Title: Trust as an emergent phenomenon in wealth management relationships

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TRUST AS AN EMERGENT PHENOMENON IN WEALTH MANAGEMENT RELATIONSHIPS

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ABSTRACT

Trust research is traditionally found in marketing, economics, psychology, sociology and organisational behaviour literatures. Complexity theory provides an alternative lens through which to conceptualise trust. Three complexity theories (adaptation, self-organisation and self-organised criticality) are integrated with marketing and psychological theory to provide an understanding of trust as an emergent phenomenon and to guide the design of an intelligent agent simulation which will be tested subsequently within the CRM data of a major financial institution.

Both fuzzy logic and evolutionary strategies are employed within a multi-agent simulation of interactions between wealth management advisors (WMAs) and their clients. In the simulation, fuzzy logic represents the agents’ behavioural rules which are derived from complexity, marketing and psychology theories. The results obtained using the RePast based simulation show the advantages of evolutionary learning in optimising WMA-customer relationships and how this learning in turn affects WMA strategies as they seek to reduce client churn.

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I. INTRODUCTION

Research on trust as a mechanism for defining order in social interaction is evident in marketing, economics, psychology, sociology and organizational behavior literatures (Rousseau, Sitkin, Burt and Camerer 1998; Lewicki, McAllister and Bies, 1998). Consequently, alternative views on trust have been posited and argued within a range of contexts. Complexity theory provides an additional, alternative lens through which to conceptualize trust. Three complexity theories (adaptation, self-organization and self-organized criticality) are integrated with theory from marketing and psychology to provide an understanding of trust as an emergent phenomenon.

The maximization of personal wealth has become an imperative with rising awareness of the wealth required to support an active and lengthy retirement. The provision of wealth management services provides an interesting and important context for modeling trust as decisions are high risk and complex, and customers are initially unable to assess the quality of the advice being provided (Seal, 1998; Stewart, 1998). In addition, customers’ skills and knowledge in wealth management will grow as they draw from the experiences of peers and the vast array of publicly available opinions and advice about wealth growth. Portfolios will be adjusted as wealth management needs change and/or performance falls below expectations, and advice may be sought from a more ‘trustworthy’ source. The objective of this current research is to develop an agent based model that integrates complexity and traditional theoretical representations of trust within the context of wealth management decision-making. In the simulation, the behavior of agents will be guided by rules that draw on these representations in the context of on-going wealth management decision-making, with a view to advancing Nooteboom, Klos and Jorna’s (2001) work on trust as an emergent phenomenon. The theoretical arguments developed here contribute to the design and implementation of an intelligent agent simulation, to be tested, subsequently, within the CRM data of a major financial institution.

II. CONCEPTUALISATIONS OF TRUST WITHIN TRADITIONAL LITERATURES

Figure 1 draws together key dimensions of trust from the marketing, economics, sociology and psychology literatures, and identifies how trust develops through experiencing interactions and reflecting on relationship and performance outcomes. A person’s background, personality type (Hofstede, 1980) and development experience (Tan and Sutherland, 2004) determine an individual’s disposition to trust, which in turn shapes trust formation (Mayer, Davis and Schoorman, 1995). Those with a high disposition to trust have generally been found to be willing to place their trust in others even with limited information on the trustee (Rotter, 1980; Mayer, Davis and Schoorman, 1995). Prior to contact, the extent and nature of a potential customer’s dispositional trust will determine the willingness of that customer to make assumptions about the trustworthiness of a Wealth Management Advisor (WMA). In this anticipated cognitive trust stage a potential customer may assume that a WMA will act benevolently and credibly based on a friend’s referral, and/or a positive corporate image (Hartnett and Travaglione, 2004). In the first few interactions between the WMA and a customer, anticipated trust will be reinforced or refuted based on interpretations of actions and behavior prior to deciding on a particular wealth management portfolio option.

