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Transaction technique during bulk deal order to run smooth transaction with crypto exchanges and banking system.

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Abstract- Rundown of transaction is the latest concern for cryptocurrency exchanges between banking and financial institute and this will happen during the panic buy or sell of the digital coins online and this situation will occur during very large scale of external source news or by most popular influencer around the world due to this there is very high trading activities has been done which may result in bulk in transaction which occurred load to the banking servers and financial institute while converting the large scale deal. So, with the help of cached paused bid algorithm. This technique us the unique way which is called as winner determination problem which is called as higher value contributor has bid set value which can choose higher value to make successful transaction.

Keywords: Digital Currency, Cryptocurrency, Machine learning, Combination bidding.

I. INTRODUCTION

Transaction is the major issue during the panic buy or sell of digital currencies and banking and financial institute. There are several exchanges who deal with the conversion of the regular currencies to digital currencies. and also due to different laws and government policies on banking and financial institute there are some restriction on dealing with funds and traditional currencies also those exchanges have deal with the digital currencies does not have any restriction and free to deal with the currencies which are make two different natures of dealing to exchange the currencies. Which can be difficult to implement online system to convert the currencies through exchanges and the research and practice of combinatorial auctions have grown rapidly in the past ten years. In a combinatorial auction bidder can place bids on combinations of items, called packages or bid sets, rather than just individual items. Once the bidders place their bids, it is necessary to find the allocation of items to bidders that maximizes the auctioneer's revenue. This problem, known as the winner determination problem, is a combinatorial optimization problem and is NP-Hard. Nevertheless, several algorithms that have a satisfactory performance for problem sizes and structures occurring in practice have been developed. The practical applications of combinatorial auctions include: allocation of airport takeoff and landing time slots, procurement of freight transportation services, procurement of public transport services, and industrial procurement. Because of their wide applicability, one cannot hope for a general-purpose winner determination algorithm that can efficiently solve every instance of the problem. Thus, several approaches and algorithms have been proposed to address the winner determination problem. However, most of the existing winner determination algorithms for combinatorial auctions are centralized, meaning that they require all agents to send their bids to a centralized auctioneer who then determines the winners. Examples of these algorithms, Bid tree and CABOB. We believe that distributed solutions to the winner determination problem should be studied as they offer a better fit for some applications as when, for example, agents do not want to reveal their valuations to the auctioneer.

In this paper we present two algorithms, pause bid and cached pause bid, which enable agents in a PAUSE action to find the bid set that maximizes their utility. Our algorithms implement a myopic utility maximizing strategy and are guaranteed to find the bid set that maximizes the agent's utility given the outstanding best bids at a given time. Pause bid performs a branch and bound search completely from scratch every time that it is called. Cached pause bid is a caching-based algorithm which explores fewer nodes, since it caches some solutions

II. PROBLEM AND SOLUTION

A bid b is composed of three elements b items (the set of items the bid is over), b agent (the agent that placed the bid), and b value (the value or price of the bid). The agents maintain a set B of the current best bids, one for each set of items of size $\leq k$, where k is the current stage. At any point in the auction, after the first round, there will also be a set $W \subseteq B$ of currently winning bids. This is the set of bids that covers all the items and currently maximizes the revenue, where the revenue of W is given by.

$$r(W) = \sum_{b \in W} b^{\text{value}}.$$

agent i 's value function is given by $v_i(S) \in \mathbb{R}$ where S is a set of items. Given an agent's value function and the current winning bid set W we can calculate the agent's utility from W as

$$u_i(W) = \sum_{b \in W \mid b^{\text{agent}}=i} v_i(b^{\text{items}}) - b^{\text{value}}.$$

According to the PAUSE auction, during the first stage we have only several English auctions, with the bidders submitting bids on individual items. In this case, an agent's dominant strategy is to bid higher than the current winning bid until it reaches its valuation for that particular item. Our algorithms focus on the subsequent stages: $k > 1$. When $k > 1$, agents have to find $g * i$. This can be done by performing a complete search on B . However, this approach is computationally expensive since it produces a large search tree. Our algorithms represent alternative approaches to overcome this expensive search

