Presentation notation:

Page 1

Today I want to briefly present the result of the market analysis about Bancor Protocol.

I will quickly review the Bancor protocol and then briefly illustrate details of simulating design. After that, I will thoroughly show my experiment results as well as my analysis based on these results.

Page 2

First of all, I present the final conclusion I draw from my simulation. And you can also view these conclusions as the summary of all my whole experiment results. In all of my later slides, what I want to do is to explain how these conclusions being summarised by Bancor protocol analysis, simulating model design and experiments.

So here maybe you can just quick scan these conclusions, and have a preliminary understanding of them.

Page 3

Since it has been a long time for us talked about Bancor protocol. Let us review the Bancor Protocol really quickly.

What it wants to do is to use the price fluctuation of smart tokens to ensure the stability of reserve balance.

For instance, imagine there is a market with initial reserve balance, when people buy smart tokens, the price of them will increase, which makes people willing to sell their tokens rather than to buy. Therefore, price of smart tokens will decrease and the balance of reserve tokens will also decrease.

Page 4

However, the design of Bancor protocol is flawed.

First of all, the frequent price fluctuation might lead bad influence to market. And many transactions might be failed due to it.

Second, the Bancor protocol neglects the potential aberrant market issues such as market craze. The robustness of Bancor awaits substantiation.

Third, the Double Coincidence Bancor aims to resolve might not exist. Even assuming it exists, Bancor shows no evidence about its superiority by experiments result.

Therefore, we try to use the simulation to analyse the Bancor protocol's protential problem.

Page 5

This is the overview of our simulating model. Since we have already talked about it, here I will skip it. But there is one thing that we should notice. That is the synchronise step in every time slot. In synchronze, simulator will tell all customers the price of smart token in the current time step. And then customers can give their valuation and launch orders.

Page 6

This is the trading rule implemented in classic market. Here I want to introduce it in brief as we are quite familiar with it.

In original state, there are some orders in market. When new order comes, it will look at the existed orders in a special sequence. Edward for instance, he always wants to buy using least money. So he first buys Stan's product, then Bob's and finally Amy's.

One thing that we should notice is in the final state, there are five orders remaining in the market, which in the next time slot will be canceled. But there is difference between these five orders. As Joe, Kyle and Kenny's orders are completely ignored, these orders are totally failed; while Amy and Cartman's orders are partly failed.

And to divide these two situation, we call the first situation — red one as failed orders. And all these five orders as cancelled orders.

Page 7

And then we start our simulation. I set three stipulations for simulating.

The first is one time one order, which means one customer at one time can only launch one order.

The second is our old-friend, that is the Gaussian distributed number of customers.

The third is quite new and important. It calls all-in and half-in. They are two policies to determine the transaction value of orders.

The reason why we implement these two policies I will show you later in experiment’s section. Results show that these two policies actually could lead really different results in classic market.

Page 8

Here is an example of the Gaussian distribution. In figure (a), the length of blue bar represents customers' number, and the x-axis such as 1.5, 14 represents the valuation of customers.

Figure (b) presents an example of how to use Gaussian distribution to simulate market craze.

The blue curve represents the normal cases of price fluctuation. And the new mu of Gaussian distribution is set as the new price of smart token in next time slot. However, if we want to simulate the market craze, the new mu needs to bounce. Just as red line curve shown, we bounce the mu to in a random range and then according to this parameter, customers generate their valuation.

Page 9

Now, we are very close to our experiment step. But before we do experiment, we need to specify the parameters we simulate in our experiment.

Here, we observe four parameters which is listed on the slide.

And in Gaussian distribution, the sigma's chosen directly influences the steepness of the Gaussian curve, as the figure presented.

Page10

So, it is time to make experiment.

Here we define several indexes for measuring market's performance.

These indexes are listed on the slide. And since only in Bancor market, the price of currency will fluctuate, the Price Slipping Ratio is designed for Bancor market only.

Page 11

First of all, let us view some pictures about the price fluatuation graph under several parameter settings. Though here I only present 9 cases. It can be found that though market craze merges which makes the price of smart token changes fiercely, the Bancor market actually is able to adjust the price to a relatively stable state. And by comparing these figures, with the decrease of σ and the increase of Nc, the price of smart token could be more stable.

Page 12

However, since these figures only plot curves by single experiment's data, with the pseudo-random seed 0, which is unrepresentative to reflect the uniform results.

And only observing the price fluctuation of smart token by figures is not accurate enough. Therefore, we quantify the price fluctuating degree by slipping ratio and analyze it by averaging data from 10 times experiments with same parameter pairs.

In Figure (a), we can find that with the growth of R, the price splitting ratio slightly increases. And Figure (b) shows when T decrease, the splitting ratio can be largely improved. And in Figure (c), it can be viewed that the splitting ratio drops when customers' number Nc decreases, i.e., market has smaller size. Also, among Figure (a), (b) and (c), with the increase of σ, the price splitting ratio, in different degree, is improved.

In summary, we can find that when market craze emerges frequently, and the market owns a large size, the price slipping ratio can be very high in Bancor market.

Page 13

Then, we study the market's performance of dealing with transactions.

This is the transaction analysis graph for Bancor market under all-in policy.

Page 14

In analysis, we learn that with the small Nc, i.e., small market size which actually represents the current status of most virtual current markets, and small σ0, i.e., the closer valuation between customers, the failure trans- action orders can even take over more than 10% in Bancor market, which is actually intolerable in real world.

Page 15

This is the transaction analysis graph for Classic Market under all-in policy.

In fact, as you can see, the performance of Classic Market is terrible as some cancel ratio is close to 80%.

Page 16

But before we analyse why the performance of Classic Market is so bad. We have another quite interesting finding, that is

Lower the sigma is, higher the canceled transaction ratio in Bancor Market, while lower ratio in Classic Market.

This phenomenon can be well explained by Figure 10.

In Bancor Market, when price of smart token fluctuates slightly, when $\sigma 0$ is small, e.g., $\sigma 0 = 0.01$, the number of influenced customers is larger than case when $\sigma 0$ is large, e.g., $\sigma 0 = 0.1$ that is red dash shadowed area is larger than blue shadowed area. Hence, much more transaction might be failed when $\sigma 0$ is smaller in Bancor market.

Similarly in classic market, when a buy order, the the number of customers who are qualified to satisfy this order is smaller when $\sigma 0 = 0.01$, as red dash shadowed area is smaller than blue shadowed area. Thus, the cancel or failed rate will be raised when $\sigma 0$ is small.

Page 17

Let us go back to the Classic Market's case under all-in policy.

We find the totally transaction number is decreasing significantly. After print every customers' smart tokens and reserve tokens by python. I find the final reason.

It is because under all-in policy, in classic market, some customers quickly run out their assets as they generate low valuation to sell and generate high valuation to buy with all they have.

Page 18

Therefore, we can find that under all-in policy, the "Double coincidence of wants" problem does exist and largely harms market's efficiency. And Bancor market can alleviate this problem to some extent.

But how about situation under half-in policies?

Page 19

This is the situation of half-in policy in Classic Market.

Page 20

We actually find under half-in policy, “Double Coincidence of Wants” might no longer be a problem.

Page 21

By comparing the transaction-oriented performance between Bancor market and classic market, we conclude several properties as below:

...

Page 22

And this picture vividly shows the comparison between Bancor and classic market under All-in policy and half-in policy.

Page 23

In summary, we can say that Bancor is flawed.

And this argument is based on solid experiment results.