An Agent-Oriented, Blockchain-Based Design of the Interbank Money Market Trading System

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Abstract. When studying the interbank money market (IMM), it is common to model banks as agents interacting through loans to tackle its complexity. However, the use of agent abstraction in the IMM is mostly limited to some specific cases. Besides, recent advancements show that it is promising to use blockchain technology to improve its security in a decentralized way. Based on this observation, this paper proposes an agent-oriented, blockchain-based design of the IMM trading systems, where the main objective is to decide on the times and methods of liquidity supply and demand by various market players based on what has been learned from the information available. The models in this paper are suitable for use by both academics and practitioners in this field.

Keywords: Interbank Money Market (IMM), Agent-Oriented Software Engineering (AOSE), Belief-Desire-Intention (BDI), Smart Contract

1 Introduction

The interbank money market (IMM) reallocates liquidity from banks with excess to banks with a deficit via borrowing and lending money at interbank rates. Therefore, the IMM plays a fundamental role in the proper functioning of the banking system and the economy as a whole. The following facts about IMM explain the complexity of decisions in this environment: (i) the secured (collateral-based) and unsecured (trust-based) methods of liquidity provisioning are varied [1,2]; (ii) the overall demand for short-term liquidity is stochastic [3,4]; (iii) there is always the likelihood of domino failures of tightly connected competitors (banks) who lend themselves vast amounts of liquidity [5,6]; (iv) it is difficult to access sufficient information from market members [7,8]. Moreover, when the central bank intervenes in the market by buying or selling government securities to expand or contract liquidity in the banking system, the decision-making process becomes much more complicated. This complexity affects the decisions of both the central bank as the regulator and banks as active competitors in the market.

Besides, for sending the funds between the banks, the centralized SWIFT[1] protocol that simply sends the payment orders is used, and also loan agreements between banks ultimately lead to binding contracts for the parties. A promising approach to tackle these issues is to use blockchain technology where an immutable, append-only, and decentralized ledger of transactions is maintained without a trusted third party (e.g., a central bank). Regarding IMM, blockchain technology has already been started to be adopted. In 2018, the first live securities lending took place with a $30.5M transaction between Credit Suisse and ING[2]. In 2020, in Italy, thirty-two banks had gone live with one of the first real-world deployments of enterprise blockchain technology in interbank financial markets[3].

To model such complex systems, a well-known approach is to use multi-agent systems [9]. The field of agents and multi-agent systems (MAS) dates back to the late 1980s and the shift in artificial intelligence (AI) to distributed AI [10,11]. However, since the late 1990s, MAS has developed a new method of analyzing, designing, modeling, and implementing complex, large-scale software systems [12,13]. Agents are software entities that are autonomous within their environment and are able to achieve social ability by exhibiting flexible, reactive, or proactive behavior [13]. These abilities are facilitated by an agent architecture, known as belief-desire-intention (BDI) [14], that can model cognitive reasoning.

Standing on these observations, in this study, two issues are addressed to improve the quality of decision-making in IMM. Firstly, since in a static model, the market configuration cannot quickly adapt to (un)intentional changes because the market design is predetermined [15,16], we propose a MAS model where the market can be dynamically rebuilt at runtime, resulting in a more nimble, flexible and stable system. Secondly, since recording loan transactions in a distributed ledger can lead to greater transparency, security, traceability, and efficiency and reduce costs arising from information asymmetry [17,18], we propose blockchain technology and its features for better designing the proposed system.

Concretely, the contributions of this paper are threefold: (i) an agent-based software architecture that supports all the functions and concerns associated with liquidity supply and demand; (ii) use of learning agents in system design; and (iii) use of blockchain as part of the architecture of the target system. To this aim, Section 2 gives background information about the IMM as a complex system and MAS applications in IMM. In Section 3, an agent-oriented, blockchain-based model of an IMM trading system is proposed. It also gives more details about the proposed architecture by providing an example covering both blockchain and learning. The main success scenarios based on this model are given in Section 4. Finally, Section 5 concludes the paper and gives future works.

