INTERBANK PAYMENT SYSTEM (RTGS) SIMULATION USING A MULTI-AGENT APPROACH

Hedjazi Badiâa[1], Ahmed-Nacer Mohamed[2], Aknine Samir[3] and Benatchba Karima[4]
[1]*Information Systems Division, CERIST Research Center on Scientific and Technical Information, Algiers, Algeria*
[2]*Information Systems Laboratory, USTHB University, Algiers, Algeria*
[3]*GAMA Laboratory, Lyon 1 University, Lyon, France*
[4]*ESI, National High School of Computer Science, Algiers, Algeria*

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Abstract: This work consists in simulating a real time interbank gross payment system (RTGS) through a multi-agent model, to analyze the evolution of the liquidity brought by the banks to the system. In this model, each bank chooses the amount of a daily liquidity on the basis of costs minimization (costs of liquidity and delaying) by taking into account the liquidity brought by other banks. Banks agents' strategies are based on a liquidity game during several payment days where each bank plays against the others. For their adaptability, we integrate into bank agents learning classifier systems. We carry out several simulations to follow the system total liquidity evolution as that of each bank agent with varying costs coefficients. The question to answer is: what are the cash amounts that banks must provide and under what costs of liquidity and delaying, the system avoids the lack of liquidity? We find that liquidity depends on costs coefficients.

1 INTRODUCTION

Real Time Gross Settlement systems (RTGS) are real-time funds transfer systems that enable banks to make large-value payments to one another (Devriese and Mitchell, 2006) (Leinonen, 2005) (BIS, 1997). Exchanged Liquidity (funds) carries "*cost of liquidity*" proportional to liquidity amount. Delayed payments imply a "*cost of delaying*". Therefore several questions arise. How much liquidity must a bank engage? What are the best values of costs' coefficients? Cost of liquidity coefficient is the interest rate paid to central bank and delaying cost coefficient is a penalty. We simulate RTGS using a multi-agent system (MAS) to show the relationship between liquidity and costs while evolutionary game theory (EGT) (Thisse, 2004) formalizes interbank strategies. Section 2 presents RTGS, section 3 existing works, section 4 our model and section 5 simulation results. We conclude in section 6.

2 RTGS FUNCTIONING

Figure 1 shows the functional architecture of a RTGS system: (1) A bank B_i submits a payment order to RTGS. (2) Order is either executed or queued. (3) Payment is transmitted to receiver bank B_j account. (4) RTGS informs receiver bank on the transfer (Bank of International Settlements, 1997).

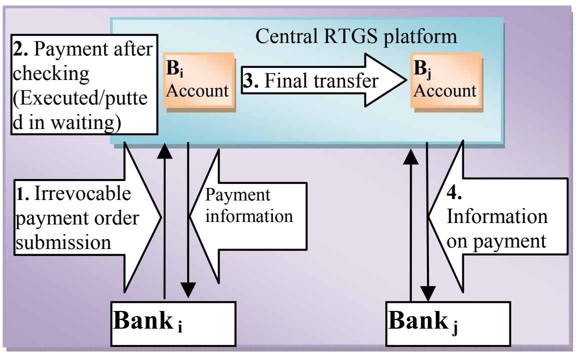

Figure 1: RTGS system architecture (Beyeler et al., 2007)

3 RELATED WORK

Several researchers developed mathematical simulation models of payment systems (Koponen and Soramäki, 1998) (Leinonen, 2005) (Devriese and Mitchell, 2006). In the mathematical approach,

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payment systems are represented through differential equations and banks behaviour is not endogenously determined but assumed unchanged. Contrary to this, multi-agent simulation describes entities behaviours explicitly (Arciero et al., 2009) and considers system total dynamics resulting from entities interactions (Parunak et al., 1998).

In (Galbiati and Soramäki, 2007) model, orders are of 1 unit only, and agents are assumed knowing all banks' past choices, which is unrealistic.

