A theoretical analysis of the Keep Network random beacon using agent based modeling

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***Abstract*—ABM is an effective tool for analysis of complex systems with long term emergent behavior. In this study we apply ABM to analyse the long term behavior of Keep's random beacon. We look for the emergence of steady state behavior, at which point we evaluate the sensitivity of specific group and signature characteristics to various parameters. The results of this study illustrates the effectiveness of ABM as an aid to the design of novel distributed systems.**

***Index Terms*—Token Engineering, Agent Based Model, Distributed Systems**

I. Introduction

II. Agent Based Modeling (ABM)

ABM has traditionally been a tool to simulate complex dynamic systems such as the spread of pathogens [1], social psychology [6], and financial markets [3]. It is well suited to systems that resist simple analytical solutions due to the interaction of complex individual agents with varying attributes. As a bottom up approach, ABM has been gaining in popularity over tradtional methods such as Discrete Event Simulation, and can provide more convincing theoretical analysis than approaches such as general equilibrium analysis [7].

The nascent field of token engineering is currently establishing its own set of tools and processes. As such, ABM lends itself well to analyzing these systems to support the design process and evaluate system state after launch. In many situations, agent based modeling maybe the only method to evaluate a cryptoeconomic system as many are opaque and do not generate significant visible data. Similar to the field of astronomy, an agent based model could be used to replicate observable system behavior and then infer causes.

III. Analysis of Token based systems

Klages-Mundt et al. [5] use agent based models to simulate a decentralized stable coin system and shows how deleveraging sprial attacks could occur. Their model is also able to explain real complex stable coin movements. Further, the study is able to show theoretically that regions of stability and instability exist for such decentralized stable coin systems.

While not agent based, Chitra et al. [2] effectively use discrete event simuation to provide quantitative estimates of how economic incentives affect security. They use a custom simulation environment to simulate Kadena's Chainweb, and provide insights into how simulation can guide and optimize protocol development in a variety of contexts.

Discuss levels of complexity, with citations. Why greater complexity may not get you much more insight. (ask Shruti?)

Identify applicable funding agency here. If none, delete this.

IV. Overview of the Keep Random Beacon

The Keep Network random beacon uses a threshold relay simuliar to the one proposed by DFINITY and based on the BLS signature scheme [] (NEED CITATION)

A. Role of the model in the design process

The initial architecture of the Keep beacon was designed by (need input from Antonio) what purpose did the simulation serve?

V. Key research questions

A. When could steady state behavior emerge?

Emergence of steady state behavior occurs as a confluence of several factors and is difficult to predict at the design stage. Specifically, process that take several blocks to complete such as DKG that often occur asynchronously can create large swings in values such as number of active groups or percentage of compromised groups.

B. How could node failures and group sizes affect system behavior?

Nodes may go offline or fail entireley. Since their participation in groups is critical to the success of the threshold relay, it is important to understand the impact of various levels of failure on group characteristics. In particular, failures can result in disproportionate ownership of groups which may cause a byzantine fault to occur.

C. How could different stake distributions affect system behavior?

Stake distributions can also skew ownership of groups and can lead to a byzantine fault. A more centralized distribution could once again lead to a greater ownership of groups by a few entities thus creating conditions for the group to be compromised.

VI. Model Creation

A. Key Terms

- Node: A computational entity with memory and computational power sufficient to to run a keep client
- Node Owner: may own 1 or more nodes and can allocate different levels of stake to each node owned
- Stake: A bond that make a node eligible to participate in a group
- Group: A collection of nodes who have successfully completed DKG together
- DKG (Distributed Key Generation): The processes of generating keys for each node enabling them to sign using Keep's version of Threshold ECDSA [4].
- Signature: The process of securely generating a random number using Threshold ECDSA [4]
- Ownership Percent: The level of ownership a specific entity has in a group or signature
- Lynchpin: A node who's ownership exceeds the maximum malicious threshold

B. Model Structure

We construct the model using the MESA ABM framework (cite). MESA consists of an agent class with attributes and methods. We generate 3 types of agents Nodes, Groups, and Signatures. TABLE shows the specific differences in each of these.

ADD table for Agent types

Decide whether all parameters should be listed?

The simulation model consists of the model class which instantiates the various agents and steps through the simulation. At each step the state of the model and each agent is updated. The scheduler manages the sequence of state changes. For this model we use a simulataneous activation scheduler, which first stages updates for each agent and then advances them simultaneously. (NEED TO CHECK SCHEDULER SEQUENCE AGAIN)

Usually steps measure a change in time. Therefore for our simulation we assume 1 step = 1 block.

