



NIST Cloud Computing Forum and Workshop VIII

Predicting Global Failure Regimes in Complex Information Systems

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Project Research Goals

- Develop *design-time methods* that system engineers can use to detect existence and causes of costly failure regimes prior to deployment
- Develop *run-time methods* that system managers can use to detect onset of costly failure regimes in deployed systems, prior to collapse

Topics

- Some past results on design-time methods
- Example → Applying one design-time method to seek failure scenarios in a cloud system
- Ongoing work on run-time methods
- Where to find more information

Summary of *Koala* Parameters to Search Over

Test Case – Can GA find VM Leakage *due to message loss and lack of orphan control?*

Failure scenario found manually by accident and described in C. Dabrowski and K. Mills, "VM Leakage and Orphan Control in Open-Source Clouds", *Proceedings of IEEE CloudCom 2011*, Nov. 29-Dec. 1, Athens, Greece, pp. 554-559.

Model Element	Parameter Category				
	Behavior	Structure	Asymmetry	Failure	Total
User	28	2	4	0	34
Cloud Controller	21	4	5	0	30
Cluster Controllers	11	5	3	0	19
Nodes	6	0	0	14	20
Intra-Net/Inter-Net	4	11	2	9	26
Totals	70	22	14	23	129

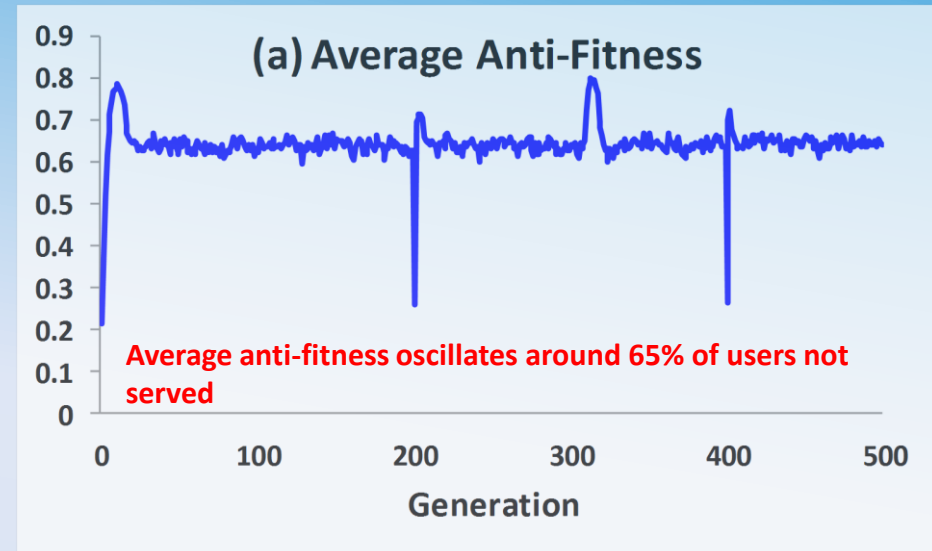
Average # values per parameter is about 6, so search space is $\approx 6^{129}$
i.e., $\approx 10^{100}$ scenarios are possible

- adapted 125-parameter *Koala* IaaS simulator to be GA controllable
- added 4 *Koala* parameters to turn on/off logic to control (a) **creation orphans**, (b) **termination orphans**, (c) **relocation orphans** and (d) **administrator actions**

