Three Sigma Labs

Economic Report

Yeti Finance System parameterization analysis

Disclaimer

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Acronyms

$AICR$	Adjusted Individual Collateral Ratio
$AMCR$	Adjusted Minimum Collateralization Ratio
ASR	Adjusted Safety Ratio
CCR	Critical Collateralization Ratio
CDP	Collateralized Debt Position
$CGBM$	Correlated Geometric Brownian Motion
ETH	Ether
GBM	Geometric Brownian Motion
ICR	Individual Collateral Ratio
LP	Liquidity Provider
MCD	Multi-Collateral DAI
MCR	Mininum Collateralization Ratio
QTM	Quantity Theory of Money
SR	Safety Ratio
TCR	Total Collateral Ratio
TVL	Total Value Locked
$YUSD$	Yeti USD
RAV	Risk-Adjusted Value
$WETH$	Wrapped ETH

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Overview

Economic Report

Yeti Finance System Parameterization Analysis

1 Overview

1.1 Background

The Decentralized Finance (DeFi) space has seen a massive growth in adoption and increase in Total Value Locked (TVL) in recent years [1]. Decentralized Collateralized Debt Position (CDP) borrowing protocols like Yeti Finance have proven their product-market fit and make up a large market share in DeFi.

Yeti Finance allows users to borrow Yeti USD (YUSD), a USD-pegged *stablecoin* by trustlessly supplying arbitrary whitelisted crypto-assets as collateral with interest-free liquidity and a low minimum collateralization ratio of 110%. Yeti Finance, similarly to Liquity [2], uses a pooled liquidation mechanism that shifts risk and capital requirements from liquidators to Stability Pool depositors, who stake YUSD and earn revenue from liquidations without having to interact with complex mechanisms such as collateral auctions [3]. Along with Stability Pool direct liquidations, the protocol also incorporates a redemption mechanism that effectively creates a lower-bound on the price of YUSD. However, unlike Liquity, which is limited to accepting only Ether (ETH) as collateral, Yeti Finance allows the user to supply a portfolio of a wide range of assets to be used as collateral. This design decision enables greater flexibility for the protocol's users and general market composability and interoperability, but may introduce risk to the platform as it is necessary to limit and understand how much YUSD can be effectively backed by risky collaterals.

1.2 Protocol Risk Factors

Lending protocols face four major risks in DeFi: security risk, governance risk, oracle risk, and market risk. While this analysis will focus only on market risks within

Yeti Finance, Section 1.2.4, we have included a brief segment on additional risks for completeness purposes.

1.2.1 Security Risk

Security risk is associated with the correct execution of smart contract code that implements the mechanisms of the protocol's design. These risks are evaluated by code auditors who are responsible for verifying that the contract's implementation adheres precisely to its high-level specifications. Yeti Finance has been audited by Haechi and Dedaub, had an audit contest in Code4rena, and has also been audited by Three Sigma.

1.2.2 Governance Risk

Governance risk is concerned with management-related challenges such as administrator inefficiency, low voter turnout, and centralization of voting power. Yeti Finance will not be launched with a governance module.

1.2.3 Oracle Risk

Oracle risk is concerned with the precision of the feed of external data utilized by the protocol. Yeti Finance and other overcollateralized lending systems depend on price oracles to communicate external asset values to the protocol. These are used to determine the value of outstanding loans and to determine which are insolvent. Manipulation of oracle price feeds may push the protocol into liquidating non-defaulting loans, resulting in the loss of investor funds. Due to the fact that Yeti utilizes Chainlink [4] and Alpha Homora's [5] price feeds, previously subjected to security assessments, the whole analysis assumes a minor oracle risk. It is crucial to highlight that although oracle attacks have occurred numerous times in DeFi, these battle-tested oracles had a key role in avoiding catastrophic capital losses.

New oracle options for collaterals in Yeti Finance will be properly examined before being integrated.

1.2.4 Market Risk

The main purpose of this report is to evaluate market risks associated with Yeti Finance and its respective performance. Market risk is concerned with the underlying lending contract's mechanisms and multiple external market conditions. When markets for collateral assets are highly volatile, decentralized overcollateralized lending protocols are susceptible to a variety of exogenous risks. The reliability of these systems is contingent upon the ability of the protocol to keep the loan collateralization ratio above solvency by incentivizing the liquidation of uncollateralized loans. However, in highly unpredictable markets, the incentives may not be sufficient to entice liquidators to join, leaving the protocol with a larger amount of debt than actual collateral.

Yeti Finance's Market Risk assessment was divided in two analysis. Results from the first guided the re-designing of some aspects of the protocol and allowed an informed parameterization of collaterals and the system itself. By virtue of the results of the aforementioned analysis a second simulation of the system using much more defined parameterizations, leading to a more realistic model, was possible.

Yeti Finance uses the Stability Pool to liquidate uncollateralized troves, mitigating the risk of cascading liquidations by spreading the risk of liquidation through all Stability Pool's depositors. Nonetheless, should the Stability Pool be depleted, Yeti Finance utilizes a redistribution mechanism which distributes collateral and debt proportionally to all borrowers in the system in an attempt to maintain solvency. The effects of this redistribution mechanism on the protocol's solvency and cascading liquidations were examined.

The different possible borrowing fee models of the protocol were analyzed. These fit the several goals of Yeti Finance's incentive structure. We also analyze the effect of asset price volatility, individual asset parameterization in the system, Avalanche gas prices, and borrower debt management strategies on the protocol and its participants. Then using this information a second analysis with concrete collaterals and a revised mechanism design was performed for more realistic results.

1.3 Yeti Mechanisms

In this section we will introduce the system's mechanisms and how they interact with the system. Please consult the official documentation [6] or contracts [7] for a complete overview.

1.3.1 Trove

A borrower may deposit a basket of assets which are used as collateral to mint and withdraw the Yeti protocol's stablecoin, YUSD. A *trove* is composed by these assets and the corresponding issued debt. Each borrower may have one trove and can actively manage it by depositing or withdrawing collateral, and borrowing YUSD or repaying its YUSD debt. When the YUSD debt is fully repaid then she is able to retrieve her collateral.

1.3.2 Risk-Adjusted Value

The Risk-Adjusted Value (RAV) reflects the market value of the collateralized assets in the system. It is determined as the product of each asset's price, quantity, and safety ratio. Safety ratio quantifies the asset's risk and effectively works as a collateral quality grade. This grade is determined by accessing risk variables such as the collateral's volatility, liquidity, smart contract implementation, and oracle solution. An extremely safe asset will have a safety ratio of 1, whereas a riskier collateral will have a safety ratio of, say, 0.8 or 0.5. The Individual Collateral Ratio (ICR) of a trove is derived by the ratio of the trove's total RAV to the trove's total debt. This ratio quantifies the trove's risk and is used to decide whether a trove should be liquidated.

1.3.3 Trove Liquidation Mechanism

Troves with a lower Individual Collateral Ratio (ICR) than the Minimum Collateralization Ratio (MCR) are susceptible to being liquidated. The MCR is set at 110%. Any user has the option of liquidating an uncollateralized trove. The protocol compensates the liquidator with 200 YUSD plus 0.5% of the trove's collateral.

Undercollateralized troves are offset against the Stability Pool. When the Stability Pool lacks sufficient YUSD tokens to offset the undercollateralized troves debt, the system employs a redistribution mechanism. This mechanism redistributes the liquidated troves' outstanding debt and individual collaterals to all other troves that share each individual collateral in a proportional manner.

1.3.4 Adjusted Individual Collateral Ratio (AICR)

Calculating the ICR of a trove only taking into account its Risk-Adjusted Value (RAV) and debt, could result in a state where the system is exclusively backed by low ICR troves, composed solely of stablecoins, and still be in Recovery Mode. Stablecoins decrease the likelihood of significant volatility that could result in a trove's RAV falling in proportion to its debt. As a consequence, it is rational for borrowers to desire having low ICR troves focusing on capital efficiency with the collateral they deposit, especially if the collateral is entirely or primarily composed of stablecoins. To avoid this situation, in which the system is fundamentally secure yet inevitably enters Recovery Mode, the Adjusted Individual Collateral Ratio (AICR) mechanism was designed. To calculate the AICR of a trove the ICR is multiplied by 1 plus the product of a stablecoin constant (fixed at the moment at 0.5 but susceptible to change) with the percentage of stablecoins in the trove. This may also be thought of as multiplying the safety ratio of each stablecoin by 1 plus this stablecoin constant. Both calculations produce the same result, but while the first explains how this adjustment accounts for the percentage of stable coins in the trove, the latter is easier to calculate when determining how much RAV value a particular isolated asset adds to the trove. Across most mechanisms, the AICR is used in place of the ICR. When no stablecoins are included in a trove, the AICR equals the ICR. As an example to illustrate this behavior, let us assume a trove has only stables as collateral. Because its stablecoin ratio is 1 (100%), its original RAV value is multiplied by 1.5 $(1 + 0.5 * 1)$. Throughout this report this value will be referred to as the stable multiplier. Using the AICR to calculate the new System Safety Ratio (TCR) introduces a risk buffer to the protocol as a whole, fulfilling the goal of not letting the system enter Recovery Mode when it is highly backed by low ICR stable troves. This approach also has a positive impact on the redemption mechanism, since it alters the order of the troves to be redeemed.

1.3.5 Redemption Mechanism

Any YUSD holder may redeem it for collaterals in the system. The system admits YUSD price to be exactly 1 USD and therefore for each YUSD redeemed, the system repays the user 1 USD worth of collateral. This mechanism creates a lower bound on the price of YUSD, 1 USD minus the redemption fee. Users incur no losses as a result of this process, as the collateralization ratio can only improve, but the user is no longer exposed to the assets chosen as collateral for their trove. Consequently, Yeti Finance compensates the borrower by returning 0.1% (20% of the 0.5% minimum fee) to them of the redemption fee. The redemption fee is explained in further detail in Section 2.4.10.

Additionally, the troves to be redeemed are ordered by risk, such that redemptions always begin with the trove with the lowest AICR. Prior to the introduction of the AICR, it was expected that troves with the lowest ICR were those comprised entirely or primarily of stablecoins and hence reasonably safe despite their low ICR. The AICR addresses this concern by effectively sorting the troves by risk, such that those with are made of a larger stablecoin collateralization will effectively be pushed further up the redemption list and will not be the redeemed against first if the system contains riskier troves.

