Innovation Criterion for Evaluating the Organizational Effectiveness of a Retail Chain using a Complex Adaptive System Model and the SWARM Simulation Environment

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Abstract

In this paper we examine the application of a Complex Adaptive System (CAS) on studying the relative organizational effectiveness of Centralized and Decentralized Retail Chains. The criterion for the evaluation of this effectiveness is the rate of creation of new (innovative) ideas, related to management policies and practices, by the Shops of the Chain, which are the agents of the CAS Model.

The diffusion of these innovations throughout the Organizational structure and finally their adoption as a new standard practice or policy by the whole chain, is also an important dimension of the evaluation criterion. We provide here some basics for the CAS modeling and their connection with the traditional Systems Dynamics modeling, justifying as well our decision to use the CAS formalism. We examine a generic Retail Chain organization, the corresponding structure of the CAS model and finally we give details on the simulation of the model with the SWARM software system. We produce various scenaria by changing the chain's main structural parameters and finally we discuss the results obtained and draw conclusions on the relative organizational effectiveness of centralized and decentralized Retail Chains.

1. Introduction

Our main objective is to study the relative effectiveness of **centralized** and **decentralized** organizational structures of a retail chain using innovation as a criterion. By innovation we mean the continuous creation of information that improves organization's ability to adapt to a constantly changing competitive environment. Since we view the organization as a collection of agents, each of whom is capable of creating new ideas, the use of **aggregated** models such as the usual stock and flow presentations, is not recommended here. Stock and flow models are good for capturing the time evolution of the **average** behaviour of the underlying original system but they are leaving out the details related to fluctuations. The missing part of the dynamics attributed to these ignored fluctuations are often extremely important for the understanding of the underlying dynamics and may be responsible for unpredictable emerging **collective properties**, which can be revealed only through a multi-agent system formalism.

This work is an extension of the work of Chang and Harrington model (afterwards referred as CH) of a retail chain (Chang and Harrington, 2000). The main modification we made on the C-H model is the introduction of the notion of the **firm topology**, which is related to how different subunits are connected and how they interact. The topology in the C-H model is extremely simple and this is the reason why the creators of the model surprisingly claim that it is the centralized and not the decentralized organization, with coordinated search for a global optimum in the competitive landscape, that is more effective in a constantly changing environment. In contrary, our study shows that when we make the firm topology a little more complicated, then decentralization outperforms centralization, almost in every case, when the markets are not stable (i.e. in a state of volatility).

The performance of a firm is related to its structure. The same firm, under the same conditions may have different performance in the same environment, depending on how it is organized and structured.

At this point we need to define the term **structure**. A working definition could be that structure is how the different sub-units constituting the firm are connected, how they interact and how they exchange information. Loosely speaking, we may understand the importance of structure in the performance of a firm, as the structure of a firm is related to how **flexible** it is, and how well it may interact with its (possibly changing) environment and adapt to external conditions. Borrowing from biology, it is related to how well an organism may take evolutionary steps and move in the **fitness landscape** towards more desirable states, (Kauffman, 1993). Thus, a crucial question in management science, is the determination of the optimal structure of a firm, depending on the nature of the firm and the market in which it functions.

The aim of the present research is to try and answer some questions related to this matter, using the methodology of **complex adaptive systems (CAS) or Multi-Agent Adaptive Systems**. To this end, we will model a firm by a CAS that will reproduce the basic functions and characteristics of a given firm. Then, by the use of computer simulations we may “run” different scenarios for the evolution of a firm, and check the performance of different structures to provide solutions. The present model is a rather “generic” model of a firm that has the basic structure of a retail chain. As a result of that we may be able to draw general conclusions about the effect of structure on a firm’s performance. The simulations were performed in the computer simulation package SWARM which is very well suited for simulations of complex adaptive systems (see section 2 for more details on SWARM). Although this work is of academic nature, the computer software developed using the simulation package may be developed into the form of a **micro-world** (Casti, J.D., 1997, Morecroft J., et.al, 2000) that may be used for the simulation of the function of a given firm. The micro-world may be used by managing directors as a tool for planning and strategic decision-making.

The present work may be considered as one of the many recent efforts of systems dynamics to encapsulate Complex Adaptive Systems (CAS) or Agent-based models into the area of the traditional Systems dynamic modeling, within the frames of new “challenges for the future” as they described in Chapter 22 of the Sterman’s book (Sterman J.D., 2000) and his related paper (Sterman, J.D., 1994).

