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Agent-Based Simulation of Online Trading

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Abstract

It is evident that sustained cooperation among online traders is absolutely essential for ensuring the success of electronic markets. This research tries to explore the underlying relationship between reputation engineering system and cooperation level by employing 'Agent Based Simulation Modeling' approach. It attempts to establish a trust based reputation system and analyze its effect on the sustainability of mutual cooperation between online traders by taking into account key factors such as level of gullibility of online traders and the weight of influence given to their past behavior. The simulation result reveals the correlation between the Smoothing Constant and the Probability of Imitation. The maximum permissible probability of imitation to maintain full cooperation decreases with the increase in the smoothing constant. The mean trader profit decreases as the smoothing constant increases.

Keywords: Agent-based modelling; Simulation; Engineering; Online trading ;Mutual corporation.

1. Introduction

Online trading between two strangers falls in the realm of a Prisoner's Dilemma (Yamamoto et al, 2003)[1]. Needless to mention, failure should be the only logical conclusion of such electronic commerce situation since a trader might never have to deal with the same buyer again given the enormous population of online traders. Thus one could argue that markets like eBay should never exist. Then what is the reason behind resounding success of such electronic markets? The answer lies in the reputation system that they established. Although the significance of reputation system is obvious, finding answers to some of the what-if scenarios can be very puzzling. For example, what if past mistakes of the traitor are absolved and more importance is given to his/her recent cooperative behaviour in order to motivate him/her to cooperate? What if the perceived reliability of reputation system decreases substantially? Would online traders stop co-operating with each other as a result of decreased reliability of reputation system? If yes, would it be possible to quantify the effect of perceived reliability of the reputation system on the cooperative behaviour of the online traders? Impact of these changed conditions on the performance of an electronic market would largely depend on the dynamic behaviour of the complex interactions between many interdependent agents.
Complex Adaptive Systems (CAS) are defined as dynamic systems consisting of a network of interacting actors like humans, processes, etc., that adapt to constantly changing environments [2]. These systems are also adaptive because they contain actors who achieve their goals by adapting to the environment over time. One problem with modelling complex adaptive systems is that non-linear and adaptive interactions in these systems are often too complex to be captured by traditional analytical techniques [3-4]. Many conventional models are also limited in their ability to capture cross-level impacts. Currently, two-by-two game settings dominate the modelling of CAS as they allow results by deduction [5], and they are tractable [6]. However, such approaches make limiting assumptions on interdependencies, strategies, and on the multiplicity of players, which contradict real-life situations. Further, game theory assumes rational choices or optimization principles. In reality, individuals are adaptive, rather than fully

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rational, and they lack the necessary behavioural sophistication to derive optimal solutions [7] .Recent advances in agent-based simulation offer new opportunities to examine complex systems. With intelligent agents as its building blocks, an agent-based simulation approach naturally accommodates such systems by modelling actors and components as software agents.
It is evident that sustained cooperation among online traders is absolutely essential for ensuring the success of electronic markets. Thus exploring the underlying relationship between reputation system and cooperation level is of great practical significance. This research tries to answer the aforementioned questions by employing 'Agent Based Simulation Modelling' approach. This paper thus attempts to establish a trust based reputation system and analyse its effect on the sustainability of mutual cooperation between online traders by taking into account key factors like level of gullibility of online traders and the weight of influence given to their past behaviour.

2. Related research

Since agent based modelling of online trading, in this paper, is based on Iterated Prisoner's Dilemma (IPD), past research done in the areas of both agent based modelling as well as Iterated Prisoner's Dilemma is discussed in this section. Furthermore, a literature review is also done for evolution of cooperation and adaptive processes. Agents in this paper use some of the standard IPD strategies to interact with each other so various IPD strategies and agent interactions are reviewed in detail too.

2.1 IPD Strategies

The player playing IPD have different options of strategies. For example, Loyal (always cooperate), Traitor (always defect), TFT (Tit for Tat i.e. cooperate on the first move and then mirror the opponent's last move), Anti-TFT (Just opposite of TFT), PAVLOV (Win Stay Lose Switch i.e. to cooperate if and only if the other player chooses the same action on the previous move), Trigger (cooperate till the other player cooperates and always defect thereafter), Punish Twice (cooperate till other player cooperates, if the other player defects, then defect exactly twice irrespective of his moves and then cooperate again), GTFT (Nowak and Sigmund)[8]i.e. Generous Tit for Tat (like TFT it cooperates after the opponent has cooperated in the previous round but also it cooperates with some probability after opponent has defected) etc. This research employs three of the aforementioned strategies: Loyal, TFT and Traitor. It is evident that full cooperation cannot be sustained unless an external policy is enforced on the supply chain. Thus policy of 'Track Record Score' (TRS) is introduced in this research to achieve robust cooperation among players.