Naturally, redemptions may occur for recently opened troves, which would degrade the user experience by requiring a one-time fee to be paid before the user could reap any rewards from their investment. A booster mechanism was designed to address this issue. This approach complements the AICR, so that if a user has recently paid a deposit fee, their trove is slightly promoted in the sorted AICR list. Each time a user makes a deposit on the site, the boost increases and then gradually diminishes. The boost amount is computed as a percentage of the asset deposit fee paid in terms of the AICR, more precisely as the asset deposit fee multiplied by the leverage utilized, as described by the following equation:

$$BoostedAICR = base\,boost * AICR * fee * leverage$$

For instance, if the base boost is 1.5 and a user pays a 1% deposit fee while levering up ten times, the boost equals 1.5 AICR per (fee * leverage), resulting in a 15% increase in AICR that decays over time. At launch, the three half life decay time (at which 85% of the original boost vanishes) is set at two weeks, but is increased to two months beyond this first period. The base boost is set to 3, which means that a user paying 3% in fees would receive an initial +9% lift in AICR, that would decrease over time as specified.

1.3.6 Stability Pool

Any user holding YUSD may deposit it into the Stability Pool. This contributes to offsetting debt when liquidations occur. Stability Pool depositors receive the liquidated collateral and YUSD is burned in equal amount as the outstanding debt of the liquidated trove, therefore successfully assuring the system's solvency.

1.3.7 Normal and Recovery Mode

The system operates in Normal Mode when the System Safety Ratio (TCR) exceeds the Critical Collateralization Ratio (CCR) threshold, initialized as 150%. The TCR is the sum of all collateral in the troves, as calculated with AICRs, divided by the total issued debt. During Recovery Mode, the system blocks borrower transactions which would result in a further decrease of the TCR, implying that borrowers may not withdraw collateral or borrow YUSD. Additionally, while in Recovery Mode all troves with lower AICR than the TCR may be liquidated. Liquidated troves in Recovery Mode experience a liquidation loss capped at 110% of a trove's debt, implying that troves that are liquidated in Recovery Mode face the same liquidation penalty (10%) as if they were liquidated in Normal Mode.

1.3.8 Risks to Users

Different users experience different risks depending on how they interact with the system.

- **YUSD holders** need the protocol to be solvent so that the stablecoin they hold and use is backed.
- **Borrowers** need the protocol to be solvent so that they can retrieve their collateral.

- **YUSD Stability Pool depositors** may incur a loss if YUSD is off-peg or liquidations are not processed in time.
- **Liquidators** may incur a loss if the transaction costs for liquidating troves are higher than the liquidation incentives.

1.4 Goals of the Analysis

Using Agent-Based simulation, the first analysis aimed to answer the following questions:

- What happens if a given collateral were to have its price fall to zero (e.g., if an Automated Market Makers (AMM) was exploited and Yeti Finance was accepting its LP tokens)?
- What is the impact of re-distributions on liquidation cascades?
- What is the impact of liquidation latency on the Avalanche blockchain for different trove sizes (both in value and collateral number)?

These concerns focus on market risk and the protocol's ability to stay afloat and minimize losses. We also comment on and recommend system parameterizations based on the outcomes of the simulations for:

- Collateral Ceiling by Risk Category
- Safety Ratio by Risk Category
- Stability Pool Ratio
- Borrowing Fee Models
- General Remarks

The results of this first assessment were employed to guide decision-making during the re-design process. Additionally, this insight resulted in a rational parameterization of the system, with an emphasis on capital efficiency while ensuring solvency even under adverse market circumstances. The second study, which utilizes the newly defined mechanisms and parameterizations, was aimed to verify that the system is truly capable of maintaining its health considering the current implementation, as well as suggesting in a much more scoped manner how the system should incentivize different user actions after the system is deployed.

Agent Based Simulation

Economic Report

Yeti Finance System Parameterization Analysis

2 Agent Based Simulation

2.1 Background

Modeling complex dynamic systems such as consensus algorithms [8], DeFi protocols [9], MEV PGAs [10], and many other non-blockchain systems [11] is considered a challenging endeavor as it is often troublesome to accurately replicate real-world systems and behaviors. To tackle this issue a computational model such as Agent-Based Modeling (ABM) is used to simulate the actions and interactions of autonomous agents with the complex system, having as purpose understanding how the system behaves and what influences certain outcomes. ABM combines elements of game-theory, computational sociology, multi-agent systems, evolutionary programming, and behavior emergence [12–17]. For random processes Monte Carlo methods are also used to comprehend the stochasticity of these models.

Typical agent-based models are composed of the following key elements:

- Numerous agents specified at various scales.
- Decision-making heuristics (informally known as policies).
- Learning rules or adaptive processes.
- Interaction topology.
- Environment.

2.2 Analysis Context

This economic study, along with its simulations and subsequent analysis, is a revised version of the initial market risk analysis economic report produced for Yeti Finance.

Several of the findings from the initial simulations were now included as input for the ensuing simulations, therefore limiting the solution space and refining the results. To provide completeness and clarity, the report will include both simulations and their outcomes, referred to as Simulation Environment 1 and Simulation Environment 2.

2.3 Simulation Framework

The Neferpitou simulation framework is a proprietary modeling platform developed for the analysis of DeFi protocols, running simulations using the corresponding protocols' smart contracts.

In Neferpitou agents are customizable using a DSL which allows specifiying different agent types (e.g. miners, keepers, arbitrageurs, borrowers), policies (e.g. when should a borrower top up his CDP depending on available information), learning rules (e.g. arbitrageurs learning competitors behaviors), and interaction mechanisms (e.g. agent-to-agent interactions or interacting with the environment).

Neferpitou's environment is a custom blockchain that allows to flexibly implement changes to both the consensus and virtual machine layers. Changes to the consensus rules typically include removing unnecessary cryptographic complexity for faster simulations and to the blockchain's average block time. Changes to the virtual machine include enabling the use of behavior mocking on particular contracts or computations, using custom opcodes, and custom gas pricing tables.

This flexibility allows the Neferpitou framework to easily adapt to every blockchain that uses an EVM-based fork as virtual machine.

For data analysis purposes the entire Neferpitou framework exhibits added tracing functionality and abstractions that allow choosing between different granularity levels when interacting with it while efficiently gathering useful information.

2.4 Model Parameters

The Yeti model used in the simulations implements the mechanisms described in Section 1.3. Initial state population, stochastic and deterministic exogenous processes, as well as the parameterization of variables are further described below. Unless otherwise specified, individual computations were performed over a time span of 86400 blocks (i.e., 2 days) with 20 Monte Carlo simulations per parameterization for each scenario.

2.4.1 Asset Price Trajectory

To simulate the price trajectories of different assets we use a multi-asset correlated Geometric Brownian Motion (GBM). By definition this stochastic process S_t satisfies the following stochastic differential equation:

$$dS_t = uS_t dt + \sigma S_t dW_t$$

Such that W_t is a Wiener process and u, σ are constants representing the percentage drift and volatility respectively. This is equivalent to:

$$S_t = S_0 exp((u - \frac{\sigma^2}{2})t + \sigma W_t)$$

In order to account for asset correlation into price asset generation, we replace the standard Wiener process for a given asset X with a Brownian motion of correlation $\rho_{X,Y}$, for every other asset Y.

This correlation is calculated based on the Pearson correlation coefficient for 7-day asset prices over the first week of December 2021 for Simulation 1 and January 2022 for Simulation 2, according to:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

Where X and Y are two random variables with standard deviations σ_X and σ_Y.

Simulation Environment 1

The first simulation employed a limited number of assets to simulate the various sorts of assets that may be used as collateral in Yeti Finance, along with their associated risks. Figure 2.1 illustrates the predicted standard and correlated price trajectories. The correlation coefficient for these assets of interest is shown in Figure 2.2, which was utilized to build the lower triangular covariance matrix using Cholesky decomposition.

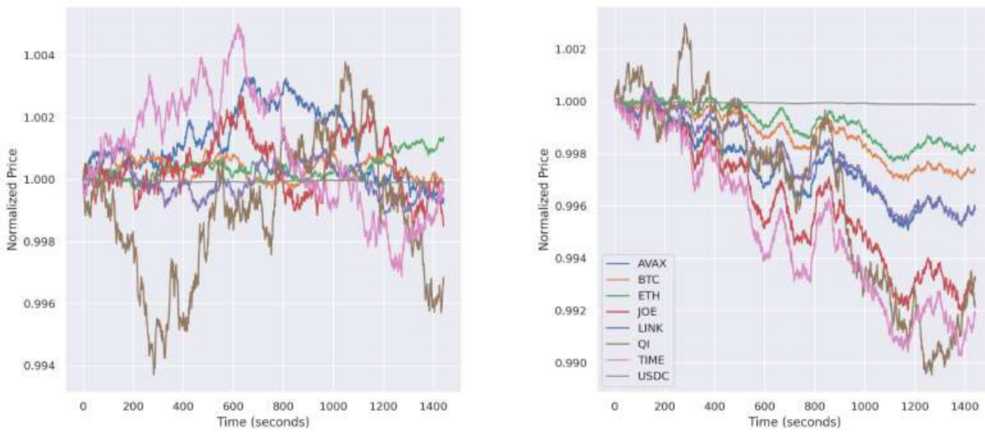

Figure 2.1: Sample paths from a standard GBM distribution (left) and correlated GBM price trajectories (right).

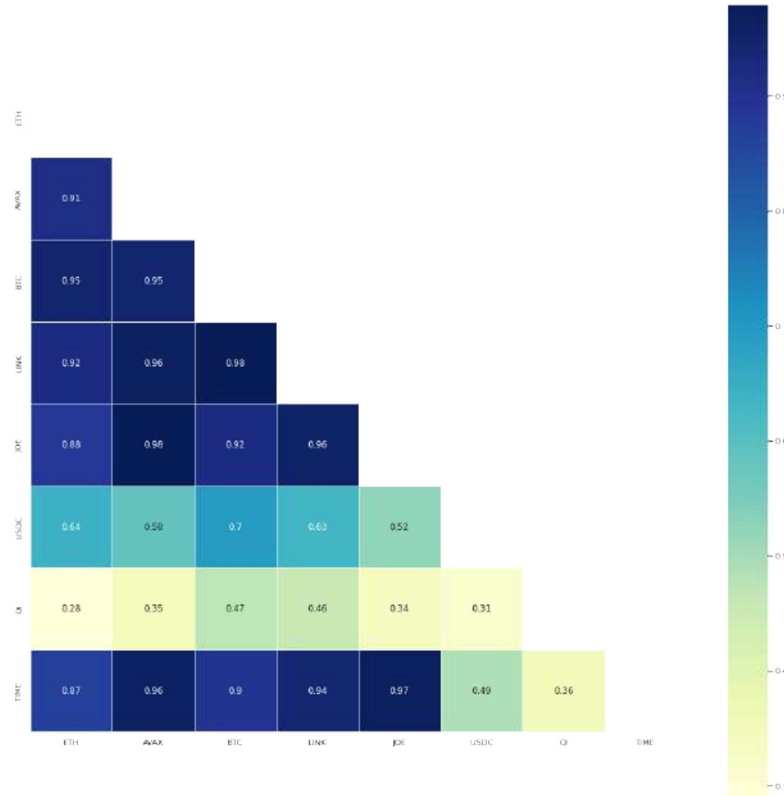

Figure 2.2: Pearson correlation coefficient for all assets of interest as of December 2021.