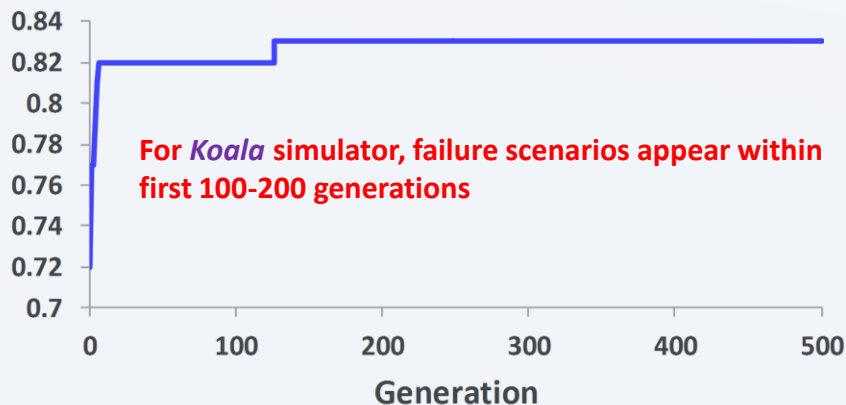
Koala GA Search over 500 Generations

GENETIC ALGORITHM CONTROL PARAMETERS

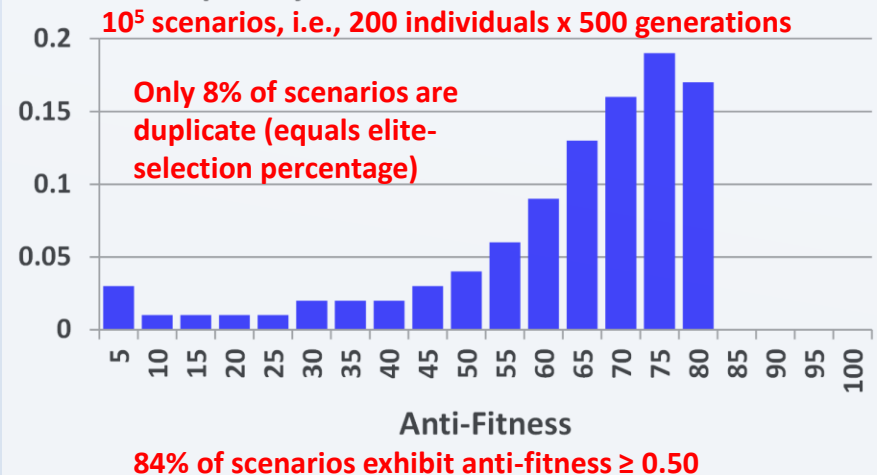
Generations	500
Population Size	200 Individuals
Elite Per Generation	16 Individuals
Reboot After	200 Generations
Selection Method	Stochastic Uniform Sampling
# Crossover Points	3
Mutation Rate	$0.001 \leq \text{Adaptive} \leq 0.01$



(c) Maximum Anti-Fitness Discovered



(b) Frequency Distribution of Anti-Fitness



Differential Probability Analysis

Let \mathbf{C} be the set of collected tuples, each containing a vector of parameter value (PV) pairs and a corresponding anti-fitness value, f

Segment \mathbf{C} into high-pass (H) and low-pass (L) subsets, where:

$$H = \{x \in \mathbf{C} \mid f_x > 0.70\} \text{ and } L = \{x \in \mathbf{C} \mid f_x < 0.15\}$$

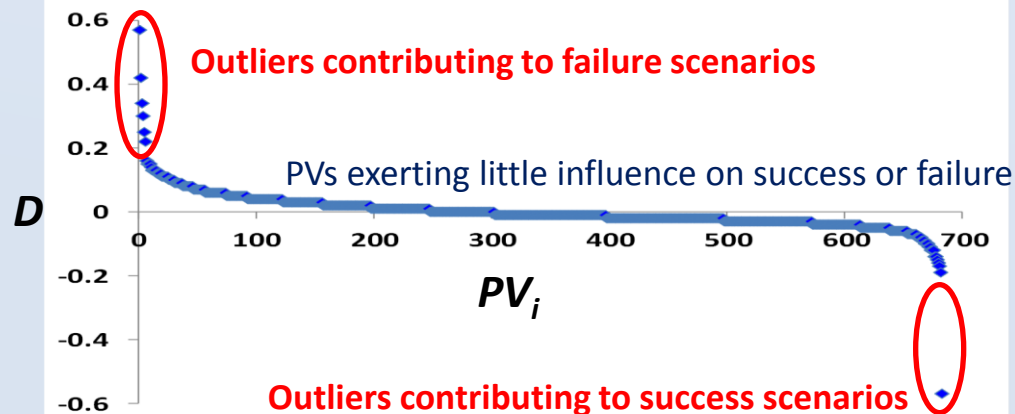
For each PV estimate the probability of occurrence in H and L :

$$P(PV_i \mid f > 0.70) = |PV_i \in H| / |H| \text{ and } P(PV_i \mid f < 0.15) = |PV_i \in L| / |L|$$