2.2 Adaptive Processes

An adaptive process controls how agents adapt or learn over time. There are two ways to model players who learn adaptively while deciding their strategies. The first is imitative approach that allows players to exactly copy the best performing strategies. This approach of imitation is based on learning heuristic. Imitation is the commonly studied adaptive process in the iterated prisoner's dilemma literature, either explicitly (Nakamura, Matsuda and Iwasa)[9]or implicitly via replicator dynamics (Nowak and May)[10] It is worth taking note that the player might or might not have access to the complete information about the profitability of all the players around them. They are thus required to make the decision depending upon the information that they have. It is assumed that players have information about profitability of all the other players in this research. The second approach is an innovative approach, whereby players form new programs by combining different parts of existing strategies along with some unique modifications. This approach is derived from genetic algorithm (Holland, 1975). Genetic algorithm is used for solving optimization problems in difficult domains. However, this approach is not used in this research.

2.3 Agent-based modeling and simulation for business problems

A software agent is a computer program that is situated in some environment and is capable of autonomous action in this environment in order to meet its design objectives. Agents possess four distinct characteristics [50] : Autonomy, which is the ability to operate without direct human intervention, interactivity, the ability to interact, communicate, and cooperate with other agents, reactivity, the ability to monitor and respond to changes in the environment in which they reside, and, proractiveness, which is the ability to take initiatives when necessary and exhibit goal-oriented or opportunistic behaviour. Agent-based modelling has become me an increasingly attractive methodology in modelling various social and natural complex systems [11].

3. Model development

3.1 Model description

(1)Traders. In this research, agent based simulation methodology has been used to model an electronic market place with 400 traders. Traders can buy as well as sell the products depending on their requirement. Every trader tries to find suitable business partners online and does business with them. The number of traders is limited to 400 because the computational load of an agent based simulation model increases exponentially with the number of traders. However, it was observed that the effect of higher numbers of traders on simulation results is statistically insignificant. Out of the total trader population of 400, 30%, i.e. 120 traders, are assumed to be 'Loyals' (always co-operate), 40%, i.e. 160 traders, are assumed to be 'Traitors' (always defect) and the remaining 30% are assumed to be 'Practical' Traders' (tit for tat). However this initial mix can quickly change once the simulation begins and traders start adopting the strategy that they perceive to be the most profitable one.
(2)The strategy space. The strategy space available to traders comprises of three strategies, namely: Loyal, Practical and Traitor .Loyal, Practical and Traitor are also referred to as AllC (always cooperate) TFT (Tit for Tat) and AllD (always defect) respectively in game theory literature. During the course of simulation model run, traders can change the strategy that has been randomly assigned to them at the start of the run. This adaptation of agents is based on the principle of imitation i.e. agents are likely to imitate the strategy of the most profitable agent. Whether or not to change the strategy is decided solely by an agent.

Table1. agent decision strategies on whether to corporate or defect

Strategy Description	Strategy Description
Loyal	To cooperate every time irrespective of the strategy adopted by the opponent
Practical	Tit for Tat i.e. to cooperate on the first move and then mirror opponent's last move
Traitor	To defect every time irrespective of the strategy adopted by the opponent

(3) Trader's payoff. A Trader's payoff depends not only on the IPD strategy that he adopts but also on the strategy that his business partner uses. Typical IPD payoff values is R=3, S =0, T =5and P= 1(T > R > P > S, and 2R > T + S > 2P) and this payoff structure is strictly adhered to throughout the simulation.
(4) Track Record Score (TRS). TRS is used as a reputation based system designed to make sure that Traitors would have to pay dearly in terms of their reduced market reputation. TRS enables honest traders to build their market reputation by cooperating with other online traders .Such a trader would be able to earn a very high Track Record Score. Each trader is allowed to decide his own strategy. He can either improve his TRS by cooperating or choose to earn more short term profit by defecting and thus sacrificing his TRS. It is worth taking note that TRS does NOT alter the Payoff Matrix. However, it does affect the chances of a trader getting accepted by other traders for an online trade. Each trader will receive an initial TRS of 100. Upon the conclusion of a deal between two agents, their scores are updated. The mechanism for updating scores is as follows:
Case 1: None of the agent adopted 'Always Defect'
- Both the agents get 100 points each