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2 Background

2.1 IMM as a Complex, Large-Scale System

In an extensive financial market network, where each node represents several market operations, many entities interact non-linearly with each other, making it a complex system. The centralized IMM is where banks exchange funds with each other using centralized software solutions (central depository system (CDS), centralized trading systems (TS) of third-parties, etc.) to balance their books. In such a market, when the liabilities side of banks' books (e.g., deposits) is lower than the assets side (e.g., loans), they are forced to make up for their lack of liquidity by borrowing from those banks in the market whose liabilities exceeds their assets. This loan might be granted based on prior trust and the preferential relationship between the parties or by using an intermediary platform to connect lenders and borrowers.

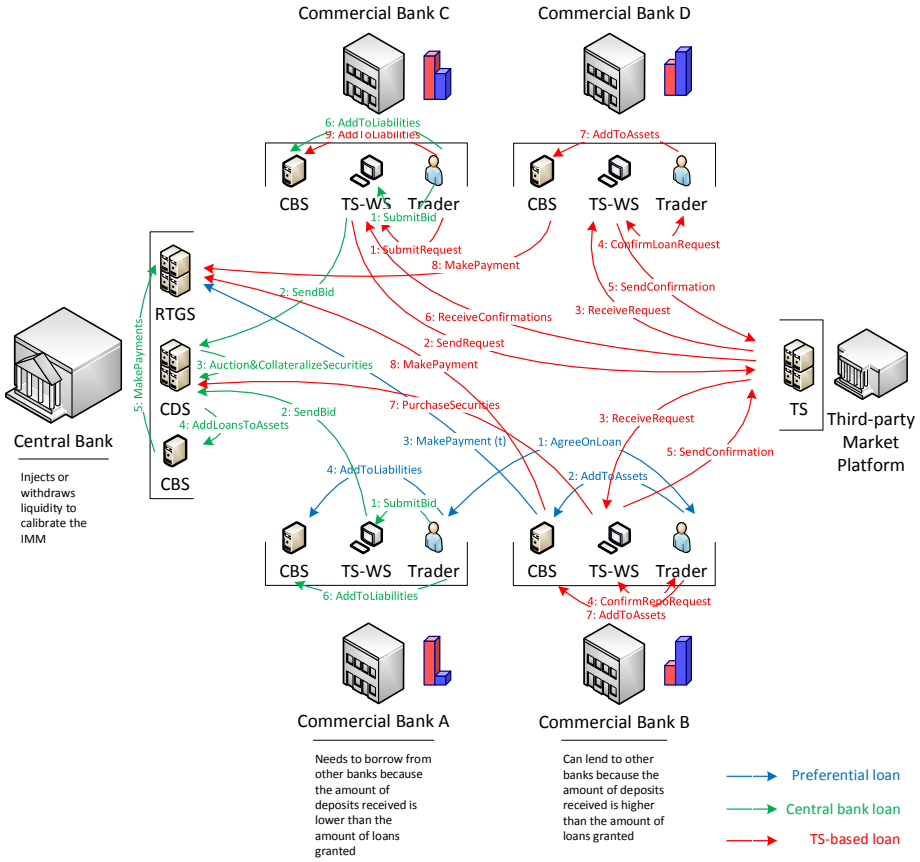

Fig. 1. The centralized approach of IMM lending.

Fig. 1 shows the three most common lending processes in a centralized IMM:

preferential (bilateral) short-term lending, central bank's long-term refinancing, and short- or long-term lending using third-party trading platforms. The first often includes unsecured overnight loans, and the last contains both unsecured short-term loans and secured long-term ones, as well as repurchase agreements (repo). Furthermore, central bank intervention is generally made in the form of long-term refinancing of banks against securities with them and through auctions.