C. Runs

We perform two sets of experiments to answer our research questions.

- Single run: Our single run of 1000 steps provide a first look at the performance of the sim, quickly. We also use this first experiment to evaluate when steady state behavior could occur. We also perform some initial evaluations of the impact of different stake distributions.
- Multiple runs: The second experiment consists of multiple runs with varying parameters. For each change in parameter we perform 6 runs. By varying parameters in these runs we attempt to identify sensitivity. We measure this sensitivity after the start of steady state behavior which we identify in the single run.

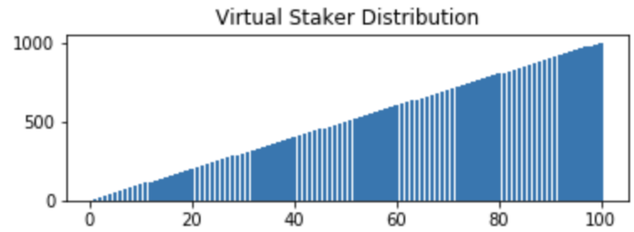

Fig. 1. Linear Stage Distribution

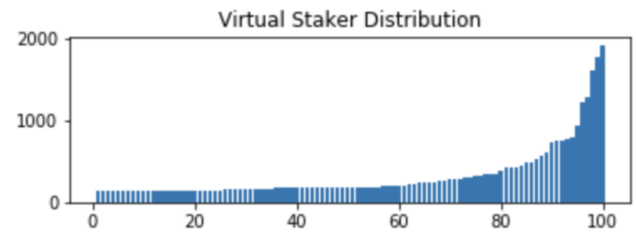

Fig. 2. Top 30 Percent Ethereum Distribution

D. Assumptions

Stochastic Assumptions

To simplify the model we make stochastic assumptions for exogenous processes.

- Node Connection Delay: We apply a random uniform distribution to a user specified range (NEED JUSTIFICATION OR A JUSTIFIED SAMPLING)
- Node Connection Failure: This is one of the parameters we intend to adjust to test for sensitivity. Therefore we randomly pick a percentage of nodes to fail using a uniform distribution.
- Node Death: We uniform randomly pick nodes to die at a user specified rate.
- Signature Delay: A delay between when a signature is triggered and when it is executed. We use a poisson distribution. (NEED JUSTIFICATION or REFERENCE)
- Node Owner Assignment: We use a normal distribution to assign owners to nodes. (NEED JUSTIFICATION)

Stake distribution

Since one of our research questions involves understanding the effects of centralization on system behavior, we use three different token distribution models with varying degrees of decentraliation to evaluate this impact.

- Linear Distribution: We assume a simple linear distribution as our most decentralized case. We take 50000 stakes and allocate them linearly to 100 nodes as shown in Figure 1
- Ethereum Distribution: In the spectrum of decentralization, we assume ETH to be moderateley decentralized. We therefore take the distribution of the top 30 percent account holders and apply it with some normalization in Figure 2. (NEED TO JUSTIFY TOP 30 PERCENT)
- Assumed Stake Distribution: Should we disclose?

Assumptions Model Assumptions

VII. Verification and Validation

Benchmark using analytical methods - from Promethea

VIII. Results

A. Emergence of steady state behavior

Using the single run experiment, we discover that system consistently appears to stabalizes to steady state usually around 400 blocks, and usually due to normalization of bootstrapping states. However, final steady state values for the percentage of total groups that are compromised appears to vary significantly and is dependent on the degree of concentration in the stake distribution.

B. Convergence pressures

The model primarily converges to steady state due to factors such as signature request frequency, node availability, and group creation/expiration. We discuss a few steady state values of interest.

Active group count Groups are generated with every request, and intially during the bootstrap phase a set number of groups are generated with available nodes. In the current simulation, requests are generated as coin tosses (binomial) at each step. The steady state number of active groups is a function of number of new requests and rate of group expiry. In the current setup, we see the number of active groups converging to 15 after 400 blocks.

Percent Compromised Groups For concentrated distributions such as Ethereum, the steady state level of compromised groups appears to vary between 0-100 percent (SHOW), with a tendancy to be either close to 0 or close to 100. For distributions with greater spread, such as our hypothetical linear distribution, we see steady steat levels within the 50-80 percent band for the given set of parameters (NOTE PARAMETER SETTINGS) 3. We expect a similar band but at different parameter levels for different parameter settings. (CHECK THIS AGAIN)

Percent Lynchpinned Signatures Why does this not fluctuate as much?

