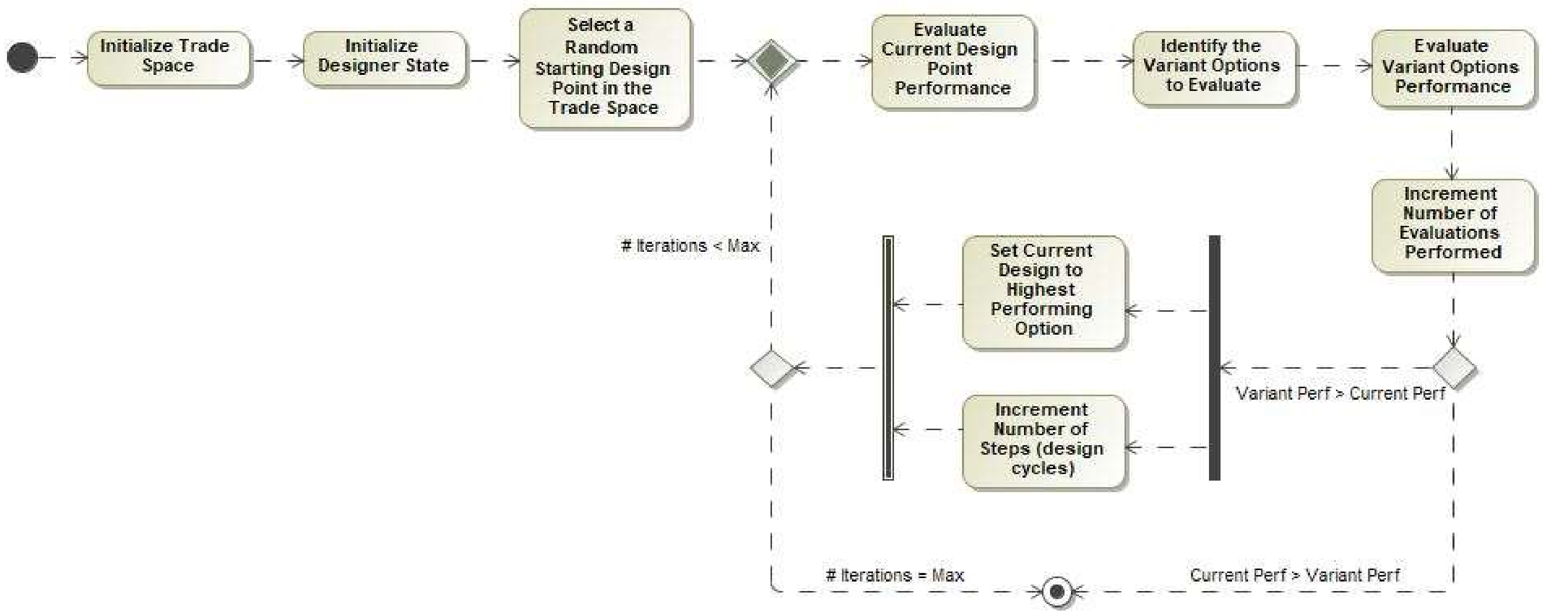


- An agent represents the Design Engineer
  - Walking the landscape to find a higher performing solution
  - Evaluation of other design points represents an analysis cycle
    - Effort spent analyzing the design and the options
  - Iterations of the evaluations represent design cycles
    - Time spent to identify and evaluate other design points and move to a new point
- Define agent behavior as in social science simulations
  - Agent represents a single design engineer
  - Agent makes a "Greedy" choice
    - Always selects the best performance of the comparison (or self if already at the local max)
- An agent's state is defined by two variables:
  - The current design point
  - The iteration (design cycle) of the landscape walk