Case 2: At least one of the agents adopt 'Always Defect'
- Agent gets 100 points if he adopts 'Always Co-operate'
- Agent gets 0 points if he has adopted 'Tit for Tat'
- Agent gets –100 points if he has adopted 'Always Defect'

This Track Record Score is conceptually similar to the Feed Back Score system implemented by eBay. However, unlike this Track Record Score system, eBay does not use exponential smoothing for scaling feedback scores.

$$New\ Track\ Record\ Score = A * Old\ Score + (1- A) * Current\ Score \qquad (1)$$

Thus the higher Smoothing constant A signifies that more importance is given to the old score of an agent.
(5) The probability of imitation. Traders will be able to update their strategy by imitating the strategy of the most profitable player with certain probability. The probability of imitation represents the skeptic nature of human beings. This level of skepticism, which is unique to each individual trader, is captured by a randomly assigned 'Probability of Imitation'. The more gullible the agent is, the higher the probability of him imitating the strategy of the most

profitable agent. Thus, as the simulation run progresses, agents keep reviewing their strategies and decide whether or not to imitate the strategy of the most successful agent resulting in evolution of different strategies.

(6)The probability of two agents agreeing to trade. The probability of two agents agreeing to do business with each other is weighted equally on 'minimum of the two agents' scores' & 'Difference between Agents' scores'. While calculating the probability of two agents agreeing to trade with each other, a 50% weight is given to the 'minimum of the two agents' scores' because it is assumed that the trader with the lower track record score is likely to get rejected by the trader with the higher track record score. Similarly the rest of the 50% weight is given to the "difference between agents' scores" because it is assumed that two agents would probably agree to trade with each other if the difference in their Track Record Scores is not high.

(7) Mean Trader Profit. Upon completion of the trading between two agents, an agent's payoff will be added to the cumulative market profit if the player has cooperated. If the player has defected then his payoff will be deducted from cumulative market profit. Mean Trader Profit will be thus calculated using the following equation:

Mean Trader Profit = (Cumulative Market Profit) / (Trader Population) (2)

A higher Mean Trader Profit indicates that traders are co-operating with each other since the IPD payoff structure is used to model agent interactions. Mean Trader profit will be used as a Performance Metric for simulation experiments since the main objective of this research is to understand the effect of changes in the trust based reputation system on the cooperation levels of online traders.

3.2. The simulation model

The Recursive Porous Agent Simulation Toolkit (Repast) is an open source modelling framework that permits researchers to create agent-based simulations. Although Repast was originally developed to simulate social behaviour, it has been successfully employed by a myriad of researchers in fields as diverse as political science [12], archeology [13], biology [14] and economics [15]. The popularity of Repast may be attributed to its vast library of objects that provide researchers in different fields the flexibility to create sophisticated models then run and display the results of agent-based simulations. Repast is well suited for social networks and interactions, and is used to build our model.

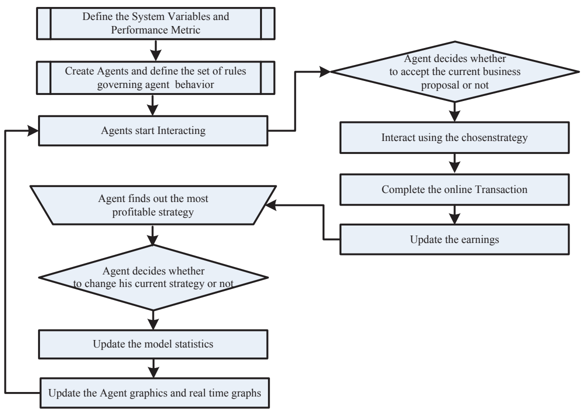


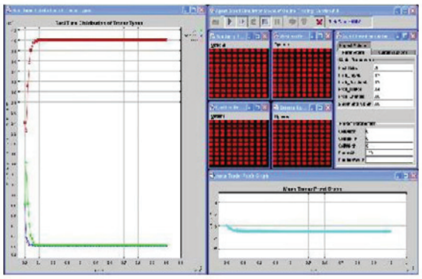
Figure1. Agent Based Simulation Model Flow Chart

As per the first step in the Figure 1 above, the Mean Trader Profit was selected as the performance metric. Smoothing Constant and Probability of Imitation were selected as the key system variables.