Then compute the estimated differential probability:

$$D = P(PV_i \mid f > 0.70) - P(PV_i \mid f < 0.15)$$

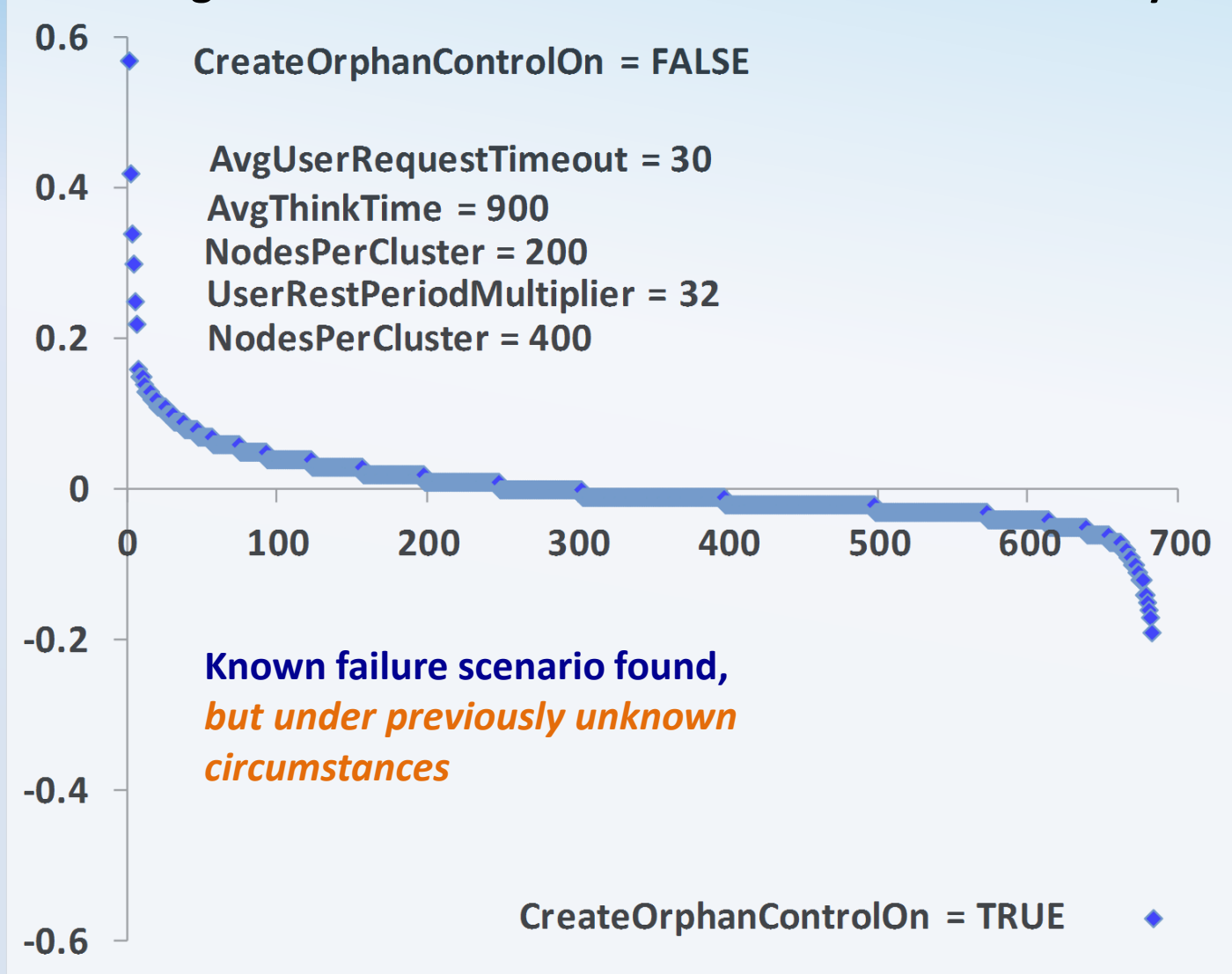
Plot D for each PV pair



PV pairs sorted by decreasing D

Analysis of Results from *Koala* GA Search 1 – 500 Generations

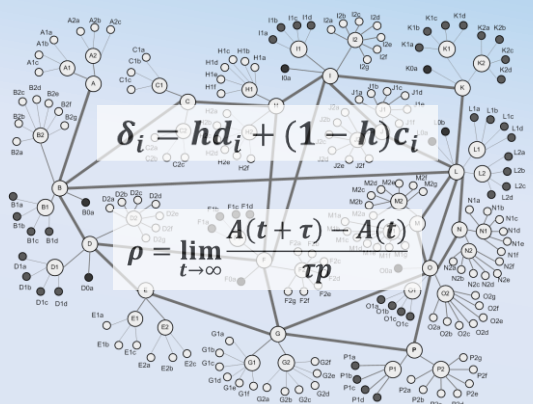
Seeking Known Failure Scenario – search duration 30 days