Game theory studies situations in which each participant (assumed rational) fate depends on its decisions and the others participants' ones (Angelini, 1998). RTGS mechanisms are seen like games where players are the banks. Evolutionary game theory assumes that players are with bounded rationality and remained strategies are those obtaining the largest gains over time. In the models of (Arciero et al., 2009) (Bech and Garratt, 2003) (Bech and Garratt, 2006) (Galbiati and Soramäki, 2007), players' utility is static and known in advance. In addition, these models cannot provide information on each entity and cannot run historical or random data or represent components as by MAS.

4 PROPOSED RTGS MODEL

In our agent-based model, a collection of banks have different payments during several days. Choices of a bank agent are formalized by an evolutionary game where a bank chooses a liquidity based on costs of liquidity and delaying and the other banks choices.

4.1 Liquidity Game of the System

Our liquidity game is inspired from aggregate game (Mezzetti and Dindos, 2006) where a player considers the others as a single opponent. Our game consists of a set of N banks. Each new day, a bank chooses its liquidity $l_i(0)$ for its payments. Each bank estimates the other banks average liquidity l_{-i} through its neighbours. For bank i, the number of payment orders received up to time t is $z_i(t)$. Number of orders executed until time t is $x_i(t)$. Payment orders number in queue at t, $q_i(t)$, is defined by (1):

$$q_i(t) = z_i(t) - x_i(t) \quad (1)$$

Payment orders are executed using the available liquidity which is defined by (2):

$$l_i(t) = l_i(0) - x_i(t) + y_i(t) \quad (2)$$

$yi(t)$ is the payments amount that bank i received until time t. Payments are executed in FIFO. Initial liquidity $li(0)$ imposes to bank i a liquidity cost (3):

$$C_l(l_i(0)) = \alpha \times l_i(0) \quad (3)$$

$\alpha \in [0, 1]$, is cost coefficient of liquidity. Payment received at time $\boldsymbol{t_r}$, executed at $\boldsymbol{t_e}$, queued for $\Delta t = t_e - t_r$, imposes to bank i a cost of delaying (4):

$$C_r(t_r, t_e) = \beta \times \Delta t \times Payment\_amount \quad (4)$$

$\beta \in [0, 1]$ is the cost coefficient of delaying. The global bank daily cost is the sum of the costs (5):

$$C = C_r + C_l \quad (5)$$

As the costs' bank increase its profitability decreases. Player i utility depends on its action $\boldsymbol{l_i}$, the others average actions $\boldsymbol{l_{-i}}$ and costs coefficients.

4.2 Multi-agent System Model

At the central level of our RTGS model, payments are settled with liquidity brought by banks on their RTGS accounts. Payment order with insufficient account balance is rejected. Each bank manages its own waiting queue. Our MAS model contains an "RTGS agent" and "Banks agents" BAi (Figure 2).

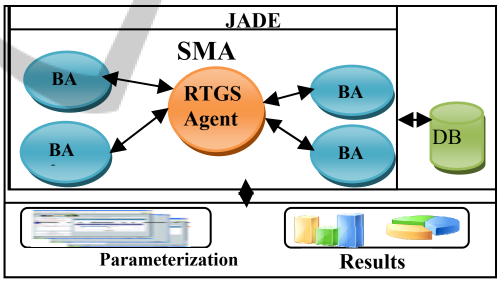

Figure 2: General representation of the system.

4.2.1 RTGS Agent (RA)

RA is a reactive agent and represents the central payment system (Figure 3). For each day, RA receives and liquidity amounts of banks agents. RA Processes banks agents' payment orders (debits and credits banks accounts).