At an initial meeting, a potential consumer will attempt to categorize the WMA through either unit grouping (using themselves as a benchmark) or stereotyping (McKnight, Cummings and Chervany, 1998). The process of categorization is reflected in Kramer’s (1999) definition of category-based trust: “trust predicated on information regarding a trustee’s membership in a social or organizational category-information which, when salient, often unknowingly influences others’ judgments about their trustworthiness (p. 577).” Shared membership of a category (for example, Rotary) will normally result in reinforced trust, because of the in-group bias of regarding one’s own group as honest, reliable, cooperative and trustworthy (Brewer, 1981). A WMA that is perceived to have characteristics of ability, judgment, character and benevolence is likely to be considered trustworthy (Mayer, Davis and Schoorman, 1995). As the WMA and potential customer interact in the early stage of the relationship, the potential customer’s trust is reinforced as he/she makes assessments about these WMA trust characteristics (Kramer, 1999). A positive categorization reinforces cognitive trust, facilitating a transaction.

If anticipated cognitive trust is reinforced, the potential customer requires no further comparative options. If additional criteria are met, for example, the timing of investment is relevant and the portfolio configuration meets the potential customer’s anticipated wealth management requirements, a transaction is likely to occur. In their seminal research on trust and commitment, Morgan and Hunt (1994, p. 23) defined trust in a business-to-business context as a steady state of “confidence in an exchange partner’s reliability and integrity”, which
reflected the emphasis placed on integrity dimensions and its measurement. However, new executive appointments, changes in relationship managers, and/or poor relationship performance could negatively affect communication, opportunistic behavior and relationship benefits, creating distrust. In the context of wealth management, a customer’s trust will be moderated through personal interactions following transaction, and through performance versus expectation evaluations. Expectations are validated or adjusted through consumption experience and explanations of performance versus expectations provided by their WMA (Kramer, 1999). If performance falls below their client’s expectations and the explanation provided by WMA is not considered to be valid, credibility trust will decline, and customer churn is possible (for a review on the performance/expectation relationship see Johnson, Anderson and Fornell, 1995; Van Montfort, Masurel and Van Rijn, 2000). Trust as a dynamic state is captured by Kramer, who stated “interactional histories become a basis for initially calibrating and then updating trust-related expectations” (Kramer, 1999, p. 576).

As the customer interacts with the WMA and peers, and absorbs sought and unsought wealth management information, his/her knowledge about investing and making wealth management decisions is likely to increase. This increase in wealth management knowledge and confidence, together with the expectation/performance evaluation, have the potential to negatively impact on WMA trust and WMA influence on future portfolio decisions. The interrelationships described above are presented in Figure 1, and a more detailed description can be found in Jarratt and Cooper (2005).

Figure 1: WMA/Customer Trust Development Cycle

III. CONCEPTUALIZATION OF TRUST THROUGH COMPLEXITY THEORY

Traditional approaches to conceptualizing trust do not capture the complexity of change, nor provide insight about the complex interactions of people in relationships and the impact of each participant’s socialization system, nor explain how and why new relationships emerge over time. The notions of complex adaptive systems and self-organizing systems are powerful concepts to incorporate in theorizing about the emergence of trust. Complex systems can be understood by looking for patterns within the interactions between their individual parts that reflect emergent behavior of the entire system, as it undergoes transition between equilibrium points through adaptation and self organization (Dooley, 1997). Complexity is not a single theory but embraces a number of theories, each independently explaining different aspects of complexity. Three complexity theories that have been drawn upon previously to advance marketing and management theory are adaptation, self-organization and self-organized criticality.
Adaptation

Complex adaptive systems are: "...composed of interacting agents following rules, exchanging influence with their local and global environments and altering the very environment they are responding to by virtue of their simple actions" (Sherman and Schultz 1998). Trust adaptation will occur through lived experiences with other business associates, media information acquired on experiences between WMAs and their clients, personally exchanged information on the experiences of other clients with WMAs, and changes in superannuation legislation. Relationships are constantly seeking equilibrium as trust within the relationship is challenged by the ongoing socialization of each participant in the relationship.

Self-organization

Self-organization is a natural result of non linear interaction, not of any tendency of individual agents to prefer or seek out order. It is driven by positive and negative feedback processes and formal rules are employed to achieve equilibrium (Anderson 1999). Each interaction and reaction in a wealth management relationship creates some change and redefines trust between actors. Trust will deepen when positive experiences consistently reinforce a priori states, however, changes in emotional trust may affect the equilibrium of the relationship. In a wealth management context, poor performance may either result in the co-existence of trust and distrust, trust may be broken and a new advisor sought, or performance may be rationalized as an unanticipated event and trust maintained. Dispositional trust may adjust as the result of these negative experiences. In addition, knowledge and skill development in both the customer and the WMA, and changes in the wealth management needs of the customer, may affect the dimensions and intensity of trust between the actors.