The implementation done on both algorithms and performed a series of experiments in order to determine how their solution compares to the revenue-maximizing solution and how their times compare with each other. In order to do our tests, we had to generate value functions for the agents. The algorithm we used is shown in Figure 1 The type of valuations it generates correspond to domains where a set of agents must perform a set of tasks but there are cost savings for particular agents if they can bundle together certain subsets of tasks. For example, imagine a set of robots which must pick up and deliver items to different locations. Since each robot is at a different location and has different abilities, each one will have different preferences over how to bundle. Their costs for the item bundles are sub additive, which means that their preferences are super additive. The first experiment we performed simply ensured the proper functioning of the algorithm We then compared the solutions found by both of them to the revenue-maximizing solution as found by CASS when given a set of bids that corresponds to the agents' true valuation. That is, for each agent i and each set of items S for which $v_i(S) > 0$ we generated a bid. This set of bids was fed to CASS which implements a centralized winner determination algorithm to find the solution which maximizes revenue. Note, however, that the revenue from the pause action on all the auctions is always smaller than the revenue of the revenue-maximizing solution when the agents bid their true valuations. Since PAUSE uses English auctions the final prices (roughly) represent the second-highest valuation, plus for that set of items.

A. Decentralized computation

In this paper we provide a model of decentralized computation based on the principle of the market mechanism. Market agents are defined as autonomous software entities with the functions of self-interest seeking. They have their own computational capabilities with utility functions defined over the market mechanism. We obtain equilibrium solutions in the context of individual optimal behavior of each market agent. We provide a dynamic adaptive model of each agents' interest seeking. We discuss how an equilibrium solution can be obtained through decentralized computation

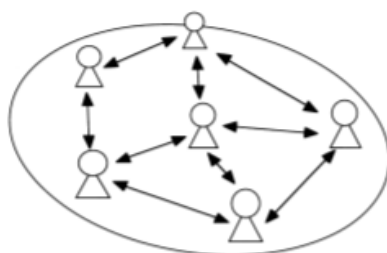


Fig 1

In this algorithm, bids are communicated with each other and compare the values with different combination in the distributed system and the maximum value has been generated by comparing and this will happen till the load is not get released and the online system of trading will not get effected agent cannot simply proceed to carry out its decisions without considering how other agents may behave. The strategy of each agent should be determined solely by how its decisions affect other market agents and how the decisions of other agents affect its own utility the research was to develop a model of decentralized computation by a set of market agents that produces complex and purposive group behavior. We have formulated and analyzed the interdependent decision-making problem of market agents. We have shown that an equilibrium solution can be realized through purposive local interactions based on individual goal-seeking. The market agents do not need to express their objective or utility functions, nor to have a prior knowledge of those of others. Each market agent adapts its actions to the actions of other market agents, thus allowing previously unknown market agents to be easily brought together to constitute a group responsible for a specific mission. This paper has also described research on competitive interactions leading to a coordinated behavior. The goal of the research is to understand the types of simple local interactions which produce complex and purposive behavior.

B. different combinational communication in distributed system

- Communication between two distributed objects by means of two different models which are called as remote method invocation (RMI) and remote procedure call (RPC). RMI as well as RPC are implemented on top of request and replay primitives.
- Block chain and banking are just the beginning. From a macro perspective, banks serve as the critical storehouses and transfer hubs of value. As digitized, secure, and tamper-proof ledgers, block chains could serve the same function, injecting enhanced accuracy and information sharing into the financial services ecosystem

III LITERATURE REVIEW

V. Kirubanand The main theme of this paper is to find the Distributed Data Transaction of an Apache web server using bulk service rule. We obtain the parameter of service rate, Arrival rate, expected waiting time and Expected Busy period. The inter arrival and inter service of HTTP request is assumed to Poisson Distribution Process (PDP) and these events are considered in the server for process sharing. The total number of requests are processed, there is no time limited to arrivals. While compared to some models, our model of M/M (1, b)/1 is more efficient to find response and request time in between client and server. This model has been validated through java programming. The performance has been found in the model of M/M (1, b)/1 which fits well to the practical outcome in client and web server.

Disadvantages: Client server model connected with number of clients may risk of chain attacking.

In cryptography the structure of the message is scrambled to make it meaningless and intelligible unless the decryption key is available. I make no attempt to disguise or hide the encoded message basically; cryptography offers the ability of transmitting information between client and server in the way that prevents from third party hacking. Cryptography can also provide authentication for verifying the identity of someone or something

Advantages: 1. The system helps to understand and identify daily changes in the market while obtaining insight into the most appropriate features surrounding price. distribution.