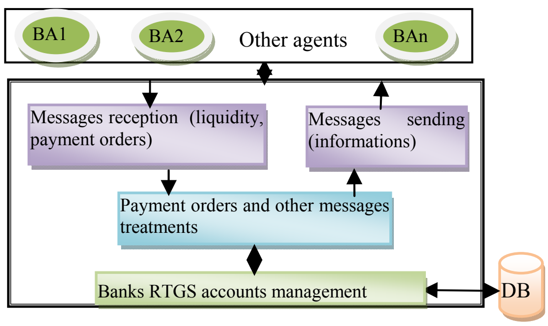

Figure 3: RA internal architecture.

4.2.2 Banks Agents (BA)

BA exchanges payments through RA with liquidities chosen at the beginning of each day. BA sends random payment orders to RA and manages its waiting queue. At the end of the day, it calculates costs and starts a learning process. BA is cognitive. It learns playing game to minimize costs and improve utility with classifier systems (CS) of LCS type (Holland, 1987). LCS is appropriate because banks evaluate actions periodically to learn quickly. BA is built on: (1) CS1 gives the others average liquidity. (2) CS2 defines liquidity (Figure 4).

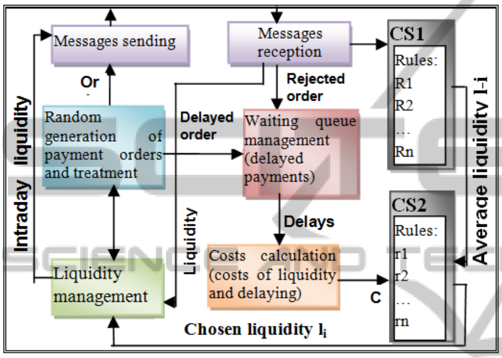

Figure 4: BA Internal architecture.

1st classifier system (CS1): CS1 estimates the others average liquidity. Each day, each agent observes the liquidity chosen by a reduced *number* (eg. 3) of neighbours chosen randomly. CS1 generated value is used as entry for CS2 to choose liquidity. CS1 rule is composed of three parts:

Condition Part: has 3 attributes (*Lbx*, *Lby*, *Lbz*) representing the 3 liquidity values of selected agents. These values are in the interval [0, 15]. So this part requires 12 bits (4 bits for each attribute).

Action Part: is coded on 4 bits, corresponding to average liquidity l_{-i} of the other agents in [0, 15].

Rules Reward: Rules are remunerated when neighbours liquidity values are close to the average.

Dispersion coefficient is calculated then between the three values of the condition and the action value.

$D(x) = \frac{\delta(x)}{x}$ Where $\delta(x)$ is the standard deviation.

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If D(x) < 0.15 Then reward=1 Else reward=0;
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2nd classifier system (CS2): CS2 allows intraday liquidity choice. The system evaluates costs (of liquidity and delaying) at the end of the day and chooses liquidity. CS2 rule consists of three parts:

Condition Part: has 2 attributes (real numbers), cost of liquidity C_l and cost of delaying C_r. C_l (Integer part in [0, 15], decimal part in [0, 99]). C_l is on 11 bits (4 for integer part, 7 for decimal one). C_r (Integer part in [0, 1000], decimal part in [0, 99]). C_r is on 17 bits (10 for integer part, 7 for decimal part).

Action Part: on 4 bits, represents the intraday liquidity l_i to be chosen in the interval [0, 15].

Rules Reward: CS2 reward depends on the action l_i, the average l_{-i} of the neighbours obtained by CS1 and the costs of liquidity and delaying (6).

$$reward = \frac{\frac{1}{|l_i - l'|} + \frac{1}{C_l + 1} + \frac{1}{C_r + 1}}{3} \quad (6)$$

With l'= l_{-i}. The reward is divided by 3 to limit it to 1. CS2 rewards actions generating less costs and which liquidity approaches l_{-i}.

Liquidity game strategies correspond to CS2 rules actions and utility corresponds to CS2 reward.

Heterogeneity between BA agents' is assured by: (1) Rules of CS1 and CS2 are initialized randomly for each BA. (2) Random neighbours of a BA.