Self-organized criticality

To break free from inertia, a trigger is required (Havila and Salmi, 2000). Triggers of change are represented through thresholds on performance, changes in wealth management objectives and changes in one or more trust dimensions, beyond which the relationship becomes unstable. Transition is likely to follow such a period of destabilization. Predicting the threshold will be important in an agent model representing trust within a WMA/customer relationship.

Self-organized criticality is the point at which no further efficiency and/or personal and portfolio performance gains can be made under the current relationship. Morel and Ramanhjam (1999) argue that self-organized criticality is an emergent property "which may, in some cases, correspond to a dynamic optimization" (p. 282). Overtime the customer's wealth management needs change and become more complex. If the customer determines that the WMA skill levels are insufficient to manage the increased complexity of the portfolio decisions, he/she may require a change in WMA. Benevolence and integrity elements of trust may continue to exist, however, credibility trust may direct relationship exit.

Relationship transition may be evidenced through the application of new relationship processes incorporating additional expert access or even the formation of a new relationship (Baker and Sinkula, 1999; Lukas, Hult, and Ferrell, 1996). Following initial interactions in the new relationship, anticipated trust will re-organize rapidly with each interaction and initial performance evaluations, as well as through an increase in wealth management knowledge, with "an important part of its dynamics tak(ing) place out of equilibrium” (p. 282). This accelerated dynamic will be evident where high initial connectivity between the actors is evident and trust is emerging.

Support for the notion of self-reorganization can be found in Mintzberg and Waters’s (1985) assertion of the distinction between intended and realized strategy. Such a distinction recognizes that as the strategic intent of a relationship is operationalized, the relationship processes reorganizes around that intent. The strategic intent is interpreted, and the processes and/or normative behavior adjusted accordingly. However, the realized strategy, i.e. the state of equilibrium, will differ from the intent, as each relationship participant interprets the imperative of the other participant and adjusts interaction processes and behavior accordingly. We can use this example as an analogy of trust, in that when trust stabilizes (or the rate of change in trust stabilizes) that state may be very different from what was anticipated at the beginning of actor interaction. Figure 2 integrates both the traditional and complexity explanations of trust from the customer’s perspective. From a complexity perspective, we define trust as a dynamic state of confidence in a relationship partner’s conduct, constantly being challenged by reflections on interactions between relationship participants, the trustor’s changing knowledge and skills, performance outcomes and the ‘trusting’ experiences of others, and influencing the way that the trustor subsequently engages with others.
This integrated perspective of trust from the customer’s perspective has provided input to the fuzzy logic descriptions of the client agent in the following simulation. Unlike the real-world, the simulation at this initial stage does not explicitly account for client agents who are unable to, or choose not to, assess portfolio performance versus competitive options or opportunity costs, or those who recognize that the performance of their portfolio has fallen below market rates given their selected risk exposure but choose to remain with their WMA for emotional or benevolence trust reasons.

IV. SIMULATING TRUST

This simulation is the first stage in the integration of real consumer behavior data and agent-based modeling. Not all aspects of the dynamics identified in Figure 2 are captured in the simulation. The simulation abstracts the multiple dimensions of trust (ability, benevolence, judgment and character) into actions of reinforcement and referral. Credibility is examined in the context of referral trust options and commitment is shown under conditions of changing trust levels. Other simulation research (for example, Nooteboom, Klos, and Jorna 2001), has examined the development of trust in a simple trading model of individual goods. Our simulation has a less deterministic reward for trade (financial markets have inherent uncertainty) and explicitly models the communication network of clients (customers).