In a centralized model, banks record their position loan data and related accounts in their own core banking systems (CBS), all payments are integrated with banks' CBSs and made by a central real-time gross settlement (RTGS) system, and securities and auctions are handled in the CDS. Also, banks require special workstations being used by their trading operators to connect to TS and CDS. It is worth noting that banks assess many counterparty risks and make their lending decisions using data provided by rating agencies and financial news providers, which are not shown in Fig. 1 for simplification.

Another aspect of complexity emerges in supporting the market participants' main concerns and their impact on banks' goals and decisions to supply and demand liquidity. In detail, the central bank seeks to reduce systemic risk and prevent financial contagion [2,5,19], as well as managing the network [1,4,7] in a way that makes the IMM more stable and resilient to shocks [1,2,6] to conserve confidence. At the same time, banks attempt to maintain their lending relationships [3,8] and reduce the risk of failure to meet the legal obligations [5,19].

2.2 MAS Applications in IMM

An approach to reduce the complexity of a system with such specifications could be to use a self-organizing multi-agent system [20]. In recent years, much partial research has been conducted using agent-based simulation on various concerns of IMM, i.e., systemic risk [19,21-24], stability [21,25], market structure [21,26], trust [27], and default [19,28]. To the best of our knowledge, except for a few studies on interbank payment and settlement systems [29-31], a serious complete work may rarely be found on designing an agent-based architecture that can cover all the IMM functions and help to make decisions. Also, the number of studies in which banks have been modeled as intelligent agents is very limited [7,15,19,25,32].

Indeed, a BDI approach, which is able to model each bank's individual concerns, coupled with machine learning, could be useful to improve banks' ability to predict and achieve a competitive equilibrium among market participants. Because the IMM consists of different banks with different and sometimes conflicting goals and proprietary information, a BDI MAS is an excellent option to model their interactions. From a problem perspective, the IMM is a dynamic, complex, and technically open environment in which interaction takes the form of both negotiation and deliberation. From a solution perspective, all three facets of data, resources, and tasks are distributed in the IMM. These features determine that this approach is appropriate for IMM [33].

Also, because loan agreements between banks ultimately lead to binding contracts for the parties, a smart contract that is non-repudiation and transparent [34] could lead to a more reliable and trustworthy market. This explains a case where private data needs to be adequately protected in a distributed manner; thus, blockchain could be a potential solution.

3 The Proposed Model

3.1 Agent-based Model

The open architecture components of the proposed system are shown in the UML class diagram in Fig. 2. The architecture is designed to support emergent behaviors and performance of agents in a volatile environment so that they can provide a higher level of adaptability, discovery, and intelligence. In this approach, each bank has its intelligent agents, i.e., their learning mechanisms that learn their preferences. For instance, in the presence of many banks with different preferences, their agents could negotiate the optimal interest rates. Also, the central bank agents could enforce the regulations that must be considered by the bank agents as influential factors in the negotiations between them.