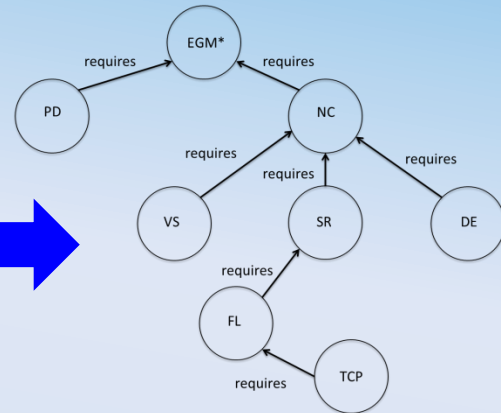
D (y-axis) for 684 PV pairs (x-axis) for first GA search—outlier PV pairs labeled.

Ongoing Work: Do published findings on the spread of congestion hold for realistic network models?

Abstract Network Model



Add 7 Realism Factors



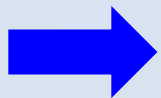
34 Valid Combinations

Config	TCP	FL	SR	DE	VS	NC	PD
C0	0	0	0	0	0	0	0
C1	0	0	0	0	0	0	1
C2	0	0	0	0	0	1	0
C3	0	0	0	0	0	1	1
C4	0	0	0	1	1	0	0
C5	0	0	0	1	1	1	0
C6	0	0	0	1	1	1	1
C7	0	0	0	0	1	1	1
C10	0	0	0	1	0	1	0
C11	0	0	0	1	0	1	1
C14	0	0	0	1	1	1	0
C15	0	0	0	1	1	1	1
C18	0	0	1	0	0	1	0
C19	0	0	1	0	0	1	1
C22	0	0	1	0	1	1	0
C23	0	0	1	0	1	1	1
C25	0	0	1	1	0	1	0
C27	0	0	1	1	0	1	1
C30	0	0	1	1	1	1	0
C31	0	0	1	1	1	1	1
C50	0	1	1	0	0	1	0
C51	0	1	1	0	0	1	1
C54	0	1	1	0	1	1	0
C55	0	1	1	0	1	1	1
C58	0	1	1	1	0	1	0
C59	0	1	1	1	0	1	1
C62	0	1	1	1	1	1	0
C63	0	1	1	1	1	1	1
C114	1	1	1	0	0	1	0
C115	1	1	1	0	0	1	1
C118	1	1	1	0	1	1	0
C119	1	1	1	0	1	1	1
C122	1	1	1	1	0	1	0
C123	1	1	1	1	0	1	1
C126	1	1	1	1	1	1	0
C127	1	1	1	1	1	1	1

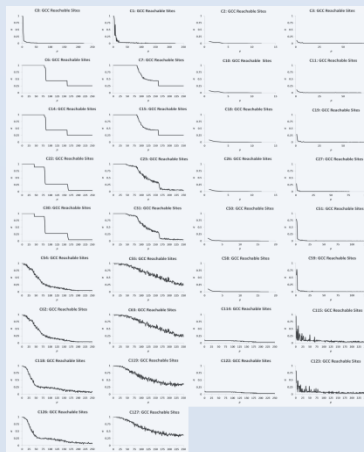
Most Abstract

Most Realistic

Y: Network Disruption



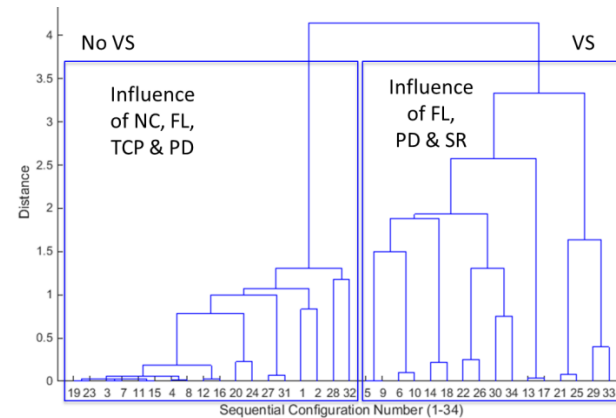
vs.



X: Increasing Load



Clustering Analysis



To Learn More

Project Team (the core four)

- **Kevin Mills**, computer scientist – kmills@nist.gov
- **Chris Dabrowski**, computer scientist – cdabrowski@nist.gov
- **Jim Filliben**, statistician – jfilliben@nist.gov
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Project Page

- http://www.nist.gov/itl/antd/emergent_behavior.cfm