Simulation Environment 2

Simulation 2 tested the employment of currently whitelisted assets as collateral in Yeti Finance. Due to the lack of a whitelist for high-risk assets in the initial deployment of Yeti Finance, two mock coins dubbed 'DANGER' and 'TOXIC' were created to represent any future high-risk assets used as collateral. Using both the normal GBM and the previously described multi-asset correlated GBM, the Figure 2.3 demonstrates the associated price trajectories. These correlations are illustrated in Figure 2.4.

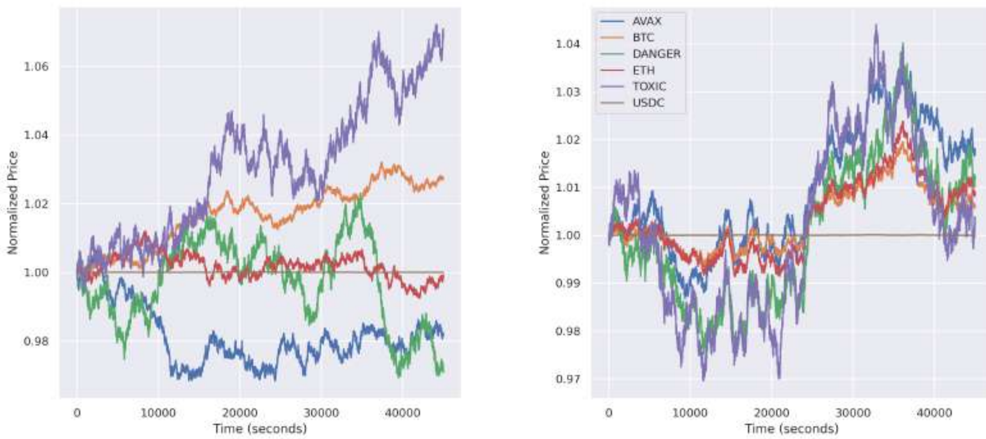

Figure 2.3: Sample paths from a standard GBM distribution (left) and correlated GBM price trajectories (right) for assets used in Simulation Environment 2.

2.4.2 YUSD/USD Price Trajectory

Owing to the fact that the analysis is primarily concerned with individual asset parameterization and insolvency, rather than with the YUSD's price peg, we rely on the Quantity Theory of Money (QTM) [18] to estimate the price action of YUSD. This implies that a delta percentage reduction in supply increases the price by a delta percentage as well. This is used to simulate the YUSD/USD price floor, rather than modeling the entire arbitrage loop. Additionally, redemptions may have a short-term positive effect on the YUSD/USD exchange rate and for that reason it was also modelled.

2.4.3 Avalanche Network Congestion

The expected delay time may be predicted by studying how long transactions stay in the blockchain's pending transactions pool, known as the mempool. Given that the Avalanche network mempool is private, it is hard to predict with a high degree of accuracy how long a transaction would take to be processed. However, it is expected that most transactions are included in the next block, since record shows that the Avalanche blockchain is very rarely congested. This is inferable from the fact that

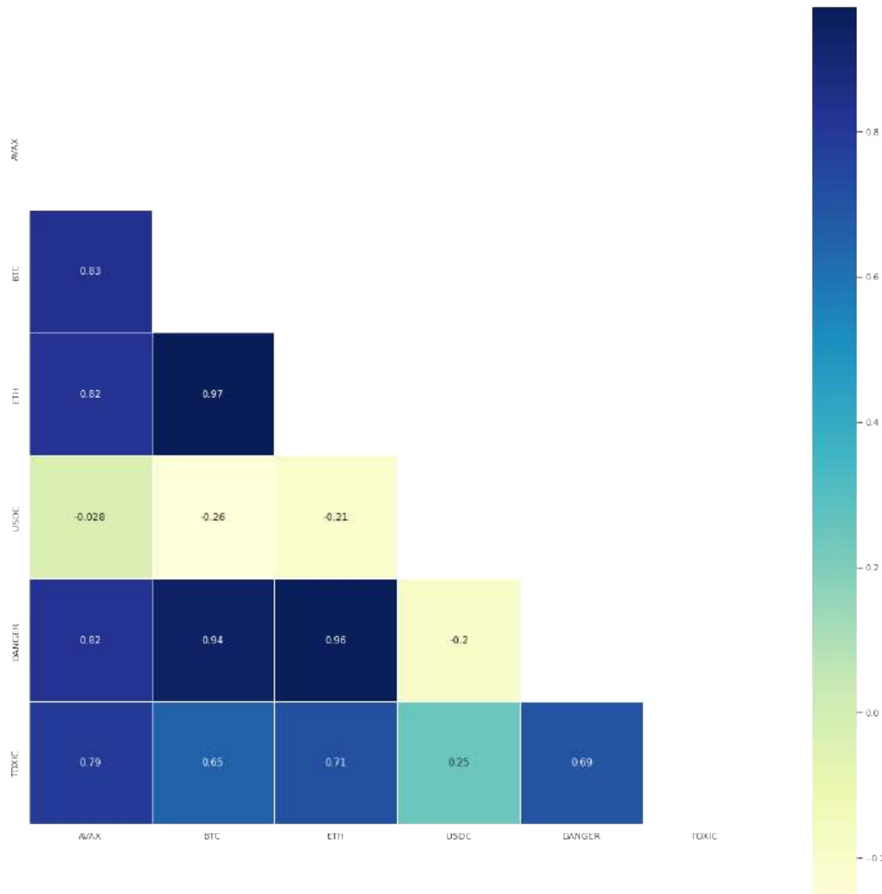

Figure 2.4: Pearson correlation coefficient for whitelisted assets.

most blocks show a very low percentage of gas used when compared to their gas limit, implying therefore that each block is expected to successfully empty the mempool.

2.4.4 Gas Price

The simulations ran under a number of gas cost scenarios, with the mean gas price for transactions set to a value based on historical mean block gas costs. These were given in nAVAX and concerned the previous 90 days as a baseline. The chosen period is justified as coinciding with the activation of Apricot phase 4 [19], an update to Avalanche improving the network's Snowman implementation (Snowman++ [20]) and reducing the overall transactions fee.

Scenario	Mean Price (nAVAX)	Historical Percentile
Normal	25	50%
High	55	90%
Extreme	3500	99.9%

Table 2.1: Mean gas price classified by simulation type and historical frequency.

The values chosen for the percentiles take into consideration the median gas cost in different situations. The assumed Normal scenario represents most of the blocks on the chain, where 25 nAVAX is then the smallest possible price for gas. The High scenario models common moments when increased network congestion plays a role, therefore projecting gas prices up to 55 nAVAX. The Extreme scenario was modeled based on data for the 22nd of November 2021, illustrated in fig. 2.5, when gas prices soared to as high as 8 USD per single ERC-20 token transfer.

2.4.5 Agent Type Definitions

The simulations aim to create a representative distribution of market participants interacting with the Yeti protocol in various roles. In our simulations, each type of agent has predefined mechanisms, utility functions, and policies that drive decision-making around protocol interactions.

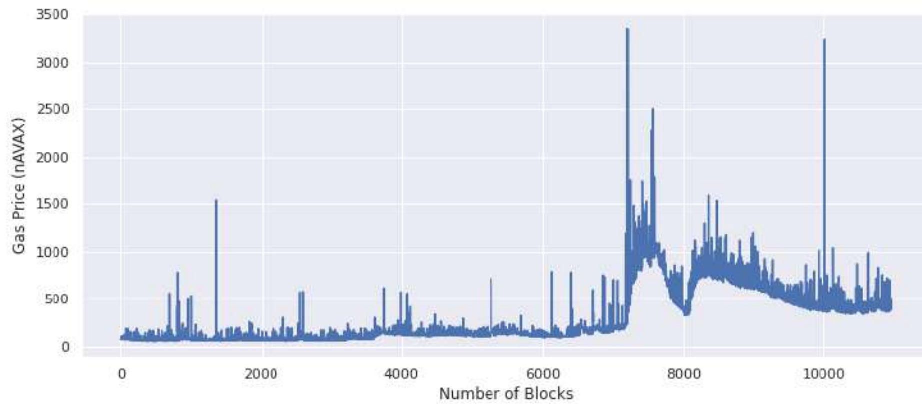

Figure 2.5: Block gas prices on the 22nd of November.

2.4.6 Borrowers

Borrowers are the primary actor type that interact with the protocol. They have direct influence on the protocol's liquidity, being the latter dependent on deposited assets. These are then used as collateralization for the contracted debt. Each borrower can top up or withdraw her collateral and repay or borrow YUSD provided that the trove maintains a minimum collateral ratio of 110%. However, should the system be in Recovery Mode, trove manipulation is restricted to actions which will never lower the TCR. In Simulation 1, it was hypothesized that borrowers check their troves on average every eight hours and alter their position by adding or removing collateral in accordance with the borrower policies specified in Section 2.4.8. Simulation 2 sampled three types of users from a normal distribution with varying average decision-making times: 3, 8, and 16 hours.

2.4.7 Opening Loans

During the simulation's startup stage, all troves are opened. The initial Collateralization Ratios and collateral sizes were sampled based on data from Liquity. Figure 2.6, shows the distribution of Collateralization Ratio by Collateral Size for Liquity's protocol. Since Liquity is restricted and only accepts a single collateral type (i.e., ETH), other data was gathered to sample the asset distribution in the system and inside each trove. This sampling was different in both simulation environments.