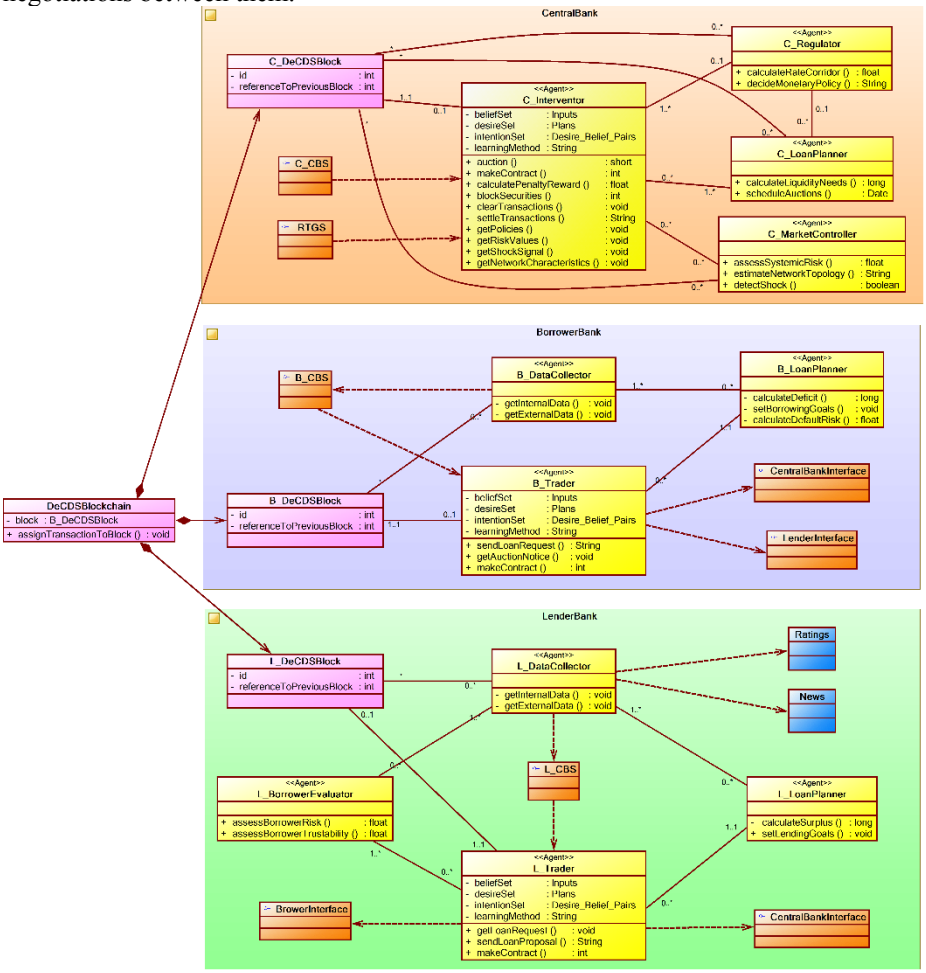

Fig. 2. The decentralized agent-based approach of IMM.

As shown in Fig. 2, the agents *B_DataCollector* and *L_DataCollector* at borrower and lender banks, respectively, collect information from data sources inside and outside the banks (e.g., news and ratings). Agents *B_LoanPlanner* at borrower banks and *L_LoanPlanner* at lender banks use this information to calculate the deficit or excess of liquidity and target loans. The central bank's similar agent *C_LoanPlanner* directly uses the data recorded in the bank's blockchain node to plan the total market liquidity needs and refinance it. Banks also use their collected information to assess their own and the counterparty's risks. This is performed at borrower banks via *B_LoanPlanner*'s operation *calculateDefaultRisk*, while at lender banks, agent *L_BorrowerEvaluator* is responsible for that.

The proposed architecture mainly focuses on negotiation behavior among a group of autonomous agents, e.g., how distributed agents negotiate their goals, achieve their goals through planning, etc. Therefore, an intelligent agent at each bank is responsible for negotiating with other banks' agents, meaning several exchanges of requests and proposals, and finally making a loan contract. This function is the responsibility of agents *B_Trader* and *L_Trader* at borrower and lender banks, respectively, and agent *C_Interventor* at the central bank.

As considered in agents *B_Trader* and *L_Trader*, each bank-specific learning method alongside the BDI model would ensure better predictions based on its past preferences and future goals because there is no need to learn all the preferences of all banks. It also means that the bank spends less learning time when faced with a new goal because it uses fewer data over fewer epochs.

The rationale for choosing BDI is that it allows us to model each bank's different beliefs, desires, and intentions, which may even be contradictory. Moreover, it has advantages for the implementation of agents with the characteristics of reasoning, communication, and planning [35,36]. It is also suitable for prediction and performance purposes [36]. The clear functional decomposition of the agent subsystem and the formal logic properties of BDI are the advantages of this agent architecture over other existing ones, such as traditional logic-based and reactive architectures [37]. In the proposed model, the BDI agent model's weakness of its inability to support the learning and decision-making characteristics of agents [36,38] is compensated through machine learning.