Nor Azizah Hitam et al. [8] presents a comparative performance of Machine Learning algorithms like Neural Networks (NN), Support Vector Machines (SVM), and Deep Learning for cryptocurrency forecasting using time series data. time-series data based on 5 years of daily history, as inputs for all models and may vary based on the availability of datasets from the source. The data is prepared from the daily open, close, high, and low prices of daily trading for a total of six types of cryptocurrencies. The paper concludes that SVM has several advantages over the other models in forecasting and provides a result that is almost or close to the actual result.

Advantages:

Samiksha Marne et al. [9] attempted to predict Bitcoin prices by the use of RNN using the LSTM model to predict the price of the cryptocurrency. The results were computed by extrapolating graphs along with the Root Mean Square Error of the model which was found to be 3.38. The use of RNN using the LSTM algorithm was done effectively.

Ruchi Mittal et al. [10] makes use of multivariate linear regression to predict the highest and lowest price of multiple cryptocurrencies like bitcoin, ripple, NMC by using features like open, low, and close. The dataset consists of over nine features relating to the cryptocurrency price recorded daily over 6 months. By using data preprocessing and examine the independent features in the dataset the highest price of the cryptocurrency was predicted.

Disadvantages: The process is only related to banking transaction and assets only.

Sean McNally et al. [11] presented a scheme for Bitcoin price prediction in USD using a Bayesian optimized recurrent neural network (RNN) and a Long Short Term Memory (LSTM) network. The LSTM achieves the highest classification accuracy of 52%. The popular ARIMA model for time series forecasting is implemented as a comparison to the deep learning models. The non-linear deep learning methods outperform the ARIMA forecast which performs poorly. Siddhi Velankar et al. [12] attempts to identify and understand daily trends in the Bitcoin market by gathering optimal features surrounding Bitcoin prices and plot a graph using normalization.

IV WORK FLOW

In this section the we have elaborated more regards the workflow of the cached paused bidding algorithm to get help for the transaction during the bulk order with the help of different distributed combination for completing the transaction between the banking and financial institute and digital currencies exchanges and vice versa.

C. Steps to triggered pause bid algorithm after bulk deal order get triggered.

- In this user has been performed the action to conversion of the assets or performed the action for the transaction.
- Then the task shifts to the load analyzer. The load analyzer has determined that weather the transaction is able to sustained the total number of transaction occurred. If the transaction is in bulk, then it will get triggered this will happen when situation such as panic transaction (in bulk) happen which make failed or rundown to deal with digital currency exchanges and financial institute.
- If the order is in bulk transaction, then load analyzer triggered to the bidding technique. The distributed combination has been generated.
- In the first stage there are only several transaction has been set called as bid set. With the bidder submitting bids on individual item In this case, an agent's dominant strategy is to bid higher than the current bid until it reaches its valuation for that particular item. Our algorithms focus on the subsequent stages: $k > 1$. When $k > 1$, agents have to find $g * i$. This can be done by performing a complete search on B . However, this approach is computationally expensive since it produces a large search tree. Our algorithms represent alternative approaches to overcome this expensive search.

$$g_i^S = \arg \max_{g \subseteq 2^B} u_i(g),$$

- In this technique only those transactions occurred successfully which are huge in process and it will take at least 12-24 hours to complete without failing to deal with different exchanges.

Paused Bidding Algorithm.

According to the PAUSE auction, during the first stage we have only several English auctions, with the bidders submitting bids on individual items. In this case, an agent's dominant strategy is to bid higher than the current winning bid until it reaches its valuation for that particular item. Our algorithms focus on the subsequent stages: $k > 1$. When $k > 1$, agents have to find $g * i$. This can be done by performing a complete search on B . However, this approach is computationally expensive since it produces a large search tree. Our algorithms represent alternative approaches to overcome this expensive search.

II. PROPOSED SYSTEM

• DATA

Here in this sample data set has been used for transaction and these data has been released randomly to test and trained the algorithm (Paused bid algorithm) to check the performance. How it will get react during bulky or less transaction loading and this transaction has been monitored and results get obtain in graph.