C. Effects of Node failures, Group Size and Stake Distributions

To evaluate the possible effects of node failure and stake distributions on group and signature characteristics, we use the multi-run study. We then observe trends in the specific parameters discussed below. We also run each multi run study for each of the three distribitions to study the correlation between the observed trends and the type of stake distribution. Additionally, byzantine taking the median measures of each variable, we hope to address the fluctuations due to distributions with increased centralization.

Group Size in all distributions group size appears to reduce the percentage of lynchpinned signatures and compromised groups. Intuitively this makes since since as we increase the size of a group, we include more group owners who may not be malicious. comment on degree of change?

Node Failure percent appears to significantly impact the lynchpinned signature percentage but have little to no effect on compromised groups. Why?

Distribution centralization appears to minimally affect these trends but, it is very likeley that the use of the median for each run is the cause of this. We would expect that highly centralized distributions would cause fluctuations in these values similar to their effect on the final steady state level. This is primarily due to the ownership of a larger number of nodes by a few operators in highly centralized distributions.

TABLE I
Linear Distribution - Lynchpinned Signatures

Failure Percent	Group Size *50*	*100*	*150*
5	0.006065	0.000000	0.000000
10	0.071656	0.009276	0.003985
20	0.399020	0.262837	0.177465

TABLE II
Linear Distribution - Compromised Groups

Failure Percent	Group Size *50*	*100*	*150*
5	0.590035	0.435403	0.407054
10	0.428957	0.710509	0.536904
20	0.557832	0.591663	0.555565

TABLE III
Linear Distribution - Failed Signatures

Failure Percent	Group Size *50*	*100*	*150*
5	0.0	0.0	0.0
10	0.0	0.0	0.0
20	0.0	0.0	0.0

TABLE IV
Ethereum distribution - Lynchpinned Signatures

Failure Percent	Group Size *50*	*100*	*150*
5	0.011012	0.000000	0.000000
10	0.073725	0.025947	0.006042
20	0.407753	0.325947	0.203095

TABLE V
Ethereum distribution - Compromised Groups

Failure Percent	Group Size *50*	*100*	*150*
5	0.592699	0.383390	0.394198
10	0.566964	0.616098	0.683071
20	0.549456	0.526661	0.454106

TABLE VI
ETHEREUM DISTRIBUTION - FAILED SIGNATURES

Failure Percent	**Group Size**		
	50	***100***	***150***
5	0.0	0.0	0.0
10	0.0	0.0	0.0
20	0.0	0.0	0.0

IX. CONCLUSION AND FUTURE WORK

This theoretical analysis highlighted possible behaviors of the Keep network beacon. we validated the model using some simple analytical methods. However, once the beacon launches we can use real data from the network to validate and adjust the model. At this point we can then use the model to better investigate future behaviours and causes of behavior.

REFERENCES

[1] Amy L. Bauer, Catherine A.A. Beauchemin, and Alan S. Perelson. Agent-based modeling of host-pathogen systems: The successes and challenges. *Information Sciences*, 179(10):1379–1389, 2009.

[2] Tarun Chitra, Monica Quaintance, Stuart Haber, and Will Martino. Agent-based simulations of blockchain protocols illustrated via kadena's chainweb. *arXiv preprint arXiv:1904.12924*, 2019.

[3] Ling Feng, Baowen Li, Boris Podobnik, Tobias Preis, and H. Eugene Stanley. Linking agent-based models and stochastic models of financial markets. *Proceedings of the National Academy of Sciences of the United States of America*, 109(22):8388–8393, 2012.

[4] Rosario Gennaro and Steven Goldfeder. Fast multiparty threshold ECDSA with fast trustless setup. *Proceedings of the ACM Conference on Computer and Communications Security*, pages 1179–1194, 2018.

[5] Ariah Klages-Mundt and Andreea Minca. (in) stability for the blockchain: Deleveraging spirals and stablecoin attacks. *arXiv preprint arXiv:1906.02152*, 2019.

[6] Eliot R. Smith and Frederica R. Conrey. Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review*, 11(1):87–104, 2007.

[7] L. Wang, K. Ahn, C. Kim, and C. Ha. Agent-based models in financial market studies. *Journal of Physics: Conference Series*, 1039(1), 2018.