Figure 2: Trust by a Customer in a WMA from a Complexity Perspective

The Agent Based Model

Complex systems in nature and society arise from the interaction of many autonomous entities, or agents. It is, in general, not possible to derive the system behavior from an understanding of the behavior of individual agents, no matter how detailed. Thus, computer simulation of the emergent system behavior is the only course of action. There are many successful simulations of complex systems in the physical and biological sciences, from climate modeling and fluid dynamics, to genetic regulatory networks and ecosystems (Bossomaier and Green 2000). On the other hand, quantitative modeling of human social systems is still in its infancy. Part of the challenge lies in the immense difficulties of modeling human behavior. However, as we incorporate progressively larger amounts of data corresponding to individual preferences and actions, our ability to model
collections of people will continue to improve. As a methodology to address the above-mentioned issues, agent-based modeling is becoming a popular technique, especially due to increasing computing power and the associated graphing capabilities available today.

WMAs seek to achieve the joint objectives of maximizing their personal profitability and clients’ trust for survival in the marketplace. In moving towards these objectives, it is essential that the WMAs adapt their strategies continually in order to maintain their financial wellbeing as well as retaining their clients via building/maintaining trust. As a methodology for modeling the complex interactions taking place, an agent-based model was built drawing on limited theoretical perspectives previously highlighted.

There are two types of intelligent agents in this model. The client agent is a representation of a real-world, bank customer looking to invest his/her wealth. Their personal attributes were taken to be: (i) trust representing the level of the client’s trust in his/her WMA (on a scale of 0 to 1 with 1 being the highest level of trust), and (ii) caution (on a scale of 0 to 1 with 0 being the least risk adverse), which is used to represent the client’s level of risk-aversion. The desire of the client agent is to maximize his/her wealth. The client is capable of two actions: (a) the client makes a decision about how to adjust their investment based on their level of trust for their WMA and the level of growth their investment has achieved in the past, (b) the client can choose to withdraw the full amount invested and invest their money with another WMA based on their distrust of their WMA and reports from neighbors’ about trust in their WMAs (which may or may not be the same WMA as the client agent’s WMA).

The second agent type is the WMA agent, which represents a real-world, Wealth Management Advisor. The only personality trait currently simulated is benevolence (on a scale of 0 to 1). Benevolence represents the level that the WMA will work cooperatively with the client in order to maximize the client’s profit at the possible short term financial detriment of their own profit, with 0 representing more concern for the potential profit of the WMA and a lack of concern about client’s profit. The WMA has a single desire, which is to maximize his/her profit which can be achieved by increasing the trust of his/her clients or recommending products that advance personal wealth without necessarily maximizing the wealth potential of clients. The most critical action of the WMA is to recommend an asset for the client to invest in based on the extent of his/her benevolence and drive for personal profit.

There are two types of non-human entities included in the simulation, Equities and Funds. Both of these entities are used to simulate both extremes of real-world investment options accessible to potential investors; that is Funds, which are a protected investment with stable but slow positive growth, and Equities, which are more volatile but potentially more profitable. Due to the complex nature of interactions between the agents during the decision making process, the behavior of agents are modeled using a fuzzy logic approach. The following represents an advancement to the model presented in Bossomaier, Jarratt, Anver and Thompson (2005).

V. MODELLING AGENT BEHAVIOUR USING FUZZY LOGIC

Fuzzy set theory (Zadeh, 1965) has its roots in the social nature of human understanding. Our abilities to ‘understand up to a degree’ have been developed through our commonality, that is, through an inevitable process of fuzzification of meaning, so that to make it understandable, acceptable and operational for a multitude of people with different mental, emotional and spiritual world views. Although fuzzy logic has many uses, it is particularly effective at capturing the way people make decisions in a semi-quantitative way.

When an agent has a diverse range of cognitive strategies and behaviors, finding a suitable conceptualization is often difficult. One can always fit some sort of decision surface to cognition and behavior, however parameterizing it and fitting it to data can be impractical and unreliable. A fuzzy model allows the fitting process to occur in two phases. The first captures the qualitative factors and forces, such as those captured by focus group research and managerial and organizational theory. The second creates a quantitative model through assigning membership functions and the other elements of a fuzzy inference system. Great flexibility is allowed on the quantitative side, while preserving the qualitative structure. The fuzzy logic component of the simulation (Orchard 2005) was developed by the National Research Council of Canada’s Institute for Information Technology, and is designed to simplify the integration of fuzzy logic functionality into java applications.
The evolutionary learning process