4. Simulation experiment

Agents were created in the model by employing the 'buildModel' method recommended by the standard RePast procedure. All the agents were given a random strategy at the beginning of the model. Once the simulation run begins, using 'interactions' method, agents search for their appropriate partner and make a business proposal. However, whether or not the two agents interact would depend on their Track Record Scores. As explained earlier in

this section, the probability of the agents interacting would be directly proportional to the minimum of the Track Record Scores of two agents and inversely proportional to difference between their Track Record Scores.
Agents use the ‘beginDealing’ method to interact with their business partners. During interaction, each agent employs his or her premeditated strategy and chooses to either cooperate or defect. The defection would result in lowering their TRS and cooperation would result in increasing their TRS as explained earlier in this section. The impact of agent behaviour on TRS depends on the ‘Smoothing Constant’ parameter. The‘profitSum’ method keeps track of the profit or loss made by agents during these interactions. Since the standard Iterated Prisonner’s Dilemma (IPD) payoff structure used in this paper, agents would make a profit only when neither of the agents uses the ‘Defection’ strategy. After the start of agent interactions, the ‘StrategyDecider’ method provides all the agents with an opportunity to imitate the strategy that they perceive to be the most profitable one. Whether or not the agents would imitate the strategy of the most profitable player would depend on the parameter ‘Probability of Imitation’. Figure3 below depicts the effect of key system variables ‘Smoothing Constant’ and ‘Probability of Imitation’ on the performance metric ‘Mean Trader Profit’. It can be seen in Figure 2(a) that cooperation can be sustained when the smoothing constant is set to 0.8 (i.e. 80% weightage is given to the past behaviour of agents while calculating Track Record Score) and probability of imitation is set to 0.4 (i.e. the probability of agents imitating the strategy of other successful agents is 40%). Since agents are somewhat skeptical in this case they did not copy the Traitors during the initial periods when Traitors were making more profit. Eventually the Traitors started losing since their Track Record Scores reduced substantially and agents with higher Track Record Score refused to do business with them. Cooperation thus is sustained in the agent population resulting in the approximate Mean Trader Profit of 3.



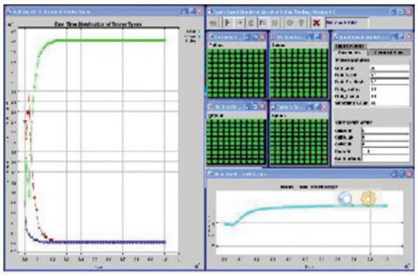


Figure2(a) Snapshot of Simulation Model Probability of Imitation=0.8 Figure2(b) Snapshot of Simulation Model Probability of Imitation = 0.4

Lack of in-depth statistical analysis often results into unreliable simulation results. In order to determine whether the conclusions from a given run are typical it is necessary to do several simulations run using identical parameters (using different random number seeds). The ability to do this is one major advantage of simulation: the researcher can rerun history to see whether the particular patterns observed in a single run are idiosyncratic or typical. The Mean Trader Profit is calculated by making 6 replications of each of the 9 experiments fed with antithetic variants of random seeds to minimize the variance. So the total number of replications carried out is 54. Run length of 100 is chosen because all the experiments hit the steady state well before that.

Table 2. Results Table 3 Experimental factors

Factor	Factor Level
Number of Agents (N)	400
Initial percentage of ‘Loyals’ (always co-operate)	0.3
Initial percentage of ‘Traitors’ (always defect)	0.4
Initial percentage of ‘Practical’ Traders’ (tit for tat)	0.3
initial TRS	100
IPD game strategies	Loyal, Practical and Traitor
Probability of Imitation	0.95，0.7，0.6，0.4，0.2
Smoothing Constant	0.9，0.7，0.4

5. Simulation results

It is critically important for a system designer to test the effect of different factors on the level of cooperation among agents. Agent based methodology can be effectively used for such analysis. This paper thus attempts to analyse changes in the level of cooperation as weightage given to the past behaviour of agents (i.e. ‘Smoothing Constant) is gradually reduced and more weightage is given to their current behaviour. This analysis is done for a variety of population mixes; ranging from the one that is predominantly skeptic (i.e. Probability of Imitation = 0.2) to the one that is mostly gullible (i.e. Probability of Imitation = 0.95).