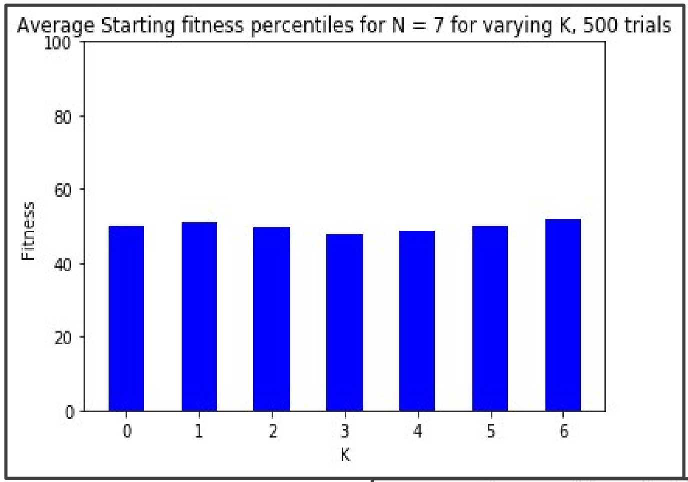


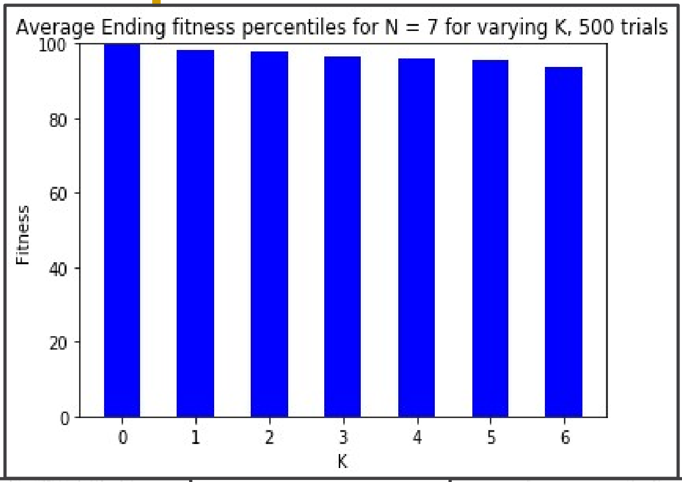
Defining the Simulation

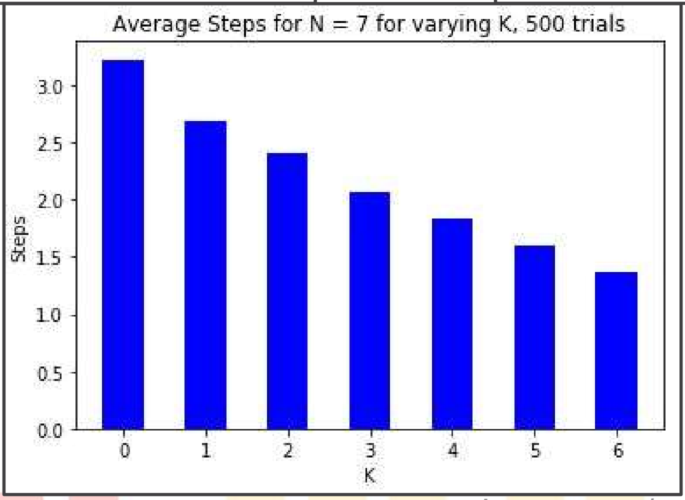
- Start from a random point on the NK landscape
- Fixed number of iterations to improve performance
- Repeat simulation for fixed number of trials at each value of K
- Perform the same simulation on the Mars Rover design landscape