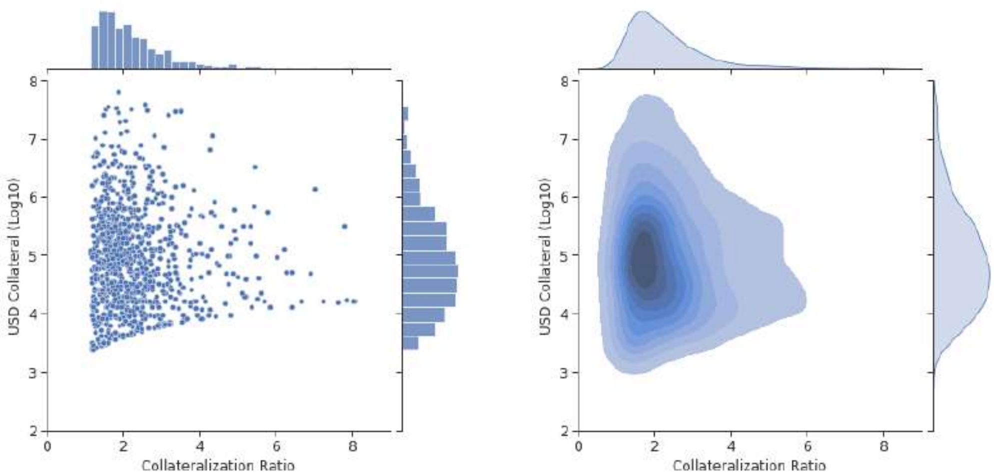

Figure 2.6: Distribution of *Liquity*'s CDP (Collateralized Debt Positions).

Simulation Environment 1

In the first simulation there was no data, real or simulated, to be used for the parameterization of the Yeti protocol, and so the previously described information from Liquity was combined with data from the MakerDAO's Multi-Collateral DAI (MCD) system, in order to sample trove collateral distributions by asset type and account for distinct Collateralization Ratios based on the underlying trove assets.

Figure 2.7 shows the distribution of Collateralization Ratio by asset type for the MakerDAO MCD system. As we can see, stablecoin collateralization (i.e., USDC), which we considered to be equivalent to Low Risk assets in Yeti Finance, follows the MCR of the system very closely. On the other hand, assets such as ETH, present much higher average Collateralization Ratios allowing the mitigation of liquidations during high volatility periods, and therefore we considered these to be equivalent to High Risk assets in Yeti Finance. Additionaly, Liquidity Provider (LP) tokens (i.e., DAI-USDC, DAI-ETH, etc) have higher Collateralization Ratios when compared to stablecoins but lower than the ones for volatile tokens, which could be comparable to Medium Risk assets in Yeti

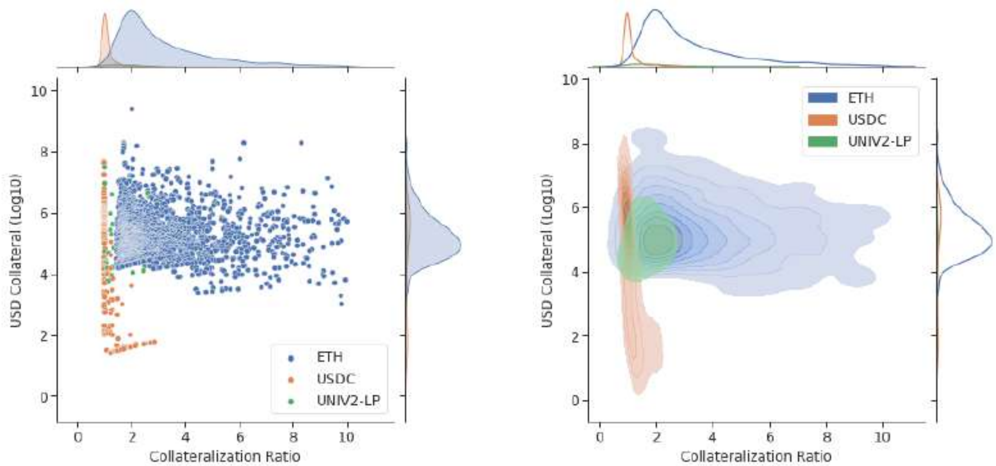

Figure 2.7: Distribution of MakerDAO's CDP Collateralization Ratio by asset type.

Finance. This comes from the fact that most LP positions accepted by MakerDAO are for pools paired with a stablecoin which reduces the volatility of the underlying asset.

The concrete initial trove distribution - trove borrowed amount, and number and size of the deposited collaterals - was varied on each Monte Carlo run. As previously mentioned, this is achieved by randomly sampling a subset of Liquity's troves, for the troves' size and their ICR's, and using MakerDAO's collateral distribution by asset type and distinct Collateralization Ratios, for the number of each trove's collaterals and backing percentages of each asset. The troves were then initialized with these characteristics using the assets present in Figure 2.2.

Simulation Environment 2

The initial Collateralization Ratios and collateral sizes in Simulation 2 were sampled using data from Liquity. These distributions are illustrated in Figure 2.6.

However, findings from the first analysis were applied to sample trove collateral distributions by asset type. To maintain the system's health, it was determined that the ceiling for High Risk assets should be established at 5% and for Medium Risk assets at 25%. These findings are discussed in further depth in Section 3.1. Given the fact that these ceilings indicate the maximum risk that the system would accept, and because this research tries to validate the protocol in worst-case situations, this was the asset risk type distribution chosen for simulation.

Apart from this, and based on usual risk behavior, it was hypothesized that practically all troves will have some amount of Low Risk collateral, 30% of troves Medium Risk collateral, and 15% of troves High Risk collateral. These total quantities for each risk type were randomly allocated uniformly to maintain a consistent percentage of each risk type in the system. The troves were categorized according to their collateral value, and this segmentation resulted in a bin list. As explained before, the percentage of troves inheriting each risk class was fixed, and a discrete random distribution was used to determine how many distinct assets these troves would receive. We employed a negative binomial distribution with $r = 2$ and $p = 0.7$ for Low and Medium Risk assets. The average for this distribution is $\mu = 1.85$ and the standard deviation is $\sigma = 1.107$. Due to the fact that there are only two High Risk assets, it was decided at random which troves included one and which had two. Troves had an 80% chance of containing just one High Risk asset. The distribution of ICR against Collateral Value for the simulated troves is shown in Figure 2.8. As expected, its distribution resembles the CDP of Liquity. The same figure depicts the average asset distribution inside each simulated trove. It illustrates how around 30% of the system is estimated to be backed by stables, resulting in a total of almost 80% Low Risk assets, 15% Medium Risk assets, and the referenced 5% High Risk assets. In Figure 2.9, the asset distribution for troves observed with the most and least stables is shown. Although the distribution of total collateral by risk type was balanced, the troves retain a beneficial randomness, with some troves containing almost 50% stables and others containing less than 15%.

2.4.8 Top-ups / Withdrawals

In these simulations it is assumed that no borrower withdraws collateral from her trove, which would result in a reduction of its ICR. Since we are stress-testing the system, the borrower focuses instead on maintaining her trove's ICR above what she considers to be a healthy ICR, based on personal preference, and the TCR, to reduce the probability of being liquidated if the system enters Recovery Mode. These personal preferences are a function of each borrowers randomly sampled risk averse behavior ϕ, striving to maintain the trove's ICR above $110 + \phi\%$ in Normal Mode and above $130 + \phi\%$ in Recovery Mode. The aggressiveness is randomly sampled from a gamma

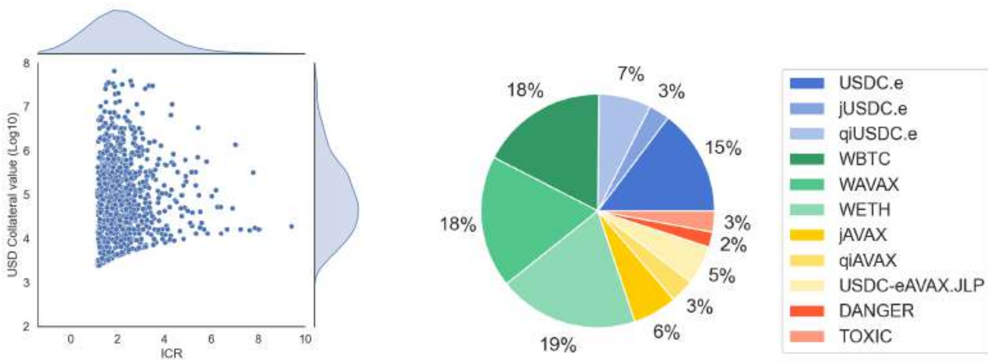

Figure 2.8: Distribution of simulated troves' ICRs (left) and Average Asset Distribution (right).

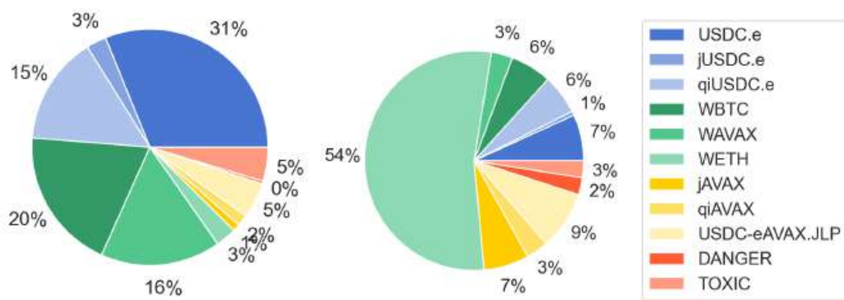

Figure 2.9: Distribution of Assets in trove with most (left) and less (right) stables.

distribution, which follows the distribution curve of MakerDAO's CDP :

$$\phi \sim \textit{Gamma}(3.8,\ 20)$$

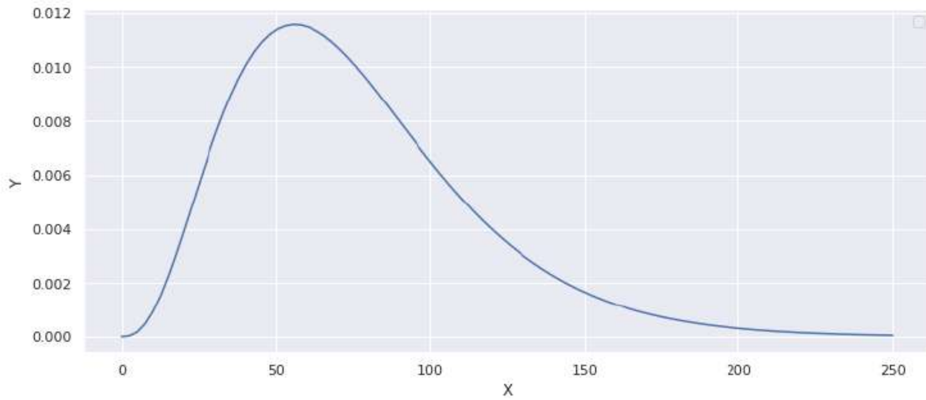

Figure 2.10: Aggressiveness threshold parameter distribution.

The key takeaway of this distribution is that the expected median ICR of a rebalanced trove is around 185 during Normal Mode and 205 during Recovery Mode. Around 3% of the borrowers will not top-up their vaults in case they check that their troves are under-collateralized during Recovery Mode. This represents the high risk seekers that expect the system to return to Normal Mode before being liquidated, effectively abstracting the borrower rational decision of only topping up her vault depending on the amount of troves necessary to be liquidated for the system to return to Normal Mode. When borrowing occurs, the fees for each asset are updated with regard to the individual asset, its risk assessment within the system and borrowing temporal rate.

