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A study on the circulation and retention levels of a Digital Social Currency using an Agent-Based Model

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***Abstract*—*Social currencies are increasingly present in several countries around the world. From management point of view, this phenomenon means that issues such as currency circulation and retention have to be addressed by local managers. In this paper, we propose the Agent-Based Model as a strategic management tool for social currencies. To do so, we introduce a case of using this approach combined with reinforcement machine learning to study the circulation and retention levels of the Sarafu Digital Social Currency from Kenya. The use of this model to study these two aspects that, at first, antagonize one another, allowed us to obtain indicators on the existence of a currency users behavior that contributes to the increase both of the circulation and retention levels. Those indicators can help Digital Social Currency systems managers to elaborate better strategies related to the circulation and retention levels, increasing the social benefits produced by the currency use in the community. The use of an Agent-Based Model to simultaneously address two aspects of the social currency allowed us to study the interactions between those two aspects and constitutes a novelty, since all the cases found in the literature using this model in this field are focused on a single aspect of the currency*

I. INTRODUCTION

Social currencies, also called local, community or complementary currencies are increasingly present in several countries around the world. In 2002, approximately 5,200 communities in 58 countries used social currency systems [1]. Social currency managers need to address, at a local level, topics normally addressed at a national level, such as currency circulation and retention.

The purpose of this paper is to present the potential of the Agent-Based Model (ABM) as a strategic management tool to social currency managers through an example of its use in the study on the circulation level and the retention level of the Sarafu from Kenya, a Digital Social Currency (DSC) based on blockchain technology issued by Grassroots Economics for the distribution of humanitarian aid.

Retention and circulation are seen as two antagonistic aspects of a currency, since common sense suggests that the lower the retention the greater the currency circulation. Some social currency systems even apply penalties, known as demurrage fees, for retaining the currency [2]. But the use of an ABM to study, through simulations, those two aspects allowed us to shed new light on the interactions between them, which would hardly be allowed by another methodological approach.

Social currencies are exchange instruments parallel to the national currency, issued by civil society with the aim of promoting sustainable development [3]. In addition to its use as a unit of account, that is, as a reference for exchanges and an instrument for appreciate goods, their use is restricted to a certain territory [4].

Several social currencies are going through a digitalization process and within this process there is an increasing adoption of DSC based on blockchain technology, creating the so-called social cryptocurrencies [5][6].

In this context, the Sarafu Currency is one of the most significant examples of social cryptocurrency used for local economic development and improvement of living conditions, being the object of study in numerous papers.

The process of creating Sarafu Currency was born in 2010 with Eco-Pesa, whose purpose was to be an ecological currency, used as payment for services of garbage collection, tree planting and accepted as payment in the registered commercial establishments' network. After seven months of use, the results obtained were 20 tons of garbage collected, thousands of trees planted and a 20% increase in sales from registered traders. The creators of Eco-Pesa later founded Grassroots Economics (GE) and over the next few years launched many social currencies in economically excluded communities in Nairobi and Mombasa [7]. One such currency was the Bangla-Pesa, which promoted a 22% increase in sales at local stores in just one week[8].

Another example was Sarafu-Credit, a social currency based on vouchers issued through zero-interest loans, backed by the assets of cooperative companies created with the help of GE. At the time Sarafu-Credit was being created, the Kenyan government accused Grassroots Economics of conspiring to undermine the national currency. GE won a court-case in 2013, proving the legality of Sarafu-Credit and the currency was implemented that same year, but it still had to deal with issues such as lack of trust and commitment from users before it took hold and incorporated the other currencies issued by GE [9].

In 2017, all currencies issued by GE merged into Sarafu-Credit. This unified currency was important in ensuring food security in communities in Kenya, where people who used the social currency consumed 78% more food than those who did not [10].

The Sarafu-Credit digitalization process began in 2018 with an approach that merged mobile payment technology with blockchain.Such approach allowed currency units in the form of tokens to be exchanged between electronic wallets installed in cell phones. A text messaging technology was also used to allow access to the system for a larger number of communities' residents in Kenya who had cell phones without internet access [11].

This digitization process has reached an important milestone in 2019, when the Sarafu system returned on being a system of multiple digital social currencies. However, in January 2020, with the goal of saving costs, the blockchain-based digital currency platform on which the currencies were been issued needed to be replaced, that forced the switch from a multi-cryptocurrency system to a single-cryptocurrency system, the Sarafu Currency. Also in early 2020, GE officially formed a partnership with the Danish, Norwegian and Kenyan Red Cross Societies, which enabled the coming through of a pilot project using Sarafu currency in Mukuru, one of the largest slums in Nairobi. The project became an important response system to the effects of COVID-19 [7].