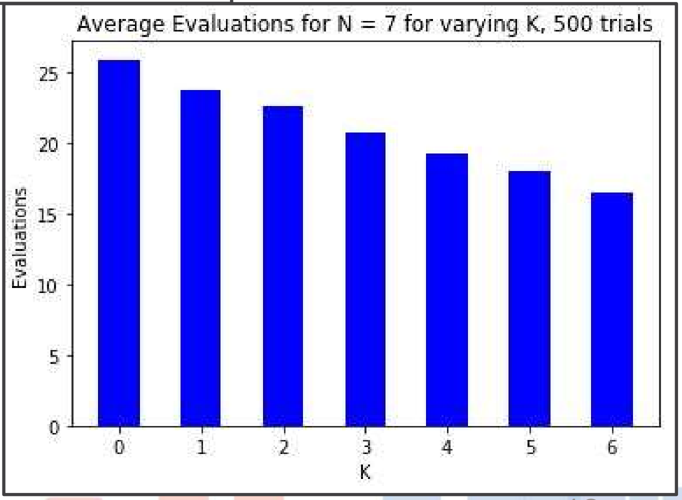


Results – NK Landscape Walk 500 Trials

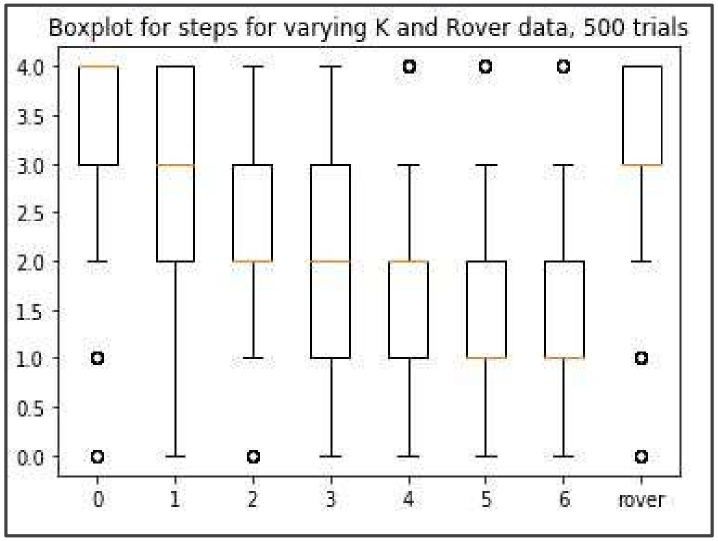


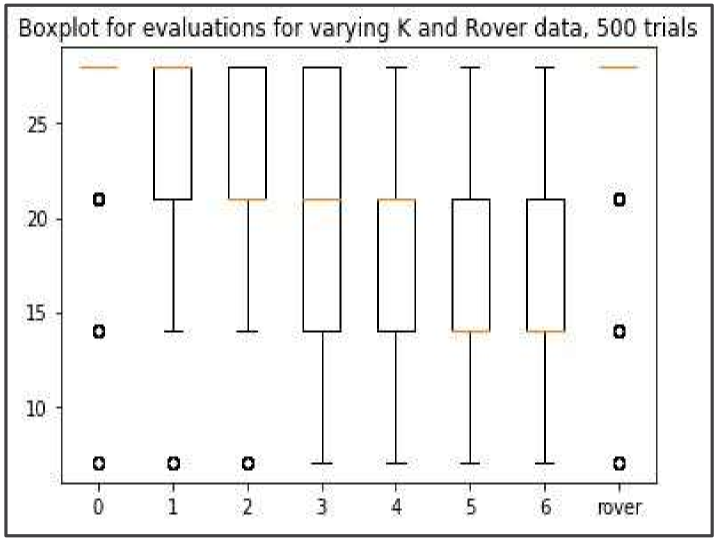






Results – NK vs. Mars Rover Walks





- Average steps for Mars rover walk: 3.148, 95% CI ±0.088
- Average evaluations for Mars rover walk: 25.676, 95% CI ±0.410
- Average steps for K = 0 walk: 3.224, 95% CI ±0.084
- Average evaluations for K = 0 walk: 25.956, 95% CI ±0.376

Discussion of Results

- Steps and Evaluations very similar between Mars Rover walk and K = 0 landscape walk
  - Suggests landscape could be considered uncorrelated
  - Could be indicative of the detailed design model development approach
  - Indicative of model and practice biases: go work in silos, bring it together and find the optimal solution
- K = 0 represents a smooth landscape
  - Only one global maximum
  - Walks were able to reach global maximum in the trials, but needed maximum cycles to do so
- Other K values still reached high performance in their walks
  - Within 6% of the landscape optimum
  - With a fraction of the steps and evaluations compared to K = 0 or Mars Rover walks

Conclusions

- Agent-based simulation of walking an NK landscape with K = 0 can represent walking a detailed design model landscape
  - Demonstrated tuneability between an NK model and Mars Rover detailed design model landscape walks
  - Valid for both evaluation metrics: number of cycles and number of evaluations
- NK Landscape could be utilized to study design engineer behaviors in development
  - Evaluate changes in agents that reduce number of cycles (time) and evaluations (effort)
- Translate agent behaviors to changes in engineering process and practice
  - To realize reductions in time and effort in development while maintaining or improving system performance

Future Work

- Expand the agent definition to better represent engineers as well as other members of design teams in a multi-agent simulation
  - For individual agents look at:
    - Impact of increased data on decisions
    - Influence of background and training on decision making and risk tolerance/avoidance
  - For groups of agents look at:
    - Impact of individuals on the collective decision
    - Impacts of data availability and periodicity on decisions and iterations
- Expand the surrogate model for the approach
  - Explore variable heterogeneity impact on the trade space
  - Explore landscape dynamics on the evaluation metrics
  - Explore how Digital Engineering changes the landscape and impacts behavior