2.4.9 Fee Models and Asset Risks

There are 3 categories of risk for assets being supplied to the system: Low, Medium and High Risk assets. Each possesses its own different system parameterizations. These different parameters are system ceilings on the relative percentage amount, risk multipliers, and borrowing fee of each collateral type.

Low Risk

Low Risk assets are defined as the assets by which the protocol should be comfortable enough to fully back the entire system. The Yeti's team preliminary suggestion was to cap specific Low Risk assets with a ceiling of 23% and have no ceiling for safer more stable Low Risk Assets. However, since the protocol also allows for riskier collaterals, the incentive for low risk collaterals compared to high risk assets shouldn't make the latter ineligible. Despite setting ceilings on the other asset risk categories there shouldn't be a direct system ceiling for Low Risk collaterals.

Some expected characteristics for a collateral to be considered Low Risk are:

- Highly liquid asset (e.g., AVAX or Wrapped Ethereum (WETH)).
- Low volatility.
- Low or null probability of being manipulated.

Figure 2.11 graphically represents different options for the fee percentage for these assets as a function of total risk asset backing percentage.

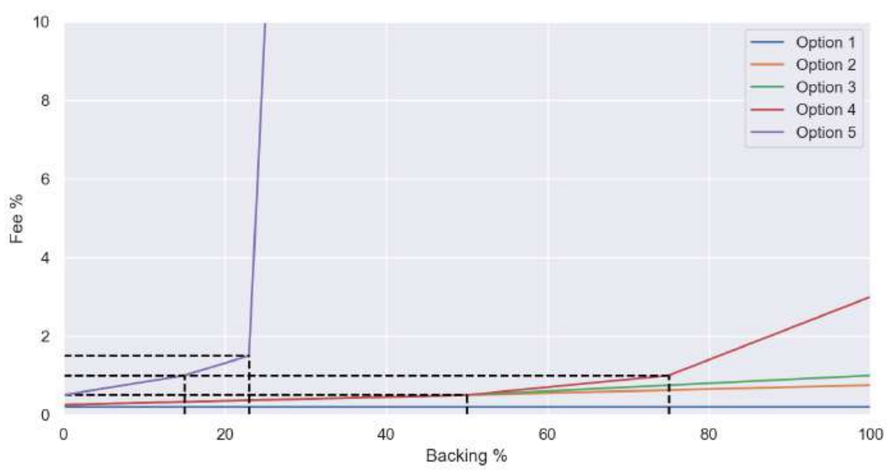

Figure 2.11: Yeti's team proposal for Low Risk assets fees.

Medium Risk

Medium Risk assets are defined as assets that could back a decent amount of the protocol. The Yeti's team preliminary suggestion was to cap each individual Medium Risk asset with a ceiling of 8%, and target around 1-5%.

Some expected characteristics for a collateral to be considered Medium Risk are:

- Liquidity between 10-50M USD, having as a main goal allowing arbitrageurs to make profitable deep trades even if delayed by a few blocks.
- Requiring trusting external "community recognized" platforms such as Benqi or Trader Joe.

Figure 2.12 graphically represents different options for the fee percentage for these assets as a function of total risk asset backing percentage.

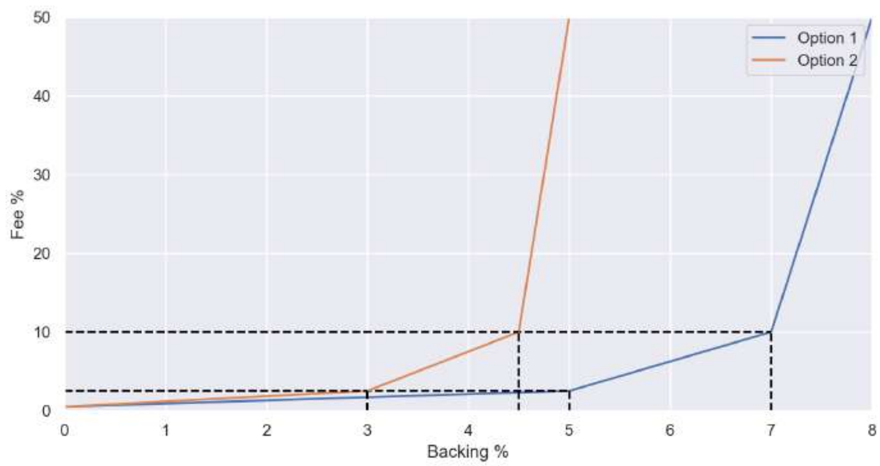

Figure 2.12: Yeti team proposal for Medium Risk assets fee.

High Risk

High Risk assets are defined to be experimental assets and should back a very small amount of the protocol. The Yeti's team preliminary suggestion was to cap each individual High Risk asset with a ceiling of 1%.

Some expected characteristics for a collateral to be considered High Risk are:

- Liquidity on a trustworthy exchange (e.g., Trader Joe) between 5-10M USD.
- Requiring trusting external platforms with at least a few months of existence and a strong presence in the community.

Figure 2.13 graphically represents the option for the fee percentage for these assets as a function of total risk asset backing percentage.

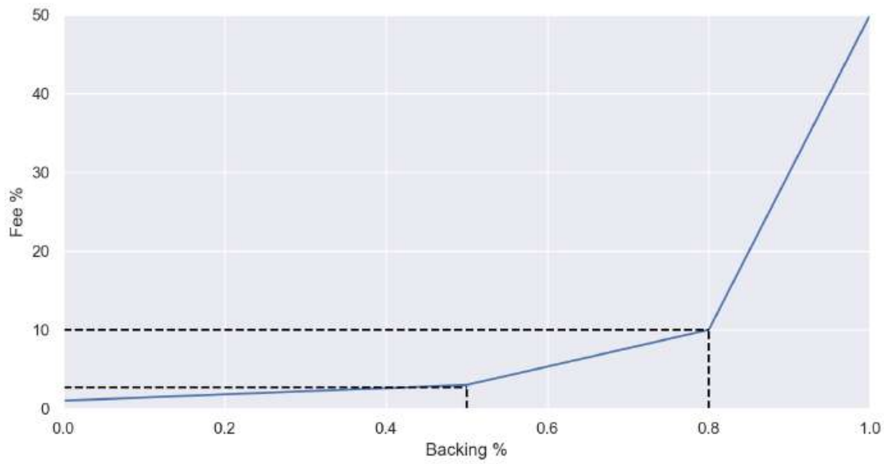

Figure 2.13: Yeti proposal for high risk assets fee.

Temporal Factor

Aside from the previously mentioned fee alternatives, each one has a temporal component, which makes it impossible to game these fee models. This component is a downward linear temporal factor with an adjustable period (in days) that is multiplied by the asset's last paid fee. The borrowing fee should never be less than this amount. For example, assuming a 5-day period, if the last fee for an asset was 1%, then 24 hours later the fee for this asset can never be below 0.8%. 48 hours after that, the fee still needs to be at least 0.4%, even if the current value shown on the graphics is lower. This temporal factor resets every time this asset is used as collateral. The goal of this fee is to defend against an exploit in which a borrower backs a huge trove with a low-cost Low Risk collateral, reducing the risky collateral's backing to a fraction of what it was before, and then removes it after adding a High Risk collateral. An example shall follow. Let's say the entire system has 100,000 USD total RAV and a backing of 5% for a Medium Risk asset. The fee expected for this collateral is quite high, as seen on the graphics. If the same borrower opens another trove and deposits

$900,000 total RAV using a Low Risk asset, the backing for the Medium Risk asset is now down 0.5% from the original 5%. This allows the borrower to open a second trove using the Medium Risk collateral without having to pay the high fee. Right after this, the borrower can return the YUSD for the low risk collateral, bringing the Medium Risk backing percentage back up. Without the temporal fee, the borrower would be able to abuse the borrowing system fees for Medium and High Risk collaterals, effectively adding risk to the protocol.

2.4.10 Redemptions

Any market participant is incentivized to purchase YUSD from the open market and redeem 1 YUSD at face value of 1 USD of collateral in the system if YUSD is trading below 1 USD, successfully arbitraging YUSD back to 1 USD. This mechanism ensures that YUSD always trades with a lower bound of 1 USD. For abstraction purposes in our simulations we model borrowers as the only YUSD holders. To determine the profitability of redemptions, a borrower checks the following conditions:

- Market price of YUSD.
- Redemption fees.

Redemption Fees

The redemption fee is computed based on the percentage of YUSD being redeemed. This fee intends to normalize some behaviours in order to avoid troves being redeemed all at the same time. To achieve this goal, the fee incentivizes users to act in these ways through the following behaviors:

- The larger the redemption, the higher the fee.
- The larger the redemption volumes, the higher the fee.
- The longer the time delay since the last operation, the smaller the fee.

The redemption fee is calculated using the following formula:

$$Y = S * (\sqrt{(1.005 + BR)^2 + \beta \frac{Z}{S}} - 1.005 - BR)$$

And knowing that:

$$Z = Y + X$$

Where:

- BR = decayed base rate
- β = 2
- S = Total YUSD Supply
- Z = balance of YUSD
- X = YUSD Fee
- Y = YUSD you can actually redeem

For redemptions, the transaction gas cost was considered negligible.

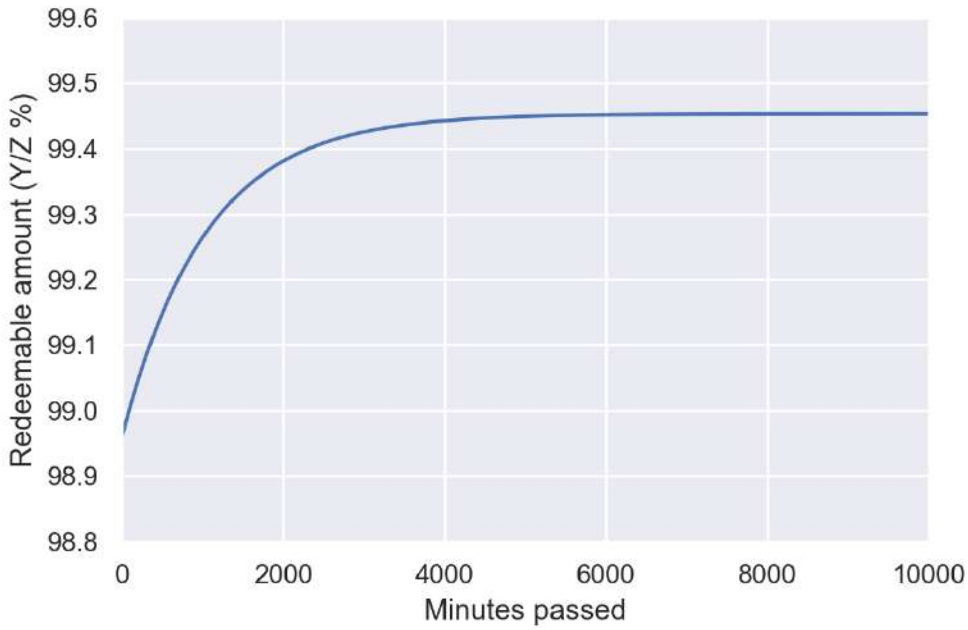

Figure 2.14: Redeemable amount vs Time (minutes).