In this way, the bank agents present in this smart market take over the negotiation process according to their individual learning mechanisms and by calling each other's interfaces. If some banks have different preferences regarding, for example, interest rates, their agents would first calculate their preferences and then start the negotiation process with other agents, where they must consider the extent of the differences between their preferences. The learning methods that can be applied by each bank are not specified at this level but can include a range of machine learning methods such as supervised, unsupervised, and reinforcement learning [39-41]. Combining these learning methods with the BDI architecture would lead to better decisions by market members [42].

As mentioned earlier, a similar learner agent (*C_Interventor*) at the central bank is responsible for market intervention. It uses information produced by other agents (i.e., open market operation objectives set by *C_LoanPlanner*, market variables monitored by *C_MarketController*, and regulations set by *C_Regulator*) to carry out auctions, lending against securities, clearance, and settlement. All data related to loan agreements

in the market would be recorded in a distributed general ledger realized by blockchain technology. This means that each bank, as a node in a consortium blockchain network, can participate in the consensus needed to record loan transaction data in blocks. Each bank's agents would also use these data as part of their input, playing a role in making their plans and decisions.

3.2 Blockchain and Learning

A blockchain is an append-only immutable data structure of transactions organized as a list of blocks linked using cryptography. It is maintained across several nodes that are linked in a peer-to-peer network (Fig. 3). A blockchain can manage a self-enforcing agreement embedded in computer code, which is called a smart contract. The smart contract code contains a set of rules under which the smart contract parties agree to interact with each other.

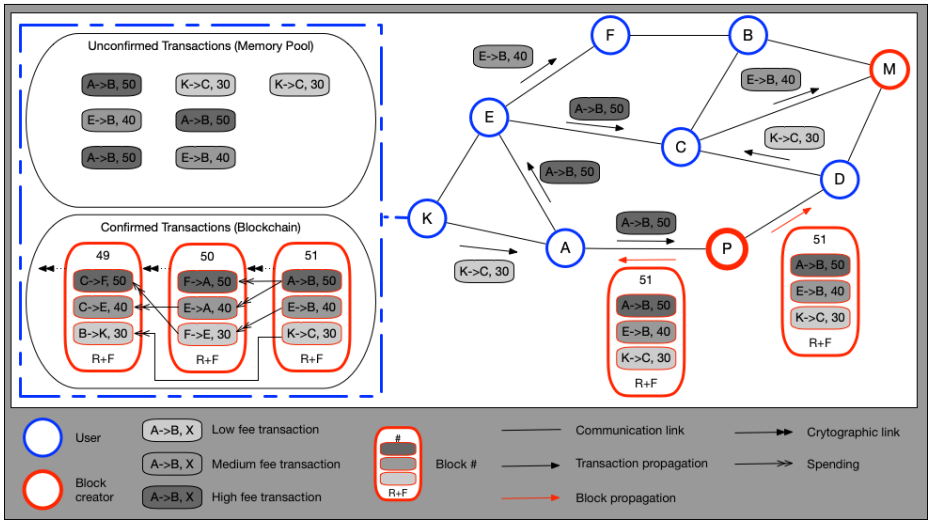

Fig. 3. Multi-Agent Representation of a Blockchain System [43].

In our study, we consider a blockchain consisting of $N = \{n_1, n_2, ..., n_m\}$ nodes (banks), of which $P \subseteq A$ are endorsing peers classified into p levels. Each bank uses blockchain for various data categories, e.g., submitting its smart contracts (loan transactions) or sharing common interest information, such as counterparty defaults. The endorsing peers examine these data before being written in the distributed ledger. The block could be written as $B = \{t_{i,j}\}$, where $t_{i,j}$ refers to the transaction j of data category i (corresponding to p levels).