Researchers in adaptive systems have been addressing issues concerned with learning and adapting from past experience (observations, failures, successes). Whereas most of this research has focused on techniques for acquisition and effective use of problem solving knowledge from the viewpoint of a single autonomous agent, recent investigations have opened the possibility of applying some of these techniques in multi-agent settings. If an agent is able to learn its behaviors, it may adapt to unpredictable, dynamic environments. Moreover, learning may reduce design and implementation costs. In the case of agent behaviors, it may not be possible to have a precise description of the desired behavior, whereas the designer is almost always able to describe the goal that should be achieved and a corresponding evaluation function. The addition of Genetic Algorithms was accomplished using the Java Genetic Algorithms Package (JGAP), which allowed us to approach the inclusion of Genetic Algorithms in a highly modular way but without sacrificing speed of efficiency.

Evolutionary learning of the Fuzzy Rules

It is seen by observation that although certain rules in a fuzzy knowledge base (FKB) could be easily determined using human intuition, some of the rules possess an ambiguous nature and are therefore difficult to determine. Therefore, it was decided to use evolutionary algorithms as a learning methodology for the FKB used in the decision making process (Michalewicz 1994). The choice of evolutionary strategies as a learning mechanism stems from the successful research carried out by Anver and Stonier (2002), who proved that an evolutionary learning process of FKBs produce better results than using FKBs generated by human intuition. In the context of the simulation presented, the most critical decision of the WMAs in optimizing their income, was deciding how to invest the client’s wealth. For the purpose of the simulation, we have just two different investment categories, which vary in risk and benefit to client and WMA. This was accomplished using a FKB where the WMA makes a decision as to where to invest the client’s wealth based on the income of the WMA and his/her personality trait of benevolence, which results in determining the tendency of the WMA in risk-taking.

As an example, rule 1 in the FKB used was (Equation 1):

\[
\text{If } (x_1 \text{ is } A_1^f) \text{ and } (x_2 \text{ is } A_2^f) \text{ then } (\text{Risk\_Taking\_Behaviour is } B^f)
\]

where on the antecedent side of the rule A

1 = High, A
2 = Medium, and in the consequent
B = Low.

These factors, namely, the income of the WMA and his/her benevolence towards the client are each fuzzified using three membership functions (Low, Medium and High). Each rule is designed to deal with a particular pattern of decision-making process based on the behavioral characteristics of a given WMA. Given a fuzzy rule base with R rules, the output Risk Taking Behavior as given in Equation below, uses a singleton fuzzifier, Mamdani product inference engine and centroid defuzzifier to determine output variable.

\[
\text{Risk\_Taking\_Behaviour} = \frac{\sum_{\ell=1}^{R} \bar{y}^{\ell} \left( \prod_{i=1}^{n} \mu_{A_i^\ell}(x_i) \right)}{\sum_{\ell=1}^{R} \left( \prod_{i=1}^{n} \mu_{A_i^\ell}(x_i) \right)}
\]

where \( y^\ell \) are centers of the output sets B.

The output of the fuzzy inference engine represents the Risk Taking Behavior of the WMA, which in turn decides the category in which the investment will be made. To evolve an optimum investment strategy, we need a unique representation of each possible rule base to identify with each string in the population defining the evolutionary algorithm. Each fuzzy rule is uniquely defined by the consequent part of each rule that is being represented by a 0 or 1 depending on whether the output variable Risk Taking Behavior belongs to the fuzzy set ‘Low’ or ‘High’ respectively. Each string in the population \( x_k \) can be represented as \( M = 4 \) FKB consequents,

\[
x_k = \begin{bmatrix} a_1 & a_2 & \cdots & a_{M-1} & a_M \end{bmatrix}^T
\]

where \( a_j \in \{0, 1\} \) for \( j = 1, \ldots, M \). The population at generation \( t \), \( P(t) = \{x_k : k = 1, \ldots, N_p\} \), where \( N_p = 20 \) is the number of strings in the population, the population size. The probability of mutation (\( P_m \)) was set to be 0.025. The selection process comprised of the Weighted-Roulette selection mechanism, for evolving each of the WMA populations. The fitness for each string \( f_k \) is formulated as (Equation 2),
where, Wealth corresponds to the Wealth of the WMA while \( \text{Average Trust} \) is the average trust of clients attached to a WMA at a given time. Thus,

\[
\text{Average Trust} = \frac{\sum_{i=1}^{N} T_c(i)}{N}
\]

where \( T_c(i) \) represent the trust level of the clients \( i \) and \( N \) is the number of clients attached to a WMA at a given instance, respectively. This gives three possibilities:

1. Case (i) (\( \alpha \neq 0, \beta = 0 \)): This corresponds to a situation where the strategy adaptation process is carried out while optimizing the ‘Average Trust of Clients’ only.