TABLE VII
NODE AGENT

Key Attributes	Node Agent
Connection Delay	Delay between when a node is created and when it can join the network
Ticket List	List of random numbers used to pick the node for participation in a group
Connection Failure Percent	Likelihood of disconnecting from the network
Death Percent	Likelihood of going offline and never re-connecting
Malicousness	determines if a node is considered malicous based on if the operator is malicious
Operator	the entity that runs this node
	Group Agent
Members	list of nodes that are members of the group. Nodes can repeat
Expiry	number of blocks before group expires
Malicious Percent	percentage of the groups members that are malicious
Offline Percent	percentage of the groups members that are offline
DKG Delay	User set delay simulating the distributed key generation process during group creation
	Signature Agent
Group	list of nodes that are members of the group. Nodes can repeat
Expiry	number of blocks before group expires
Delay	user specified time between being triggered and being published on chain
Offline Percent	percentage of the groups members that are offline at the time of the signature
Lynchpin operator percent	percent of the group owned by a single operator

[a]Sample of a Table footnote.

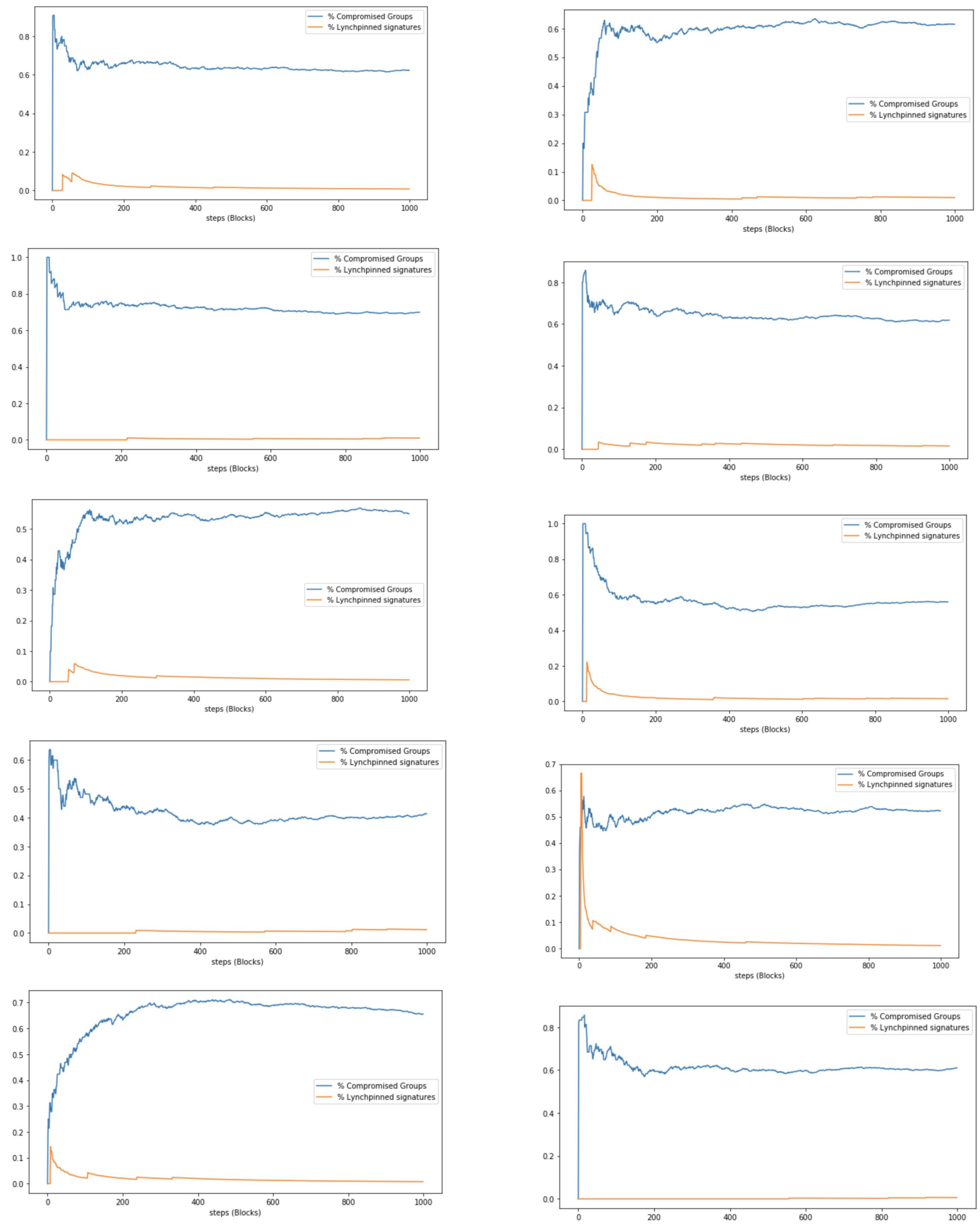

Fig. 3. Emergence of Steady State Behavior