Endorsers calculate each transaction's score by tracking the number, volume, riskiness, and impact of transactions. When two banks, which agree upon a smart contract and sign it with their private keys, want to add this new transaction to the blockchain, they must collect a minimum prerequisite score from endorsing peers (i.e., consensus). This score is obtained based on recommendations from other related nodes at the moment of submitting the transaction. It means that other nodes check the state

of the blockchain, including the exact contract code, and validate that those parties are whom they say they are. Also, a state transition function checks the behavior and the results of that code when it is executed.

Once a new block is created, all claimed transactions to be included in it are checked for legality by the consensus protocol, and transactions that fail to collect the required score for the selected level are discarded. To reach higher levels, the bank must increase its contributions to the blockchain and make high-impact, trusted transactions. To this aim, the bank uses intelligent mechanisms to make the optimized decision at the right time, based on the available network data as well as its own data. Adapted from Mbarek et al. [44], the score of a given transaction could be calculated according to formula 1:

$$S_l = \sum_{i=1}^{p} \left(\sum_{j=1}^{q} s_{l,j} \right) w_i \quad \textbf{(1)}$$

where, w_i denotes the weight of the endorsers of level i; $s_{l,j}$ is the score given to the loan transaction l by the endorsing bank j at the same level that accepts the transaction scoring request. Also, q is the number of required endorsers at that level.

In this mechanism, each member bank in the blockchain network has to establish trust with its peers, especially the endorsing ones. Trust relationships would be particularly helpful in gaining recommendations from higher-level endorsers. In the proposed system, the bank can intelligently identify its current options, plan its actions, and reflect on the results to establish and maintain trust and identify appropriate endorsing partners. As proposed in Fig. 2, learning is the responsibility of intelligent agents *B_Trader* and *L_Trader* at borrower and lender banks, respectively, and agent *C_Interventor* at the central bank.

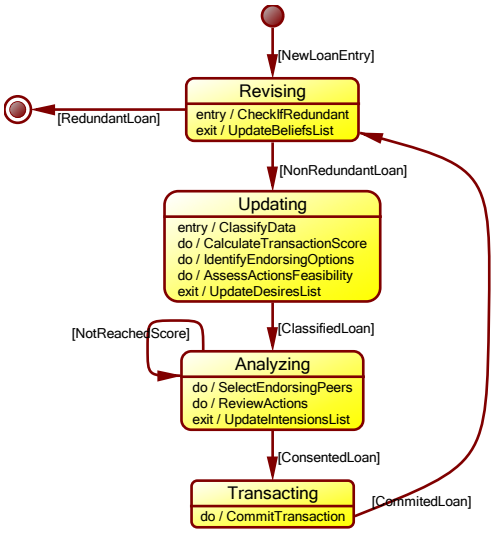

Fig. 4. States of a loan transaction registered in the blockchain.

Fig. 4 shows the UML statechart diagram of the loan registration in the system's blockchain, borrowed from its detailed design model. Based on the BDI architecture,

'beliefs' include information that the intelligent agent has about itself (e.g., its current liquidity, market strategies, default risk, etc.) and its surroundings (e.g., network structure, potential/actual banks for a relationship, and events of interest, such as other banks' defaults and announced auctions). The beliefs also include a copy of the blockchain containing data belonging to the categories to which the agent has access (state *Transacting*). Beliefs can be right or wrong and change over time as the market operates (state *Revising*). In this system, 'desires' reflect the objectives that the agent wishes to achieve and include such things as receiving/granting loans, sharing information, or accepting/refusing other agents' endorsement. Based on the new beliefs, the agent's desires must also be updated (state *Updating*). Finally, 'intentions' refer to the actions that the agent chooses to execute. For each possible action, the agent calculates the reward, cost, priority, etc. Once a set of possible actions is identified, the agent analyzes the calculated results to prepare and execute an action plan (state *Analyzing*). The output of the actions is assessed, and the intentions of the agent are updated accordingly.