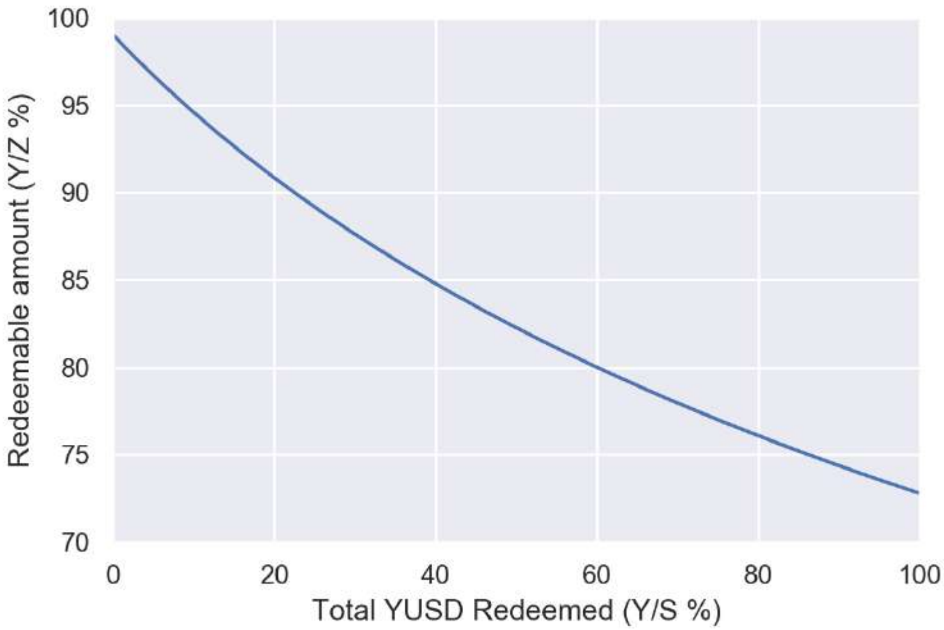

Figure 2.15: Redeemable amount vs Redeemed YUSD.

2.4.11 Stability Pool Depositors

When liquidations occur, collateral needs to be sold to offset the outstanding debt left by the liquidated trove in order to keep the system solvent. In other protocols, this collateral is usually sold at a discount using auction mechanisms or bought directly by the liquidator. In high volatility periods there can be scenarios where there are no auction participants or liquidators due to perceived market risk. In Yeti Finance the Stability Pool acts as protection against defaults during periods of increased collateral volatility. When liquidations occur debt is burned from the Stability Pool and the collateral liquidated is distributed amongst its depositors, effectively acting as a purchase of the collateral at a discount by its depositors, and therefore offsetting system debt. This does not remove the need for liquidators, but essentially reduces their role into executing the liquidation process. As opposed to other protocols, where liquidators end up taking the role of participants in collateral auctions, in Yeti Finance this responsibility is delegated to Stability Pool depositors. A larger Stability Pool, along with prompt liquidations, minimizes the amount of debt likely to remain in insolvent troves. The size of the Stability Pool is determined by the anticipated return on staking YUSD tokens in the pool, consequently increasing when high-value liquidations occur more often. Stakers must have an intuition on the amount of future liquidations in order to accurately estimate the rewards on YUSD staking.

Depositor behaviour

In Simulation Environment 1 as well as in Simulation Environment 2, the starting Stability Pool deposits were varied as a function of the total supply of borrowed YUSD. The simulations use increments of 10% that range from an initial deposit of 10% to 70% of the total supply being deposited in the initial state. If the YUSD price ever surpasses 1.1 USD, then depositors withdraw their funds, because if liquidations were taking place this would then result in a USD denominated loss for depositors.

Throughout the normal runs of the simulation model, the state initialization described above was employed. When running simulations to stress-test redistributions and their influence on liquidations cascades, the Stability Pool was assumed to be empty at the start with no additional deposits. This effectively abstracts the depositors fear of ending up holding a collateral that might be experiencing excessive volatility.

2.4.12 Liquidators

As mentioned in Section 2.4.11, Liquidators in Yeti Finance only execute the liquidation process. This implies that the capital requirements for a liquidator are minimized to just having enough AVAX to cover gas costs, thus a liquidator has the incentive to liquidate a vault if the trove liquidation fee is higher than the transaction cost associated with it. The Yeti team proposed a fee of 200 USD + 0.5% of the troves collateral to the liquidator. In this model, it is assumed that the amount of liquidations possible per block varies with respect to the number of distinct assets deposited as collateral in the liquidated troves as well as in the system as a whole. It was concluded by the Yeti Team that the amount of gas needed to liquidate a trove could vary between 1.4M and 8M. Using the Avalanche block gas limit of 8M gas per block this implied that the amount of liquidatable troves per block ranged from 1 to 5. Should the Stability Pool be empty, redistributing a fraction of every collateral to every other trove in the system consumes a high amount of gas. Assuming that liquidators do not have access to Avalanche's mempool and cannot backrun oracle updates or actions that will leave certain troves unsafe, the impact of imperfect liquidators in the system was modeled by varying delays between 1 and 10000 blocks.

Results

Economic Report

Yeti Finance System Parameterization Analysis

3 Results

3.1 Collateral Risk

Black swan events are common and there is always the possibility of a certain asset crashing abruptly to insignificant values on a period as short as a single block. This widely affects the TCR of the system based on the total RAV derived from risk assets. For clarification, the total possible debt backed by a certain asset depends on two parameters: the risk multiplier associated with it along with its risk ceiling. Consequently the protocol's solvency directly depends on each collateral asset's volatility, stability pool liquidity and outstanding debt.

The term *rugged* is commonly used to describe assets whose prices are abruptly reduced to zero as a result of any byzantine circumstance. Simulations were done with a protocol's collateral being rugged to observe how much of the protocol could be backed by rugged assets while still remaining solvent in the case of a failure. For Simulation Environment 1, a straightforward technique was employed to determine the maximum amount of rugged assets that the system may hold as collateral while preserving solvency. The findings of these first simulations were used to define ceilings for various risk categories and to assist in the development of a system for calculating safety ratios. The whitelisted collaterals were then applied in Simulation Environment 2 to determine if the set parameterizations maintain the system solvent during extreme scenarios.

Simulation Environment 1

An initial simulation provided a ceiling for the amount of rugged assets the protocol can have as collateral. We varied the backing percentage of these collaterals in the system and executed Monte Carlo simulations to understand how the system behaves.

From Figure 3.1 we can observe that if rugged assets compose up to 5% of the system's debt the system maintains a healthy collateralization ratio. It is also clear that under certain market conditions, the system would handle this occurrence should the collateral constitute up to 10% of the total collateralized value. This means that if an AMM was exploited and Yeti Finance accepted its LP tokens, the system would be unaffected if said AMM's assets did not account for more than 10% of the protocol's total assets. Whereas if the total value of the assets exceeded 30%, the system would not be able to recover easily. Naturally, if more than 50% of the collaterals are rugged it is highly likely that the protocol becomes insolvent.

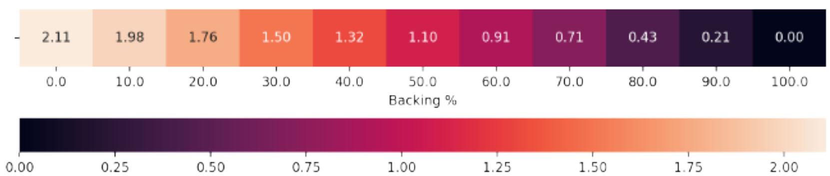

Figure 3.1: TCR changes with rugged asset backing %.

These conclusions justified the recommendation of having the ceiling for High Risk assets in the protocol be 5%, as by definition these have an higher likelihood of being depleted of value. In case of such event, the protocol will likely remain unaffected. If the protocol assumes an higher risk profile we believe that this hardcap could be pushed into an upper bound of 10% but do not recommend it. By fixing the High Risk asset hardcap to 5% we then proceed to analyze the distribution of the remaining 95% of the backing collateral between Low and Medium Risk assets. Considering an AMM's related assets as Medium Risk assets and the extreme scenario of said AMM being exploited we ran simulations ranging the Medium Risk system collateralization percentage between 15% and 35%, respectively and varying the Low Risk system collateralization percentage between 80% and 60%.

After running simulations varying the asset backing percentage of the protocol, the minimum TCR throughout the executions is sampled to provide insight on how the system behaves. For these simulations we assumed the price of Low Risk assets to maintain stable while Medium Risk assets rapidly declined. As we can observe in Figure 3.2 when using a backing percentage of 15% Medium Risk and 80% Low Risk the system is always solvent and so these percentages can be used as a safe boundary for the system's risk asset ratio. As in these simulations we aim to address worst case scenarios using imperfect liquidations and sub-optimal borrower strategies we believe that the system can be safely pushed to 75% Low Risk and 20% Medium Risk. If the Medium Risk assets are determined to not be extremely volatile this ratio can be further pushed but we do not recommend using a ratio lower than 70% Low Risk and 25% Medium Risk as it may deeply impact the system's ability to remain solvent.

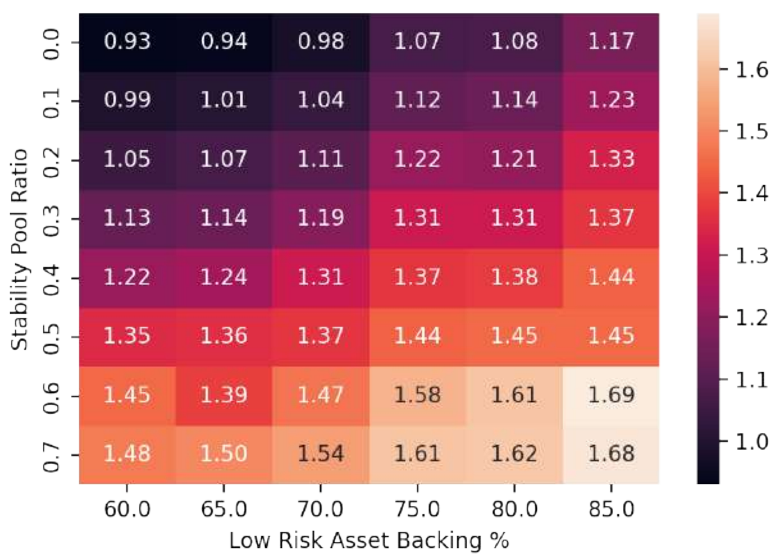

Figure 3.2: Minimum TCR for different Medium and Low Risk backing percentages.