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Backup

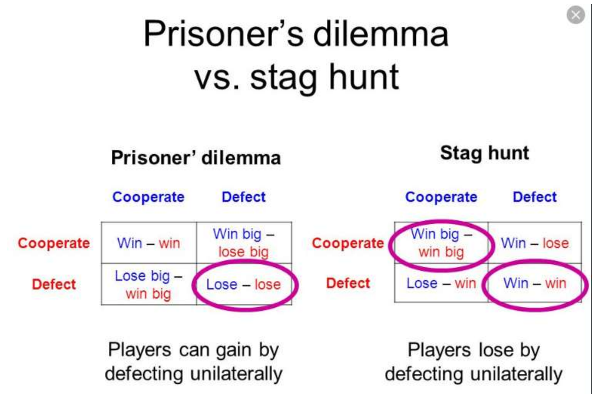
Dedication

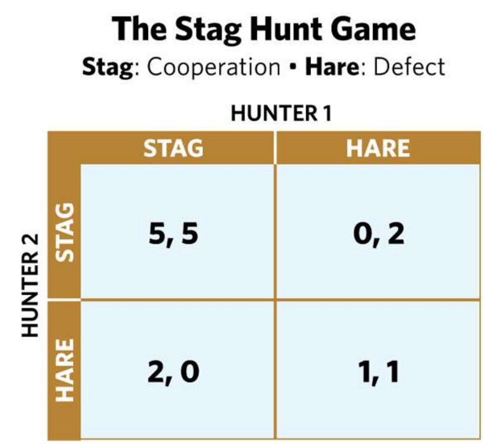
- Charles Andrew Sharo
  August 18, 1948 – April 18, 2019

- Andrew Scott Chiesi
  October 24, 2017 -

How do we study decision-making and choice in social systems

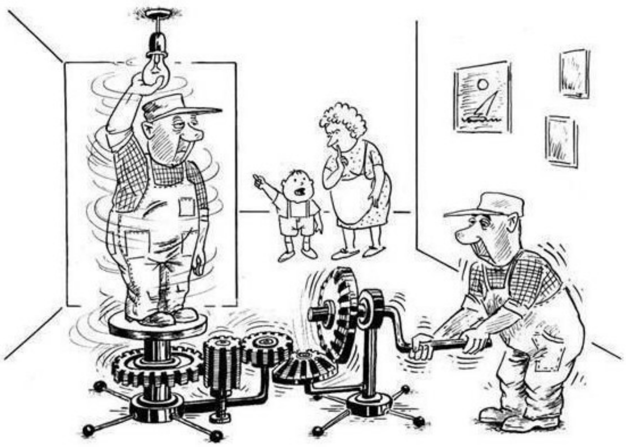
- Look at studies of social systems and the social sciences
  - References: 14, 15, 16, 17, 18, 19, 20
- Decision-making for rational choice and expected profit
  - Co-evolution
  - Development of social structure
  - How cooperation evolved and is practiced
  - How competition contributes to these decisions
  - What is collaboration and what are the dynamics of collaboration
- Considerable on-going research in these areas for engineering
  - In SSE as well as other SERC universities and beyond





What is the influence of background on decision-making?

- How experience and training impacts decisions
- More data may not mean a better answer
  - Potential for data overload leading to lower performance
- More background and history may give a better solution
  - But may be hampered by data that is not understood
  - Data that may not be relevant may cloud decisions and solutions
  - How calibrated are the designers to knowing what they do and don't know
- How do we address these topics and how they change with digital engineering
  - References: 21, 22



How do data rights and standards impact Digital Engineering

- Digital engineering and data connections rely on open standards and tool interoperability
  - References: 23, 24, 25, 26
- Company Intellectual Property (IP) impacts how well this can be applied
  - Engineering company's IP
  - Contract data rights for customers
  - Tool vendor IP – limits connectivity
- What are the limits of data usage that change behaviors
  - Data spill concerns and that impact on design in a digital engineering environment

References (1)

1. O. of the D. A. S. of D. Systems Engineering, “Department of Defense Digital Engineering Strategy,” Jun. 2018.
2. W. J. Larson and J. R. Wertz, Space mission analysis and design, 2nd ed. Torrance, Calif. Dordrecht ; Boston: Microcosm ; Kluwer, 1992.
3. P. D. Collopy and P. M. Hollingsworth, “Value-Driven Design,” J. Aircr., vol. 48, no. 3, pp. 749–759, 2011, doi: 10.2514/1.C000311.
4. S. A. Kauffman and E. D. Weinberger, “The NK model of rugged fitness landscapes and its application to maturation of the immune response,” J. Theor. Biol., vol. 141, no. 2, pp. 211–245, 1989.
5. D. A. Levinthal, “Adaptation on Rugged Landscapes,” Manag. Sci., vol. 43, no. 7, pp. 934–950, 1997.
6. S. Chiesi et al., “Rapid Modeling of Mars Robotic Explorers,” 2003.
7. S. S. Chiesi and P. T. Grogan, “Modeling Spacecraft Design Activities as Rugged Fitness Landscapes,” in AIAA Scitech 2019 Forum, American Institute of Aeronautics and Astronautics.