The use of Sarafu Currency in money transfer programs in Kenya throughout the Covid-19 pandemic has evidenced that even a small-scale transfer of social cryptocurrency can have a significant impact for recipients. There were, for example, increases in several socioeconomic indicators in the communities attended, such as an increase of US$ 93.51 in the accounts' balance of these programs' beneficiaries, of US$ 23.17 in the amount received monthly in social currency, of US$ 16.30 in monthly expenses using Sarafu, of US$ 6.31 in the average trade values made in DSC and of US$ 28.43 in expenses with food and water. One of the characteristics of the money transfer programs that used the Sarafu Currency is the charging of retention fees (or demurrage fees) to decrease the currency retention level in order to increase its circulation level [12].

This paper aims precisely at studying how the levels of currency retention and circulation interfere with each other. For this, we used an ABM, which is a computational methodology that simulates systems of multiple interacting agents [13]. This methodology can also incorporate behavioral assumptions to assess the consequences of interactions between those agents to model the real world [14], and allowed us to study how the interactions between the currency users produce both the retention and the circulation of the currency. From now on, we will refer to currency users as "agents".

ABM has already been used in some studies on social currencies, which allows us to state that this is a promising approach. An ABM was used to estimate how the introduction of a social currency could accelerate economic processes in an agricultural region of the Russian Federation [15]. Another was used to analyze the parameters of a community currency in an Oregon county, USA, in order to assess its impacts on the region's average household income [16]. The circulation of a community currency in mountainous areas of Japan was examined by the use of an ABM [17]. However, in the cases presented, the results produced by the models were focused on only one aspect of the use of DSC, be it the acceleration of processes, the impact on family income or the circulation of currency. In the present study, the ABM simulations were used to obtain indicators on two aspects of DSC, the level of currency circulation and the level of currency retention, in order to study how they influence each other, based on the analysis of behaviors and of the interaction that produce them.

From the results obtained in this study, we noticed that an agent behavior that contributes to the increase of currency retention can also contribute to the increase of its circulation, indicating that there are situations in which these two aspects do not antagonize each other.

The following section of this paper describes Agent-Based Model, reinforcement machine learning and how we measured DSC circulation and retention levels. In the sequence, we will present the results obtained and discuss them. Finally, we will talk about the conclusions.

II. METHOD

To carry out our research, we used an Agent-Based Model, which is an innovative approach because it goes from micro to macro, that is, from the agents' individual and independent actions it produces the systemic behaviors studied. Therefore, it opposes traditional approaches, which goes from the macro to the micro and takes the object of study to break it into smaller parts, based on assumptions that cannot always be verified in the real world. Besides, ABM assumes that reality is complex and non-linear, that small causes do not always result in small effects and that causes do not accumulate in a stable way [18].

ABM usually consists of input validation, simulation, calibration/descriptive output validation and prediction/predictive output validation [19].

In the input validation phase, we collected the necessary information for the construction of the ABM, such as what types of agents exist and how each type behaves in relation to the aspects of DSC studied. This information must come from real data and from previous studies, which can be both quantitative and qualitative. That's why this phase is described as a validation in the theoretical level, which aims to make the model consistent with the theory on which the modeled system is based [20]. The information resulting from this stage, besides being the basis for the construction of the ABM, can be useful to DSC managers, since they present a picture of the aspects studied and the behavior of agents at the time the study is carried out.

Simulation is the phase in which a computational algorithm emulates a real system, through the execution of subroutines that emulate the system's agents. Such subroutines, in turn, perform operations to reproduce the agents' behaviors, according to the parameters specified in the input validation. During the simulation phase, we have full control over the agent's behavior and over the conditions of the environment, allowing us to carry out experiments. We can also follow the simulation process step by step [21]. The results of the experiments can provide DSC managers with indicators on how changes in the behavior of agents and in the environment parameters would affect the studied currency aspects. Following the simulation process step by step allows the identification of important factors for the construction of systemic behaviors. These two characteristics were fundamental to reach the result presented in this paper, as will be seen forward.

In calibration phase, we change the agents' features and behavior, the environment parameters and the model itself in order to make the results of simulation being close to results from the real world [13]. Calibration incorporates descriptive output validation, defined as a process of comparing the data produced by the simulations with the real data [19].