4 Main Scenarios

In this section, UML sequence diagrams are used to describe how and in what order a group of agents work together in the proposed system to execute the most common IMM scenarios according to Liu et al. [15], Barroso et al. [19], and Gurgone et al. [21]. We model two scenarios: one for overnight lending based on trust among banks and another for long-term refinancing by the central bank against banks' securities.

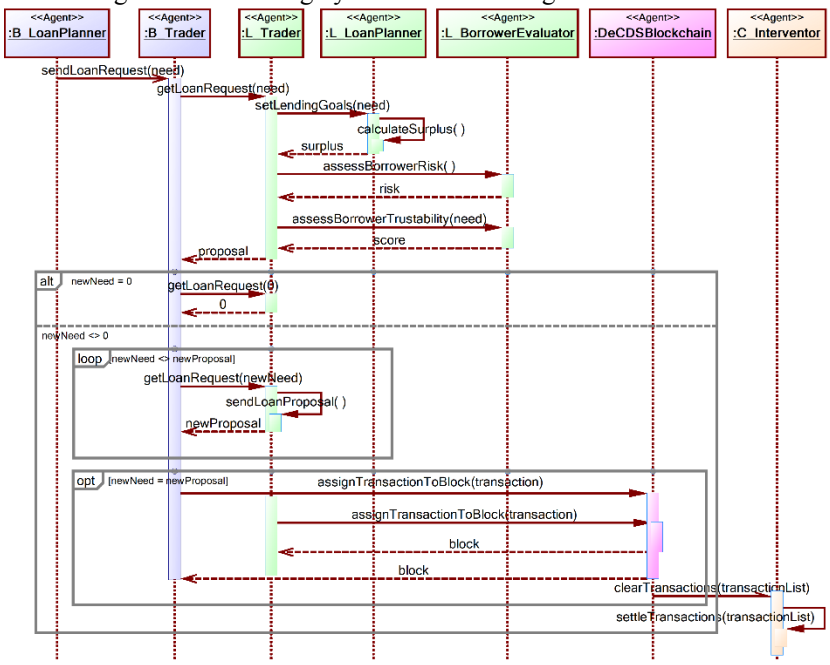

Fig. 5. Agent-based Scenario for Overnight Loans.

For the first scenario, as shown in Fig. 5, the borrower bank's agent *B_Trader* uses *need* data generated by agent *B_LoanPlanner* and sends its request to the lender bank's agent *L_Trader*. To decide on the loan terms and conditions, *L_Trader* inquires the liquidity *surplus* as well as the borrower bank's credit *risk* and trust *score* from agents *L_LoanPlanner* and *L_BorrowerEvaluator*. According to the results of these inquiries, *L_Trader* suggests loan terms (e.g., interest rate) to *B_Trader*. This offer is based on all that *L_Trader* has learned so far about the overnight loan in the smart IMM.

After receiving a *proposal* from *L_Trader*, based on what *B_Trader* has learned, it may immediately accept or reject the offer or enter into a negotiation process with *L_Trader*. As mentioned earlier, the negotiation is based on the learnings of the two agents from their past, market conditions, and other players' behavior and progresses in the form of changing goals and preferences. In any case, if no agreement is reached, the process ends here; otherwise, if the negotiation between the two agents succeeds, a smart contract would be made, which would be recorded in a *DeCDSBlockchain block* of each of these two banks as well as other market members.

Finally, the agent *C_Interventor* at the central bank would perform clearance and settlement of the banks' *transactionList* at the end-of-day based on the information recorded on the smart contracts. Also, the systemic effects of banks in the IMM network could be evaluated by this agent based on these smart contracts, and if one bank's transaction is accordingly subject to a reward or penalty by the central bank, the amount is calculated and deducted from that bank's account with the central bank.