2. CAS and the SWARM computational environment

In this section we provide some basic information on CAS, their relation with the traditional Systems Dynamics modeling and the SWARM simulation environment.

2.1. CAS basics

We take complexity to mean the intricate inter-relationships that arise from the interaction of agents, which are able to adapt in and evolve with a changing environment. The theoretical framework being developed is based on work in the natural sciences (in physics, chemistry, biology, mathematics and computer simulation) studying complex adaptive systems (CAS).

In an organizational context, complexity provides an explanatory framework of how organizations behave. How individuals and organizations interact, relate and evolve within a larger social ecosystem. Complexity also explains why interventions may have un-anticipated consequences. The intricate inter-relationships of elements within a complex system give rise to multiple chains of dependencies. Change happens in the context of this intricate intertwining at all scales. We become aware of change only when a different pattern becomes discernible. But before change at a macro level can be seen, it is taking place at many micro-levels simultaneously. Hence micro-agent change leads to macro system evolution.

Complex Adaptive System (CAS) is found in everyday life. A crucial distinguishing characteristic of such systems is that their component elements are living “agents” capable of autonomous behaviour, which can be adapted to changing circumstances. This contracts with complex systems in chemistry, physics and engineering founded on established theories explaining observable phenomena encompassing interactions between non-living elements.

An overwhelming spectrum of living systems falls within the scope of current research, from stock markets to supermarkets urban traffic networks, national economies to global ecosystems and business organizations. However, although many effective models have been created (Casti 1997), there is still no real science to provide theoretical foundations for building these kinds of systems. One of the main reasons for this slow progress is that researchers into social and behavioural phenomena have not had the ability to conduct the controlled, repeatable experiments that are an integral part of the methods employed in natural sciences to test hypotheses and establish new theories.

Until the advent of widespread and usable computer power, it was generally impractical to perform experiments on everyday social and behavioural systems. For example, Wall Street cannot be asked to change its rules to allow an economist to check a new theory of financial markets. And even if such an unlikely event happened, a genuinely repeatable experiment could not be conducted because too many variables would have to be considered. In other cases, experiments would take too long to be of practical value or may pose too much danger to the real world, say by trying to evaluate a theory about biological diversity by introducing a new species to an environment.

The power and versatility of computer technology has now reached the point where we can create realistic “silicon surrogates” (Casti, 1997), encapsulating inside a computer the full scope and richness of interactive patterns of the social systems we want to experiment with.

Research at SFI (Casti 1997) has indicated that the existence of a medium-sized number of intelligent adaptive agents making decisions on the basis of local information can be regarded as the "fingerprint" indicating that a system being studied can be classified as a CAS. However, these features do not constitute a full definition of complex adaptive systems.

The three distinguishing characteristics of a CAS fingerprint involve:

1. **A medium-sized number of individual agents**. An agent is the basic element in a CAS. A customer in a shop, or a shop in a retail chain of an industry, are examples of potential agents in industry microworlds. The number of agents must be neither so small that all their interactions could be worked out "on the back of the envelope", nor so large that statistical aggregation methods could tell you everything you want to know about the system. In the type of CAS we are concerned with, here the actual number of agents can be considered "low grained", in the range of a few hundred to a few thousand.
2. **Intelligent agents with the ability to adapt**. Agents need to be "intelligent" in the sense that they can use in-built rules to decide what actions to take at any given moment. If they find a current rule isn't working well, agents should be **"adaptive"** in their ability to discover and change to new or different rules.

3. **Local information only.** All agents invoke their rules to make decisions on the basis of only partial, or “local”, information. This means there is no agent within the system, which knows what every other agent is doing. The “localness” can relate to physical or informational dimensions.