To carry out this phase, we will use reinforcement machine learning, which is a method that allows identifying patterns through a trial and error approach [22]. This method consists of simulation, comparison of simulated values with real values and application of adjustment factors to input parameters.

The results of the processes of this phase allow DSC managers to better understand how the studied currency aspects are built from the interactions between agents. It also allows discovering behaviors that, at first, had not been noticed. Finally, it allows the comparison of numerous combinations of input parameters, as it assumes that there is no single "optimal" combination to obtain a result, that is, it admits that different combinations of parameters can lead to similar results [23]. For instance, the currency circulation level depends on the value and quantity of transactions as well as the value and quantity of benefit deposits. The reinforcement machine learning algorithm will test many combinations of these four parameters, identifying which ones produce the best results, until it finds one that produces currency circulation levels close to those seen in the real world.

The last phase of the Agent-Base Model is prediction/predictive output validation. The objective of prediction is to estimate a value or set of values at a future time, however, an ABM can also produce more qualitative predictions about the behaviors associated with the studied aspects, or about the agents' reactions to exogenous shocks [24]. Predictive output validation means verifying the proximity between the predicted results and the actual data as soon as there are real data available to make. In this kind of validation, we also analyze the causes of the predictions as being correct or incorrect and create a record with the results of this analysis. The results of this phase provide DSC managers with indicators on what to expect from the studied currency aspects in the face of several possible scenarios. This record of these results also helps to make more accurate future predictions and provides a sight of the possible evolution of the system.

The simulations of an ABM produce metrics that numerically represent the aspects of the Digital Social Currency under study. Such metrics must also be applied to real data, to allow the comparison between the studied aspects that were produced by the simulation with those observed in the real world. In this way, before an ABM is built, it is necessary to define the metrics that represent the aspects of the DSC that will be studied through it.

A possible metric for representing the level of circulation of a currency is velocity, defined as the ratio between the volume circulated and the monetary base. This metric was used to study the level of circulation of 9 social currencies, based on data from 2011 to 2013. However, the database we had on the Sarafu Currency did not contain information on the total amount of currency in the system [25].

To adapt the velocity metric to the available information, we replaced the total amount of currency by the amount of social currency introduced into the system. Therefore, the resulting metric was the ratio between the total value of purchase transactions and the total value of social currency entering the system in a unit of time. This metric can provide relevant indicators to DSC system managers. For example, if it presents values lower than 1, this means that there are less currencies circulating than entering the system, which may indicate that the insertion of new social currencies in the system is not contributing to increase the local economy and, therefore, actions to promote increased currency circulation need to be taken. In addition, the study of the variation of this metric over time can provide indicators of how the insertion of new currencies influences their level of circulation.

To measure the retention level, we defined an index calculated in a period between two balance increases by dividing the sum of daily balances by the highest balance multiplied by the number of days in the period. This index assumes values between 0 and 1, and the higher its value, the higher the retention level. That is, it assumes higher values for agents that hold the currency longer and lower values for agents that hold the currency for less time. For example, for an agent that starts a 4-day period with a balance equal to 10 currencies and spend 9 on the second day, the ratio will be 13/40. If, instead of occurring on the second day, the spend of 9 currencies occurs on the third day, the index value will be 22/40. And if it occurs on the fourth day, it will be 31/40. We also define average monthly retention ratio as the weighted average of retention ratios in a month.

III. RESULTS

In this paper, we propose that there is a behavior that contributes to an increase in the retention level of a DSC and that can also contribute to an increase in its circulation. We came to this conclusion from analyzing the input validation and calibration processes. Therefore, we will detail the results obtained in these phases and the processes which led us to the conclusion of the existence of that behavior. We found other results in the prediction phase, however, as they are not part of this paper scope, we will not address them.

The input validation results indicated that the level of Sarafu Currency circulation was much higher in the second half of 2020 than in the first half. While in the first semester, the average level was 3.7, in the second it was 16.5. In October 2020, for instance, this level was over 43, meaning that for each Sarafu received by agents as a benefit, 43 were spent in purchase transactions.

On the other hand, the results showed that the retention level was high throughout 2020, being above 0.9 in almost every month, except in October, when it was in the range between 0.8 and 0.9.

The results of the calibration phase are not described numerically, but by the analysis of both the process of approximating the simulated results to the real results and the monitoring of the simulation process.