The careful analysis of the simulation results reveals the correlation between the Smoothing Constant (i.e. weightage given to the past behaviour of an agent) and the Probability of Imitation (i.e. level of gullibility of traders). The maximum permissible probability of imitation to maintain full cooperation decreases with the increase in the smoothing constant. In other words, as weightage given to the old TRS is gradually increased, sustaining cooperation becomes increasingly difficult if the population is very trusting. This is quite intuitive since giving higher weightage to the old TRS would result in making defection an attractive strategy for the traders. Furthermore, such dishonest traders would be able to quickly proliferate since the agent population is very trusting. Probability of imitation i.e. level of gullibility of agents also affects mean trader profit. Mean trader profit decreases as the agent population becomes more and more trusting. In other words, the nuisance value of dishonest traders increases substantially as agents become more trusting. The extent to which the mean trader profit gets affected depends on the value of the smoothing constant. The higher the smoothing constant, the greater is the impact of level of gullibility on mean trader profit.

5.1 Effect of Change in Probability of Imitation on Mean Trader Profit

A Smoothing Constant of 0.9 signifies that very high weightage is given to the old TRS. Figure 3(a) depicts the effect of a change in probability of imitation on mean trader profit for smoothing constant = 0.9. For this value of the smoothing constant, the mean trader profit decreases with the increase in the level of gullibility of agents. In fact, as the percentage of gullible agents in the population approaches 60%, the mean trader profit becomes -1 indicating that agents have stopped cooperating. This is an important observation. For a particular population mix, it helps the system designer to understand the range of smoothing constants with in which the cooperation can be sustained. Figure 3(b) depicts the effect of a change in the probability of imitation on mean trader profit for a smoothing constant = 0.7. The reduction in Smoothing Constant from 0.9 to 0.7 signifies that weightage given to the old TRS is reduced. The mean trader profit becomes -1 when the probability of imitation approaches 95%. It is worth noting that the maximum permissible probability of imitation to avoid negative mean trader profit increases with the reduction in the smoothing constant. Figure 3(c) depicts the effect of a change in the probability of imitation on mean trader profit for a smoothing constant = 0.4. The further reduction in Smoothing Constant from 0.7 to 0.4 signifies that lesser weightage is given to the old TRS. As seen in the previous scenarios, Mean Trader Profit decreases with an increase in the probability of imitation i.e. as the traders become more and more trusting.

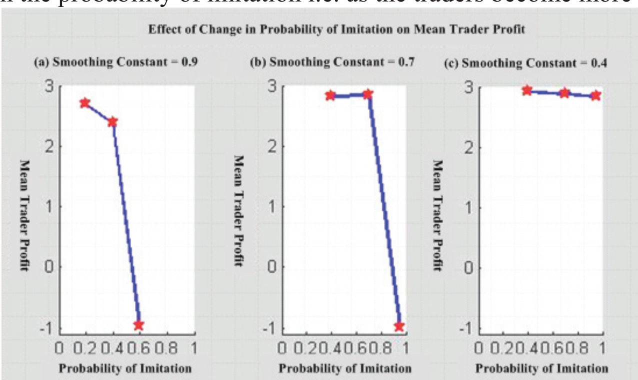


Figure3. Effect of Change in Probability of Imitation on Mean Trader Profit for different Smoothing Constant

5.2 Effect of Change in Smoothing Constant on Mean Trader Profit

If the population mix (i.e. level of gullibility of traders) is known then the simulation model can be used to predict the mean trader profit at different levels of smoothing constants. Figures 4(a)、(b) and(c) depict the effect of a change in smoothing constant on mean trader profit for different values of the probability of imitation. It can be seen that mean trader profit decreases as the smoothing constant is increased gradually, i.e. more weightage is given to the past behaviour of agents. In other words, if excessive weightage is given to the past behaviour of an agent then some of the agents with good track record scores might decide to defect and earn more profit without affecting their track record score much since their past behaviour was exemplary. Soon other agents will start imitating these traitors and thus mean trader profit will reduce. Furthermore, the drop in the mean trader profit is substantial for the agent population with high levels of gullibility simply because higher levels of gullibility allows traitors to proliferate very quickly.