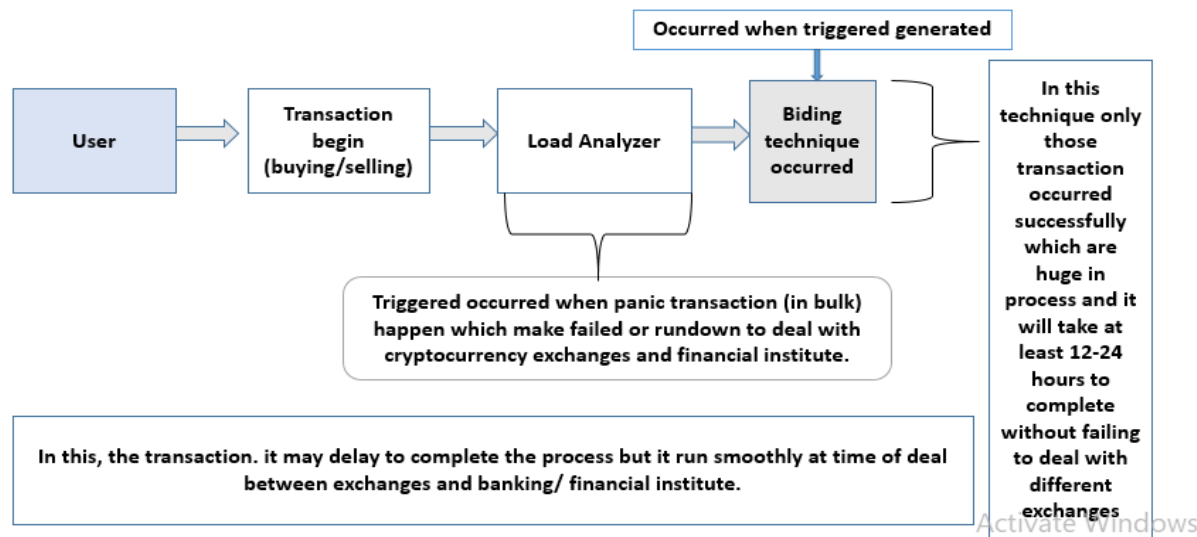
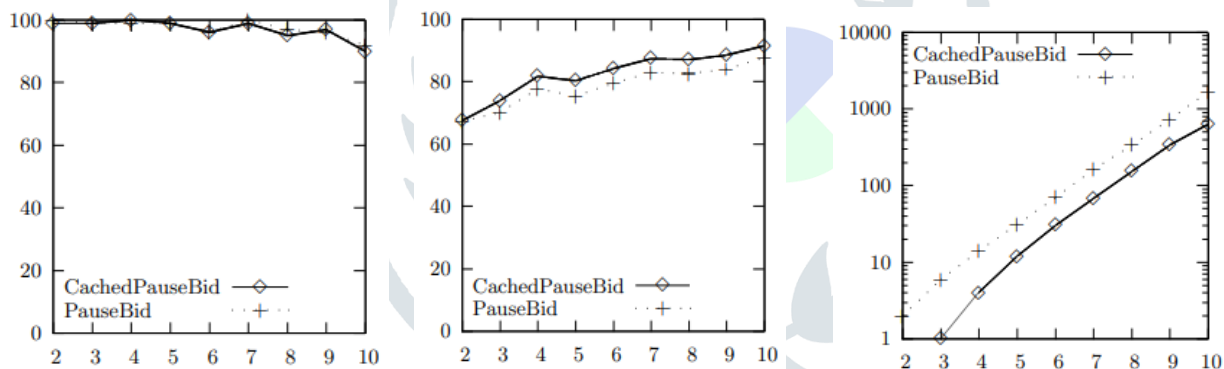


Figure: - System Architecture.

III. ACKNOWLEDGEMENT AND RESULTS

Our motivation is during the bulk transaction between the digital currencies and financial institute has to be run smoothly with the help of bidding technique and the highest value determination problem and with the help of load analyzer the bidding technique has been occurred which take action to handle every bid and compare with the other bid with agent 'i' and every value of bid as been compare with other bid set. the running time of our algorithm remains exponential but it is significantly better than a full search. Pause bid performs a branch and bound search completely from scratch each time it is invoked.



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