5 SIMULATIONS

MAS' implementation has been done using JADE platform and CS with ART (Artificial Reasoning Toolkit).Our simulations duration is 1000 days with 10 BA then 20 BA and different α and β values.

Figure 5 shows the global liquidity evolution of 10 BA. For all our simulations, we notice that liquidity and total cost of delaying (Figure 7) stabilize at certain values. This shows that agents performed successfully their coordination leading to satisfaction. As costs coefficients increase, total liquidity becomes unstable. We notice that coefficient β destabilizes liquidity more than α.

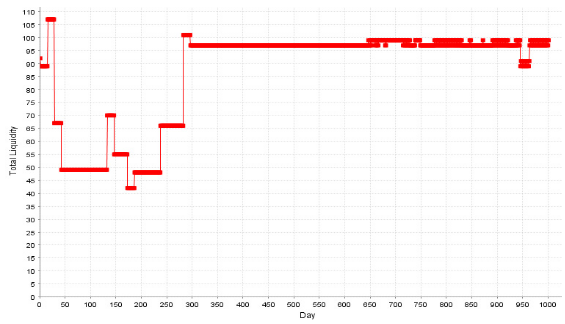

Figure 5: Global liquidity (for 10 BA) α =1%; β=10%.

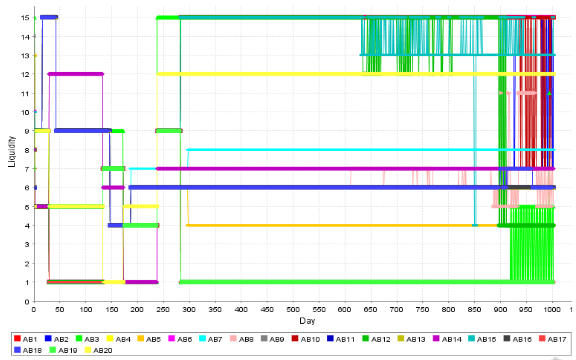

Figure 6: Liquidity of the 20 BA α =1%; β=10%.

Figure 6 shows that liquidity value for each BA is more stable when *α* and *β* are small and that β coefficient influences the system evolution more than α. Figure 7 shows total cost of delaying. We notice that as the number of BA increases, the cost of delaying decreases. This indicates that more there is sources of liquidity, less there is delaying.

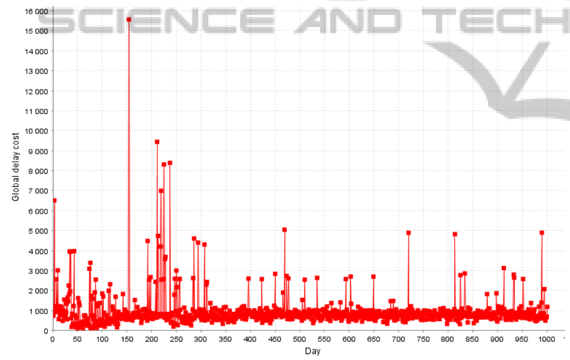

Figure 7: Cost of delaying of 10 BA α=10%; β=10%.

These results show that the best configuration of the coefficients is α=10%; β=1%. For these values, global liquidity is more stable. BA agents propose closer liquidity values and minimized costs of delaying. All these experiments show that efficient RTGS management is possible with smart choices of costs coefficients. They also help to determine daily liquidity values that stabilize the system and allow RTGS decision makers implementing policies specifying liquidity values that banks must choose.

6 CONCLUSIONS

In this paper, we have presented a multi-agent model for simulating RTGS systems. This model has been implemented and tested with different parameters. Our tool can be used as a decision support system by adapting it with real RTGS data in the codification of real liquidity and cost values in CS rules. Decision support is possible by searching liquidity values, costs coefficients that cause stabilities or instabilities. Our simulation model is intended for central banks, private banks, specialists or any person interested by RTGS systems. Some improvements could be added to this work such as: (1) considering payments of different priorities; (2) taking other parameters such as bank reputation.

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