Simulation Environment 2

As previously stated, the first simulation findings enabled the development of ceilings for the various risk categories. With this in mind, some assets were identified and whitelisted as collateral for Yeti Finance's launch. The safety ratios for these assets were computed and utilized in this simulated environment to examine how the system responds when the value of these collaterals drops and how the system's health is affected by the quantity of YUSD deposited in the Stability Pool in these instances. The price delta of collaterals corresponds to the difference between the total combined initial value of all assets (weighted average of price measured in USD) and the same total at the end of the simulation. Each collateral itself doesn't necessarily drop by the same percentage.

Concerning the safety ratios for the assets, these were determined by an individual examination of each asset, taking into consideration aspects such as volatility, liquidity, distribution, apy of yield-bearing assets, smart contract risk, oracle risk, and team risk. These assets include WAVAX, WBTC.e, and WETH.e base tokens, as well as the vault tokens jAVAX, jUSDC.e, qiAVAX, qiUSDC.e, and USDC.e/AVAX JLP, all of which have a safety ratio ranging from 0.925 to 1.035. Two fictitious assets were added with the labels 'DANGER' and 'TOXIC' to represent high-risk collateral. The system's percentages for each risk class were determined using the outcomes of the initial simulations.

In these simulations, the percentage of YUSD in the Stability Pool and the decline in value of collaterals (according to their volatility) were varied. The initial collateral distribution of the troves was likewise altered in each Monte Carlo run. The findings are illustrated in Figure 3.3. The system demonstrates that it can remain healthy with a minimum TCR substantially above the amount required to enter Recovery Mode, even when collateral assets value decreases 60%. Further examination of how the system acts across the various simulations reveals the Monte Carlo runs in which the variations resulted in the system achieving the healthiest and unhealthiest TCR. This is displayed in Figure 3.4 and Figure 3.5, respectively. Even with a 60% price difference and an empty Stability Pool, the lowest TCR is 268% in the healthiest run. Under the identical settings, the run that resulted in the worst system health has an TCR of 175%, implying that the system did not enter Recovery Mode.

Figure 3.3: Minimum TCR for different price reductions and Stability Pool per debt ratios.

Figure 3.4: Minimum TCR for different price reductions and Stability Pool per debt ratios for healthiest Monte Carlo run.

Figure 3.5: Minimum TCR for different price reductions and Stability Pool per debt ratios for unhealthiest Monte Carlo run.

As anticipated, these Monte Carlo runs correspond to the initial troves with the highest and lowest stablecoin collateral proportion, as shown by Figure 2.9. Again, this emphasizes the critical nature of having stables supporting the system and validates the mechanism's implementation. When we calculate the amount of YUSD burnt from the Stability Pool, we see that when prices decline, the amount of YUSD burned increases disproportionately for the unhealthiest run, where the system is backed by less stablecoins. Indeed, when more stables are used to support the system, the Stability Pool liquidation usage is reduced by a factor of 18.

3.2 Liquidations during Network Congestion

With the goal of maintaining the system's solvency troves with ICR below the MCR need to be liquidated. To ensure that these liquidations occur the liquidation incentives need to be higher than the costs of executing the liquidation. As explained previously the costs of executing a liquidation are the costs of executing the correspondent transaction as in Yeti Finance liquidators do not purchase the defaulted collateral. The liquidation incentive is 200 USD + 0.5% of the liquidated trove's collateral.

In our simulations, as mentioned in Table 2.1, we sampled gas costs from the day where the Avalanche network was the most congested to ensure that even in extreme situations liquidating a trove is still profitable. The amount of gas necessary to liquidate a trove varies with three parameters: proportionally with the number of different collaterals in the trove, the number of different collaterals in the system, and if the collateral is distributed to the Stability Pool or being redistributed between all other troves. The liquidation gas costs and calculations were provided by the Yeti team.

The conclusion was that the cost of liquidating a trove increased by 30,599 for each different whitelisted collateral in the system. Additionally, each collateral in the liquidation trove raises the cost by 171,164. Given that the basic liquidation cost for a trove with a single collateral when the system likewise has a single collateral, is around 515,020, the amount of gas consumed in a single trove liquidation was computed as follows:

$$515020 + (x - 1) * 30599 + (y - 1) * 171164 \tag{3.1}$$

Where x is the number of collaterals in the system and y in the trove. In Avalanche, the gas limit per block is 8.000.000, which may be achieved during a liquidation with around 25 unique collaterals in a trove and 110 in the system. The minimum gas payment for a liquidation is anticipated to be roughly 1.400.000, which is the consequence of the system having around 30 collaterals and the trove having one collateral. Due to the fact that a trove must always be liquidatable and not be restricted by a block gas limit, the proposed maximum values for these parameters were 20 collaterals per trove and 100 collaterals in the system.

The data used in Section 2.4.7 shows that most troves have a RAV ranging between 10K and 1M USD and therefore we used the values 10K, 100K and 1M USD for the trove's outstanding debt (i.e., its size) and 1.500.000, 4.750.000 and 8.000.000 units of gas for the liquidation gas prices. The following diagrams show the liquidation cost of a trove for different units of gas. The horizontal green line represents the base 200 USD reward of liquidation. Any data point below the green line represents null risk. The red line represents the sum of the 200 USD plus the 0.5% of the trove's VC. Any data point above the red line represents a non-profitable liquidation and constitutes insolvency risk.

As it is observed, for troves above 1M USD, the 0.5% variable fee ensures that there is always liquidation profitability. For troves worth 100K USD, there was a lengthy period of time during which liquidations were unprofitable due to the high cost of gas for liquidation. This poses a significant risk to the system, as these large amounts of debt have the ability to force it into insolvency. Troves with 10K USD represent a large risk as well, as they were not profitable to liquidate for a sustained period of time, even when the amount of gas needed was relatively small. These troves can constitute a considerable risk to the protocol in high network congestion.

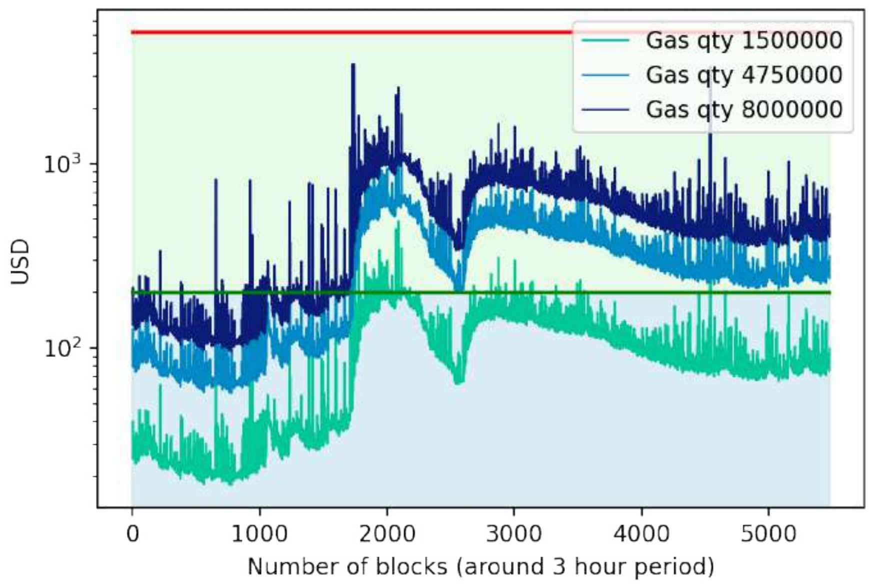

Figure 3.6: Liquidation profitability with 1M USD trove.

We acknowledge that the network congestion analyzed represents an extreme scenario that is an atypical occurrence, nonetheless, it should be viewed as a severe concern.

Since the Avalanche network has been subjected to continuous updates and an inflow of new users we believe that the liquidation fee should be reassessed after system deployment using the protocol's real troves and whenever there's a change to Avalanche.

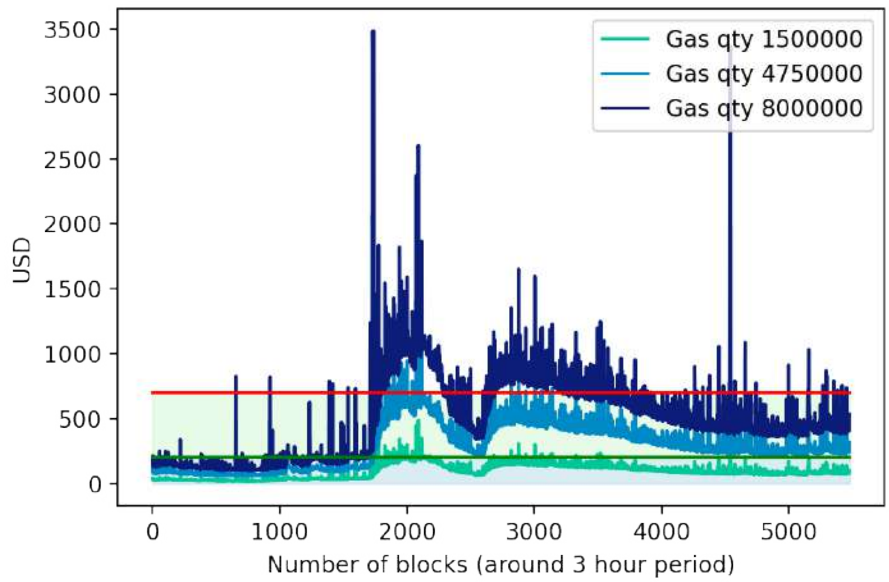

Figure 3.7: Liquidation profitability with 100K USD trove.

3.3 Liquidations with Delay

As previously stated, regardless of external factors, a trove should always be liquidated if brought under liquidation conditions. One potential factor for liquidation delays is network congestion, as discussed in Section 3.2. Another significant impediment can be caused by slow liquidators. Collaterals were determined and parameterized in the system using Simulation Environment 1. These were employed in Simulation Environment 2 to evaluate the system's response to various sources of stress, one of which being delayed liquidations.