References (2)

8. S. A. Kauffman and S. Johnsen, “Coevolution to the Edge of Chaos: Coupled Fitness Landscapes, Poised States, and Coevolutionary Avalanches,” J. Theor. Biol., vol. 149, pp. 467–505, 1991.

9. J. S. Buzas and J. Dinitz, “An analysis of NK and generalized NK landscapes,” ArXiv13023541 Cs, Feb. 2013.

10. N. Manukyan, M. J. Eppstein, and J. S. Buzas, “Tunably Rugged Landscapes With Known Maximum and Minimum,” IEEE Trans. Evol. Comput., vol. 20, no. 2, pp. 263–274, Apr. 2016, doi: 10.1109/TEVC.2015.2454857.

11. B. Skellett, B. Cairns, N. Geard, B. Tonkes, and J. Wiles, “Maximally Rugged NK Landscapes Contain the Highest Peaks,” in Proceedings of the 7th Annual Conference on Genetic and Evolutionary Computation, New York, NY, USA, 2005, pp. 579–584, doi: 10.1145/1068009.1068107.

12. R. Li et al., “Mixed-Integer NK Landscapes,” in Parallel Problem Solving from Nature - PPSN IX, Berlin, Heidelberg, 2006, pp. 42–51, doi: 10.1007/11844297_5.

13. R. Arthur and P. Sibani, “Decision making on fitness landscapes,” Phys. Stat. Mech. Its Appl., vol. 471, pp. 696–704, Apr. 2017, doi: 10.1016/j.physa.2016.12.068.

References (3)

14. C. A. Lave and J. G. March, An introduction to models in the social sciences. Lanham, Md.: University Press of America, 1993.

15. R. Axelrod and W. D. Hamilton, “The evolution of cooperation,” Science, vol. 211, no. 4489, pp. 1390–1396, Mar. 1981, doi: 10.1126/science.7466396.

16. “The Stag Hunt and the Evolution of Social Structure by Brian Skyrms.” [Online]. Available: https://www.cambridge.org/core/books/stag-hunt-and-the-evolution-of-social-structure/AB3181FA469D6EA411E05D6CBF644507. [Accessed: 07-Jul-2019].

17. M. Dorigo, V. Maniezzo, and A. Colorni, “Ant system: optimization by a colony of cooperating agents,” IEEE Trans. Syst. Man Cybern. Part B Cybern., vol. 26, no. 1, pp. 29–41, Feb. 1996, doi: 10.1109/3477.484436.

18. M. Klein, H. Sayama, P. Faratin, and Y. Bar-Yam, “The Dynamics of Collaborative Design: Insights From Complex Systems and Negotiation Research,” in Complex Engineered Systems: Science Meets Technology, D. Braha, A. A. Minai, and Y. Bar-Yam, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 158–174.

References (4)

19. J. Panchal et al., "Understanding Design Decisions under Competition using Games with Information Acquisition and a Behavioral Experiment," ASME J. Mech. Des., vol. 139, no. 9, p. 091402, 2017, doi: 10.1115/1.4037253.

20. C. McComb, J. Cagan, and K. Kotovsky, "Lifting the Veil: Drawing Insights about Design Teams from a Cognitively-inspired Computational Model," Des. Stud., vol. 40, pp. 119–142, 2015.

21. M. Gladwell, Blink: The Power of Thinking Without Thinking, 1 edition. New York: Back Bay Books, 2007.

22. A. Nolan, A. C. Pickard, J. Nolan, R. Beasley, and T. C. Pruitt, "How Many Systems Engineers Does It Take To Change a Light Bulb?," INCOSE Int. Symp., vol. 28, no. 1, pp. 777–790, 2018, doi: 10.1002/j.2334-5837.2018.00515.x.

References (5)

23. “ANSI-American National Standards Institute.” [Online]. Available: https://www.ansi.org/. [Accessed: 07-Jul-2019].

24. “ISO - International Organization for Standardization,” ISO. [Online]. Available: http://www.iso.org/cms/render/live/en/sites/isoorg/home.html. [Accessed: 07-Jul-2019].

25. https://themeforest.net/user/dan_fisher, “OMG | Object Management Group.” [Online]. Available: https://www.omg.org/. [Accessed: 07-Jul-2019].

26. “OASIS | Advancing open standards for the information society.” [Online]. Available: https://www.oasis-open.org/. [Accessed: 29-Feb-2020].