2. Case (ii) (\( \alpha = 0, \beta \neq 0 \)): This corresponds to a situation where the strategy adaptation process is carried out while optimizing the ‘Wealth of the WMA’ only.

3. Case (iii) (\( \alpha \neq 0, \beta \neq 0 \)): This corresponds to a situation where the strategy adaptation process is carried out while optimizing both the factors, namely, ‘Average Trust of Clients’ and ‘Wealth of the WMA’.

Each WMA evolves his/her own strategy, predicting the market forward to estimate the fitness of each FKB.

VI. SIMULATION DESCRIPTION

RePast allows the agents to manifest themselves onto the canvas of the simulation. As each object has generic mutator and accessor methods, reporting can be done simply by outlining which attributes to watch and having the system poll each agent in turn. Accordingly, both the WMA agents and the client agents were represented in the simulation canvas by red circles and blue squares respectively (see Figure 3). At the initialization of the simulation, the RePast model creates a classic ‘Watts Strogatz’ (W-S) small world network (ring substrate) between the Client nodes. This is designed to simulate the average pattern of relationships between real-world Clients for the purposes of evaluating WMAs.

Half the Client nodes are connected to random WMA nodes to simulate a real-world situation. Following this, the agents are added to a display surface to visually track the relationships between the agents (see Figure 3). At the initial step of the simulation, the population for each WMA’s genetic algorithm is generated along with the starting wealth for each of the Client agents. The clients with no WMA will gradually acquire one through the trust networks as described below.

The main process for each iteration can be separated into a number of steps:

- The Client’s wealth is incremented a set amount defined by the model to simulate a steady income.
- The population of the genetic algorithm is used to determine the rules for the WMA behavior for this iteration of the model.
- The Clients invest their money. This is a process of their WMA suggesting a particular asset (either an equity or a fund), and then the Client either accepting or rejecting the suggestion (based on fuzzy rules) and, if the suggestion is accepted, they decide how much they want to invest in that asset.
- After the Clients have invested their money, the model undergoes iteration of the funds/equities market. Based on an algorithm taking into account risk, noise and growth, a new value for the asset is generated. After this, the WMAs are informed of how much their Clients investments grew or fell.
- The Clients are then informed as to how much their investment is now worth and then make a decision based on fuzzy logic as to how much they now trust their WMA, taking into account how much they gained/lost and their level of caution.
- The fitness for the population of the genetic algorithm is then evaluated based on the total trust of that WMA by all his/her clients and how much the WMA profited.
- Finally, the Clients decide if they trust that WMA enough to stay with them or if they want to withdraw all their investment from that WMA and select another WMA. Rapid and/or extensive flux in the mapping of clients to WMAs is usually referred to as churn and is usually disadvantageous to one or both parties. They do this by means of a fuzzy logic decision which is based on the trust of neighbors in their WMAs in the network. If the neighbors’ trust in their WMAs is inadequate, a WMA is chosen at random.
VII. EXPERIMENTAL RESULTS

In our research, we experimented with variable numbers of WMA and client agents. Each j\textsuperscript{th} WMA (j ∈ [0, numOfWMAs]) had a population of chromosomes corresponding to different possible strategies that it could adapt, and the corresponding fitnesses were evaluated. The best chromosome was taken to be the best strategy a WMA should use for the process of choosing investment category in order to optimize client trust.

The experimental results obtained after running the simulation for 60 generations (representing a period of 60 months or 5 years) are presented in Figure 6. During the experiment, evolutionary learning was applied to the most critical decision making process, namely the investment behavior of the WMA. That is, the decision as to where to invest clients’ money was under evolutionary control. While the simulation was run for a period of 5 years (60 months), the evolutionary optimization was carried out every 5 months. The idea behind this was to let the simulation stabilize and then to evolve the WMA strategies. The concentration of wealth and market share in two WMAs overstates the real-world where some clients are unable to assess comparable performance within a specific risk profile and others are emotionally bound to their WMA.