The delay was varied between 1 and 10000 blocks, and the collateral value loss was set to the maximum value loss seen during the Black Thursday event, namely 60%, with the rate of reduction according to each asset's individual volatility. The Monte Carlo run that results in the system being backed by less stable assets was examined in further detail in this context, particularly when Stability Pool deposits equal 70% of debt. The findings indicated that the system never entered Recovery Mode or expe-

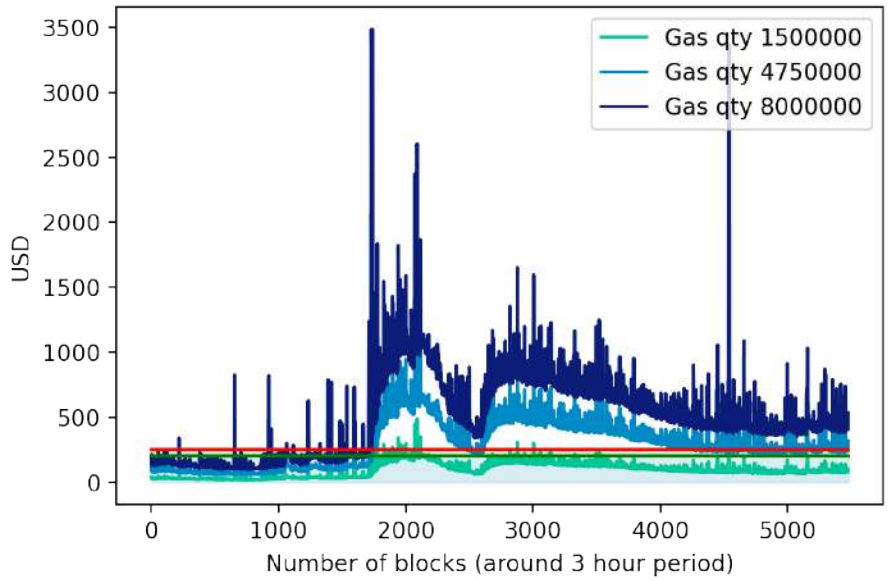

Figure 3.8: Liquidation profitability with 10K USD trove.

rienced insolvency as a result of the delays. Even with a 10000 block delay, which is nearly 5.5 hours, the system stays healthy enough to avoid entering Recovery Mode.

3.4 Redistribution Mechanism

As explained in Section 1.3.3, the redistribution mechanism is used when a liquidation occurs and the Stability Pool is depleted, effectively redistributing the defaulted trove's collateral and debt proportionally to each trove's debt between all other troves in the system. Since we're studying the Redistribution mechanism in this section we assume that the Stability Pool is empty throughout our simulations and conclusions. It is trivial to infer that in Normal Mode when redistributions occur the TCR does not change as the amount of collateral and debt in the system remain unaltered. In Recovery Mode troves can be liquidated under 150% and with lower AICR than the TCR, but they're only liquidated with the same penalty as in Normal Mode. For that reason, a redistribution in this situation would effectively lower the system's TCR and so these are not permitted, effectively avoiding liquidation cascades.

This redistribution mechanism also ensures that the number of collaterals in a trove remain equal. This adds the benefit of not changing any trove's liquidation gas costs, however heavily impacting particular troves if there is a scarce amount of them with a particular collateral. To mitigate this issue we discuss in Section 4.1 a possible improvement to the borrowing fee mechanism. Nonetheless, as discussed with the team and by simulation results we believe that this redistribution mechanism is superior to one where all the collaterals are blindly redistributed between all troves for a wide variety of factors.

3.5 System Solvency

Throughout the first simulation process we encountered several situations where the system became insolvent, either temporarily or permanently. As described in Section 2.4, this enabled us to parametrize the system and define a process for whitelisting and calculating safety ratios. Using this knowledge and the improvements made to the mechanisms, the second simulation environment indicated a far healthier system that can tolerate poor market circumstances without entering recovery mode, all other variables remaining constant. This indicates that the adjustments to the mechanisms were beneficial and that the parametrizations used for risk type ceilings, fees, whitelisting, and computation of collateral asset weights properly maintain the system's health.

Naturally, the possibility of the system staying solvent at any moment in time will depend on how users interact with it, including the collateral assets and combinations chosen for their trove. While these simulations make use of Liquity to sample trove size and TCR, we acknowledge that the usual Avalanche user risk profile may vary. The custom parameters used to approximate the startup settings of the system were based on MakerDAO and the projected risk behavior. However, understanding Yeti Finance users' genuine risk behavior requires deploying the system and with real data perform an in-depth study of behavioural patterns.

Using our recommended asset risk parameterization and fee models even in the scenario of a riskier asset class being exploited or a Black Thursday market-wide event in our simulations the system remains solvent, unless liquidations are not being processed, either by the lack of liquidators or network congestion. Additionally, the system stays solvent even when liquidations are postponed due to the newly implemented mechanisms and whitelisting, enhancing the system's security. Regardless, it was established that liquidations might stay unprofitable for extended periods of time when the network is crowded and can continue to be a point of failure. To mitigate this potential issue we suggest a possible variation to the liquidation reward in Section 4.1.

Recommendations

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4 Recommendations

The following chapter serves the purpose of summarizing all the analysis comprised and shared along the report. Through various parametrizations, assumptions and a fully cohesive simulation environment, it was possible to come to key conclusions. The initial simulations created for Yeti Finance yielded several critical findings that were expanded upon in this paper. The new simulations assessed in this report employed the suggested collateral ceilings for the various risk classes (Low, Medium, and High) reported in the first study and included in Table 4.1 for context.

This enabled the system's behavior to be evaluated when the system's maximum allocation for each risk class is full. While the safety ratios in the following table were suggestions based on initial results, the ones employed in the second simulation were already based on individual asset analysis and subsequent whitelisting. These are depicted in Table 4.2. The final suggestions for collateral ceilings and borrow fee alternatives were left unchanged from the first simulation, since they were demonstrated to maintain the system's health. Not every asset within a given risk category has the same safety ratio. Indeed, certain Medium Risk assets, such as qiUSDC Vault Token, have a higher safety ratio than certain Low Risk assets, such as WAVAX. USDC is a stablecoin, and due to its low volatility, it is regarded as extremely secure to use as collateral, resulting in a high safety ratio. However, because its wrappers may not be as secure, this asset should not provide a significant portion of the system's backing.

The full spectrum of recommendations for Yeti Finance's protocol is supported by the simulation results and its subsequent data analysis.

The recommended ceiling for High Risk collateral is kept at 5% and for Medium Risk collateral at 20%. Considering that the best case scenario for Yeti Finance is having the whole protocol being backed by Low Risk assets there shouldn't be a ceiling for these.

It is critical to ensure that the liquidator is constantly operational since borrowers may

Parameter	Conservative	Aggressive
Collateral Ceiling (Medium Risk)	20%	25%
Collateral Ceiling (High Risk)	5%	5%
Safety Ratio (Low Risk)	0.97	1
Safety Ratio (Medium Risk)	0.75	0.85
Safety Ratio (High Risk)	0.55	0.55
Stability Pool Ratio	0.60	0.45
Borrow Fee Option (Low Risk)	3	4
Borrow Fee Option (Medium Risk)	1	1

Table 4.1: Parameter recommendations summary from Simulation Environment 1

try to game the protocol if there's a noticeable lack of liquidations, and that the troves are always ordered according to AICR. It was demonstrated that the proportion of stables in the system has a significant effect on its health. Thus, incentivizing customers to deposit stables and, if required, adjusting borrow fees accordingly should be a top priority. Additionally, it was demonstrated how increasing the number of stables reduces the requirement for the Stability Pool to carry a sizable portion of YUSD debt. Stability Pool depositors' incentive structure should reflect this, so that if the system is heavily supported by stables, depositor incentives can be reduced. If the system is not significantly collateralized by stables, the incentives should aim for a 30 to 40% share of YUSD debt in the Stability Pool. However if the system is absolutely devoid of stables, the objective should be higher, targeting 60%.

Collateral Asset	Risk Type	Safety Ratio	Adj. Safety Ratio
jAVAX Vault Token	Medium	0.925	-
jUSDC.e Vault Token	Medium	1.035	1.55
qiAVAX Vault Token	Medium	0.95	-
qiUSDC.e Vault Token	Medium	1.025	1.54
USDC.e/AVAX JLP Vault Token	Medium	0.95	-
WAVAX	Low	0.98	-
WBTC.e	Low	0.98	-
WETH.e	Low	0.99	-

Table 4.2: Safety Ratios recommendations summary for whitelisted assets

4.1 General Remarks

A change to the borrowing fee models was considered while examining the influence of redistributions on the protocol's health and solvency. This modification adds a new variable that would monitor either the percentage of troves in the system that have each accepted collateral or the standard deviation of each collateral's amount in the troves. These two options might be thought of as heuristics for assessing the impact on ICR's when a redistribution occurs. If this variable fell below a specific health threshold, it may introduce a slight reduction on the borrowing fee for the related asset, with the goal of incentivizing a healthy number of troves for each collateral and reducing the impact on each in the event of a redistribution. These changes were not accounted for in any simulation and these are provided to the Yeti Finance team as a remark.

In order to ensure that liquidations are profitable we believe that an additional variable making use of the BASEFEE opcode, EIP-3198, which was added to Avalanche in Apricot Phase Tree, should be studied with the goal of ensuring a proper liquidation reward when there's an increase in network congestion.

Appendix

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A Appendix

A.1 Glossary

- Stablecoin - Crypto asset that attempts to offer price stability and are backed by a reserve asset. Usually pegged with USD in order to have a constant 1 USD in value.
- Risk-Adjusted Value - Collateral value as perceived by the protocol, weighted by the Safety Ratio.
- Safety Ratio - Weight assigned to a collateral asset that reflects the protocol's perception of its safety.
- Debt - Amount of borrowed YUSD associated with a trove.
- Individual Collateral Ratio - Ratio of the amount of collateral that a borrower has compared to the amount of debt that they have.
- Adjusted Individual Collateral Ratio - Ratio of the amount of collateral, valued with an adjustment for the amount of stables in the system, that a borrower has compared to the amount of debt that they have.
- Under-collateralized/Over-collateralized - A trove that is under-collateralized means that the collateralization ratio is below 110% and is vulnerable to liquidation. A trove that is over-collateralized means that the collateralization ratio is above 110%.
- Backing percent - How much of the protocol is backed by that particular asset in percentage. It is calculated using RAV.
- Total Collateral Ratio - Represents the ratio of the sum of all trove's AICR value, to the entire system debt.
- Recovery Mode - System state that only exists when TCR is below 150%.

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