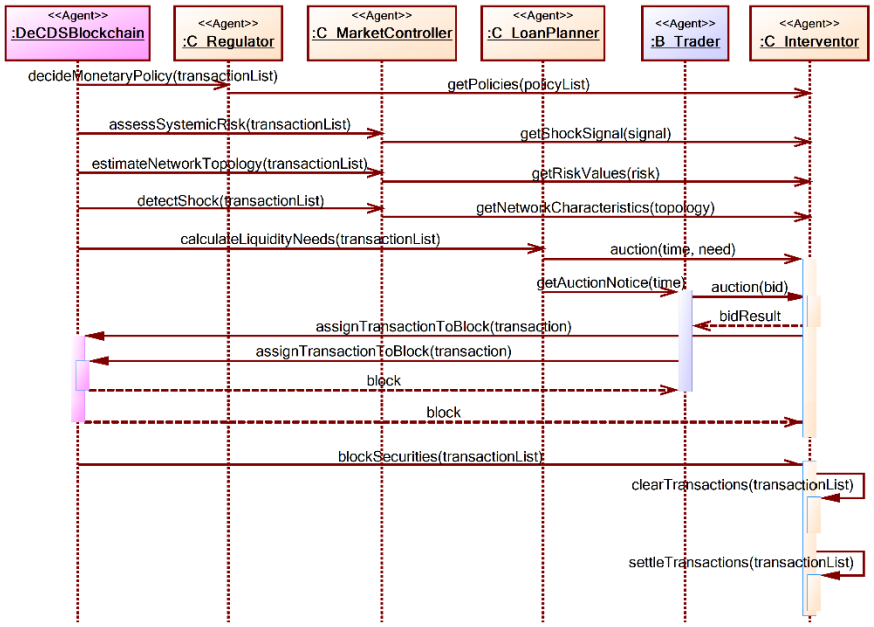

Fig. 6. Agent-based Scenario for Central Bank Refinancing.

The second scenario, in Fig. 6, starts from the central bank. First, *transactionList* stored in the central bank's *DeCDSBlockchain* blocks is used to determine *policyList* by agent *C_Regulator* as well as calculating systemic *risk*, estimating network

topology, and detecting possible shock *signal* by agent *C_MarketController*. Similarly, agent *C_LoanPlanner* determines market *need* using *transactionList* and specifies *time* for auctions. *C_Interventor* then receives the results of calculations by these three agents as well as *B_Trader*'s *bid* for the central bank's loan. After auctioning and determining the winners, if a loan is granted to the bank, *C_Interventor* notifies *B_Trader* of *bidResult*.

Like the first scenario, a smart contract would be made between *C_Interventor* and *B_Trader* and stored in a *DeCDSBlockchain block* of the central bank and the borrower bank, as well as other market participants. The central bank would employ the information stored in the form of these smart contracts to clear and settle the borrower banks' *transactionList*. Also, the central bank and the other banks use the information recorded in these smart contracts in their future forecasts and plans.

5 Conclusion and Future Works

This paper describes a software architecture that uses intelligent agents to execute the interbank market functions and make decisions on behalf of the market actors. In this proposed solution, the BDI architecture is employed to model the cognitive part of the agents and execute goal-based scenarios. Also, data obtained from the interbank lending transactions are recorded and stored in a consortium blockchain platform, of which the banks and the central bank are nodes. To better understand the designed agents and the mechanisms of using information and learning, some of the most widely used IMM scenarios have been modeled using the UML diagrams.

The main limitation of the work is that only a high-level design is presented, and no part of it has yet been implemented and tested to validate the proposed architecture and ensure performance. Therefore, the next step is the detailed design and implementation of the proposed system prototype. In addition to the full realization and testing of the system, further studies could also be directed at improving the system's machine learning aspect, alongside the greater use of blockchain in designing the new processes required for trading the new financial instruments such as crypto-securities. Agent-based modeling and simulation of the desired system in which agents can learn from each other and their past data when loan transactions are stored in a blockchain network is another topic for future work.

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