Preliminary simulations were carried out with varying values of $\alpha$ and $\beta$ included in the Fitness Function($f_k$) given in Equation 2 above, but the results obtained from all three cases showed very similar characteristics. This suggests that it is possible for WMAs to retain their customer-base and thereby increase their own financial wellbeing by adopting strategies corresponding to either increasing their clients’ trust, increasing their own financial wellbeing or by taking both of the above into consideration. Case (ii) (described in section 4 above) was then adopted for the results presented here (optimizing for wealth only). For the purpose of maintaining clarity, we state below the results obtained, with reference to the diagrams presented in Figures 3, 4 and 5, in point form. (Note: Due to similarity of results, the experimental results obtained have been presented below for Case (ii) only).

- Figure 3 depicts the initial setup of the WMA/Clients networks. Each link resembles an existence of a contract between a WMA and a client. The WMA agents and the client agents were represented in the simulation canvas by red circles and blue squares respectively. This network is continually updated as clients change WMA.
- Figure 4 shows the overall growth in WMA wealth with time, and the corresponding growth in average trust and reduction in client churn. The WMAs rapidly find that client trust and thus client lock-in achieves growth of wealth.
- Figure 5 shows the behavior of a typical WMA in several different runs. The link between churn and wealth growth is readily seen. However, there are situations in which a WMA will “exploit” clients, creating short term wealth for himself/herself, but losing out long term as the clients churn.

Figure 3: The small world network of clients and their links to their WMA at one instant in time
VIII. CONCLUSIONS

In this paper we discussed how an evolutionary learning approach of FKBs can be coupled together with a multi-agent based model of wealth management advisors and clients, where the WMAs adapt their strategies to optimize their financial wellbeing through maximizing clients’ trust. We made use of the RePast agent modeling toolkit and two other third party java toolkits for the purposes of implementing the fuzzy logic and the evolutionary components of the simulation.

We showed how the WMAs’ income increases with respect to time as they adapt strategies to maximize the average trust of their clients at any given instance. Further, it was also seen that this strategy adaptation reduces client churn. Reducing client churn is of paramount importance in today’s banking industry and independent wealth management advisor sector. Future work will improve the simulation of the financial market and improve the coupling between client needs and WMA decision making.

The simulations to date show the effectiveness of a simple model in capturing the dynamics of client-advisor interactions. However, as previously noted, the simulation at this point does not explicitly account for client agents who, as a result of limited understanding of investments and superannuation, time constraints or lack of urgency with respect to wealth growth, hand the responsibility for their investments to a WMA. In addition, even in the presence of evidence of poor market performance when compared to similar risk profile investments, some will choose to remain with their WMA for emotional or benevolence trust reasons. The next stage of the simulation will take into account these client agent behaviors, prior to training the agents on real-world, CRM data from the finance industry.

To date, the results highlight the importance of the role of trust in minimizing client churn. A client will exhibit trust in a WMA whom he/she perceives to be placing clients’ wealth maximization ahead of the WMA’s personal wealth growth. The client’s understanding of the ‘trustworthiness’ of the WMA will be developed through on-going evaluation of performance versus expectations and through exchanges about WMA recommendations and performance with clients of other WMAs. While the industry norm remains of WMAs being rewarded through specific product recommendations and annual fees requiring no further client engagement, it is unlikely that client trust in wealth management advice will grow. New legislation requiring full disclosure of disbursements on financial service provision is encouraging financial service organizations to challenge current practice in WMA remuneration and the criteria against which their performance should be assessed.
Figure 4: (a) WMA that does not adapt to a new client soon loses that client. (b) A WMA that continually drains client funds will eventually lose all its clients. (c) WMs that adapt quickly soon maximize both trust and income.

Code: FPA ≡ WMA
Figure 5: Two high performing WMAs take the lion’s share of the market

Figures 6: Mean WMA performance post-evolution; shows an optimal level of ‘trust’ and ‘total cut’ for efficient WMA behavior.

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X. REFERENCES