The calibration phase was performed by application of the reinforcement machine learning algorithm, whose objective was to find a set of adjustment factors that, when applied to the input parameters, would make the circulation and retention levels simulated to be close to the real levels. We expected to reach this objective after repeating the algorithm application a sufficient number of times. However, for the months in which the level of real currency circulation was higher, we found that, after repeating the algorithm application a large number of times, the simulated circulation stabilized at a level below the real values (between 7 and 10) and the correction factors stopped producing significant effects on the simulated values.

To find out why the simulated values were not approaching the real values, we followed, step by step, the simulation process for the month of October 2020, in which there was the biggest increase in the level of currency circulation. Then, we noticed that, as the amounts or quantities of purchase operations increased, the balances of many agents dropped to 0, causing them to stop making purchases until they received new benefits. Besides, correction factors on values and quantities of purchase operations became innocuous for agents who had a balance equal to 0. We also realized that increasing the benefits makes agents buy again, but did not contributes to the increase in the circulation level, as this level is calculated by dividing the monthly total of purchases by the monthly total of benefits and an increase in benefits means an increase in the denominator of this division.

IV. DISCUSSION

For the study of the interaction between currency circulation and retention levels, the results of the input validation phase indicate that it is possible to have a significant increase in the circulation level without a decrease in the retention level. The average Sarafu Currency circulation level for the second half of 2020 was more than 4 times higher than the average level of the first half, however, the average currency retention level remained high throughout the year. There was a small decrease in the retention level in October 2020, and analysis of the actual data indicated that the probable cause of this decrease was that GE closed of a large number of inactive accounts that month. However, this level increased again in the following months.

The calibration phase results, mainly the observations made in the simulation follow-up indicated the existence of real agents' behavior that had not been noticed in the input validation phase: real agents rarely spend all their balance in a single purchase. The high retention rates observed in the real data corroborate the existence of this behavior.

This behavior was incorporated into the simulated agents, in such a way that they started to spend up to a maximum percentage of the balance, in a single purchase. In this way, agents managed to maintain a positive balance to continue carrying out purchase operations, until receiving new benefits, allowing an increase in the level of currency circulation. Several maximum percentages were tested for a single purchase and, with a limit of 40%, it was possible to approximate the simulated values to the real values for both the currency circulation level and the currency retention level. This double approximation is one more indicator of the existence of this behavior.

Therefore, the fact that agents show the behavior of spending only a percentage of the balance on a single purchase contributes to an increase in the currency retention level, but also contributes to an increase in the currency circulation level.

This result provides DSC managers with an indicator that can be taken into account in the strategic planning of actions to reduce the level of currency retention, such as the application of penalties for demurrage, for example.

We emphasize that the use of an ABM was fundamental to reach this result, as it was only noticed because of the analysis of the input validation and calibration phases, and by the step-by-step monitoring of the simulation phase. The fact that the ABM was used for the simultaneous study of the levels of circulation and retention of the DSC was also decisive. If we had only studied the level of retention, we could explain the high values observed only by the increase in the value and quantity of benefits. On the other hand, if we had only studied the level of currency circulation, we could explain the high values observed in some months only by the increase in the value or quantity of purchase operations.

This result is an example of the potential of using Agent-Based Models in DSC studies, especially when these studies refer to more than one aspect of currency.

V. CONCLUSION

In this paper, we presented a case of using an Agent-Based Model in the study of the circulation level and the retention level of the Sarafu Currency. The analysis of the input validation and calibration phases and the step-by-step monitoring of the simulation phase allowed us to reach the conclusion that the behavior of spending only a part of the balance on a single purchase contributes to the increase of both aspects studied.

This study can also be complemented by researches on how agents spend and retain their DSC over the period between receiving benefits. The results of such research would be incorporated into the ABM, helping to bring the results of future simulations closer to those observed in reality.

The development and application of ABM requires specialized personnel and sometimes computers with high processing power. However, we believe that the costs involved in using an ABM are outweighed by its advantages.

As a strategic management tool, ABM provides DSC managers with relevant information for decision making. Such information can be obtained throughout the entire process of applying the model and allows managers to better understand how agents' behaviors determine important aspects of the system and how these aspects influence each other. The ABM also allows us to obtain indicators on the system's reaction to changes in the agents' behavior. In this way, we propose that social currency managers who use ABM will have a significant advantage for the strategic management of their social currencies.

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