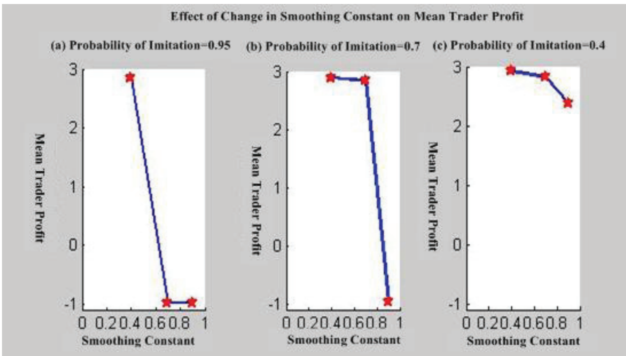


Figure 4. Effect of Change in Smoothing Constant on Mean Trader Profit for different Probability of Imitation

Table3. Below summarizes results for the different what-if scenarios

List	Probability of Change	Smoothing Constant	Mean Trader's Profit	Standard Deviation	95% C. I. for Mean
1	0.6	0.9	-0.969	0.02	(-0.952,-0.985)
2	0.4	0.9	2.381	0.3	(2.621, 2.141)
3	0.2	0.9	2.690	0.1	(2.768, 2.612)
4	0.95	0.7	-0.977	0.02	(-0.966, -0.989)
5	0.7	0.7	2.839	0.04	(2.871, 2.807)
6	0.4	0.7	2.818	0.05	(2.859, 2.778)
7	0.95	0.4	2.840	0.07	(2.899, 2.781)
8	0.7	0.4	2.891	0.04	(2.926, 2.856)
9	0.4	0.4	2.924	0.03	(2.947, 2.901)

Note: C.I. for Mean Confidence Interval

5.3 The sensitivity analysis of the results

It is also necessary to test the sensitivity of the results for changes in the values of 'percentage of dishonest traders in the initial population mix' and 'payoff structure for agents'. To test this, the regular payoff structure is doubled ensuring that the fundamental T > R > P > S and 2R > T + S > 2P conditions as explained in the previous section are satisfied. The new payoff structure is R=6, S =0, T =10 and P= 2. Also the percentage of dishonest traders in the initial population mix was also doubled from 40% to 80%. As expected, the results did not change except for the fact that the Mean Trader Profit was doubled because of the changed payoff structure. This is intuitive since the percentage of the dishonest traders in the initial population mix will not affect the results as long as cooperation emerges as the most profit making strategy and thus is likely to get adopted by other agents.

6. Conclusions and Implications

6.1 Conclusions

It is essential to take into account past behavior of a trader while calculating his current Track Record Score because it serves as a deterrent for agents that are tempted to defect and earn larger short term profit. However, the weightage given to the past behaviour should be decided after taking into account the level of gullibility of agents. It is observed that the cooperation would be difficult to sustain among relatively trusting online traders at higher values of the Smoothing Constant, i.e. if higher weightage is given to the past behavior of a trader. It is also observed that for a given value of the Smoothing Constant, the Mean Trader Profit decreases with an increase in gullibility of traders. This is exactly what happens in the real life online trading where dishonest traders feed on the relatively naïve and gullible traders who can be easily cheated.

6.2 Implications

The results presented in this thesis can be extended in several different ways. One of the several extensions could be to give more importance to the feedback from agents that have higher Track Record Score. In other words, importance given to an Agent's feedback would be directly proportional to his/her Track Record Score. This would help honest traders to punish the dishonest traders even harder by quickly bringing down their Track Record Score and help honest traders to build their reputation sooner. The Track Record Score could be considered as the single most effective weapon against dishonest online traders and thus helping honest traders to build their reputation quicker would certainly shield them from being preyed upon by their dishonest counterparts.

This research assumes that all agents report the feedback meticulously. This unfortunately is not always true because many agents do not see any incentive in providing feedback. This in turn weakens the reputation system since many dishonest traders would be able to get away with their bad behaviour simply because their business partners just did not report their misbehaviour. Furthermore, the honest traders would find it difficult to build the Track Record Score because of less than 100% feedback reporting. It would thus be important to see the effects of imperfect reporting on the overall cooperation levels. A group of agents might decide to do fake transactions and provide excellent feedbacks to each other in order to increase their feedback scores. The reputation system should have enough checks and balances in place to avoid such cases from happening. One more possibility is that some of the honest traders might be complacent. After collecting a certain amount of wealth, they might just decide to quit the business. Such complacent traders might make it harder to sustain the cooperation levels. Similarly, the traders with the low Track Record Scores might decide to quit and re-enter with different identities to hide their dishonest behaviour in the past. The research could be extended to quantify the effect of such agent behaviour. The cost of searching for suitable business partners could also be introduced in this agent based model.

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