2.2. CAS and “Traditional” System Dynamics Models

So far, traditional system dynamics and complex adaptive systems have been treated as two completely separated aspects of reality, whether physical or social. However, nowadays with complexity and nonlinearity coming of age, it is high time to reconsider and view things under a new perspective. We should therefore try and reconcile the two approaches into one unified view of reality (Sterman, J.D., 1994). Our philosophy is that complex adaptive systems and system dynamics are just two different glimpses of the same phenomena but in different scales. Modeling uses one and unique methodology but depending on the coarse graining and the detail with which we wish to study a system, we may end up with a system dynamics or a complex adaptive system model. As a matter of fact, we wish to stress that a complex adaptive system model, being more detailed, may under appropriate **averaging**, or **coarse graining** be reduced to an appropriate system dynamics model. The degree of coarse graining used in a system, may be equivalent to different averaging procedures, which in turn reduce the original fully detailed complex adaptive system to a series of system dynamics models of increasing level of complexity. This is the analogue of **interacting particle systems models** and **mean filed** approximation models used in the physical sciences.

2.3. The SWARM Simulation System

The Swarm simulation system's objective is to provide researchers with a standardized, flexible, reliable set of software tools for experimenting with complex adaptive system of the type we will discuss in this paper. SWARM is a set of libraries that facilitate implementation of agent – based models. Artificial life, which tries to explain biological phenomena, is the inspiration of SWARM.

At the time of Swarm's inception, researchers in the field of CAS were finding that ad-hoc programming was not a sufficiently powerful, reliable, or economical way to ask the kinds of questions that needed to be asked.

Chris Langton of Santa Fe Institute (Langton, C., et al 1995) having seen this problem decided to initiate the SWARM project in 1994 at the Santa Fe Institute.

Virtual machine is the primary feature of SWARM. The virtual machine allows the researcher to describe agent behaviors one by one, agent by agent, context by context, all while keeping an exact notion of time and currency in the world. Swarm also makes it possible to compose or decompose hierarchies of agents. This is the **composability** attribute**.**

This notion of composability is useful because it often isn't clear where to begin a modeling effort. For example, in modeling a **large organization**, it may be the case that the subjective understandings of individuals' or departments' roles and responsibilities differ widely, and that this variance includes poor performance in some cases and outstanding performance in other cases. Rather than seeking denotation on how the organization should work and looking for deviations, one can built independent model components from many perspectives and then combine them (mirroring abstractions of people for real people). This **bottom-up** approach has the advantage of documenting the both unexpected bad and good things in the organization, as well as contextual sensitivities (Casti, J., 1997).

A **Schedule** is an **agent's to-do list**. There are different kinds of to-do lists, and different attributes that **Action** items on the to-do list can have. An **Action is something that happens** in the world. In Swarm, Schedules and Actions are typically **closely associated** with an agent or model component. Agents may have their own Schedules (perhaps several) and a repertoire of Actions they know how to perform.

3. A model for a retail chain

We will briefly describe a model of a retail chain that may easily bring into the general framework of complex adaptive systems. The model is very broad and versatile, and can be used in the modeling of a wide rage of firms but here to be precise we will present a brief description of how this may be used to model a retail chain. The model is a generalization of a model for a retail chain that was first proposed by Chang and Harrington (CH) (Chang M. -H. et al, 2000).

3.1 The original model of Chang and Harrington

In the original model of a retail chain, first proposed by Chang and Harrington, there is a **headquarters (HQ)** controlling the activity of M **stores (sub-units).** The stores interact with each other only through the headquarters. Each store has N dimensions in its **policy**. A dimension is related to some activity of a store e.g. pricing policy or customer support policy. Every dimension consists of R **practices**. In this abstract model each store at any time may be described by an N dimensional vector $z=(a_1,a_2,\ldots..a_N)$ where each of the a_i may take R distinct values. The vector z will hereafter be called the **store policy**.

The market of each store is assumed to consist of a collection of economic units-consumers **(agents).** Each agent has some preference towards the policy of each store, and is considered to be a rational entity, acting to maximize some **utility function**. This utility function depends on the quantity that an agent will buy from a store, on the price and on the "distance" of the agents **preferred store practice w** and the store's **actual practice z**. The price is considered as given by the store and the agent only has control over the quantity that will consume. This is chosen optimally, and is a function of the price, the preference and the policy.

At the next level, the store itself may be modeled as a collection of agents, having a distribution of preferences. The **probability distribution** of **agent's preferences F(w)** is considered to characterize the market in which the store acts. For each store we may define a **profit function P_i**, which is simply the total demand for some product (weighted average over all agents) multiplied by the net profit per unit. This profit function depends on the price (over which the store has control) and the deviation of the stores actual practice from the preferred practice by the agents. **The aim of each store is to maximize its profit**. This is done by choosing optimally the price p of the product in question.

Finally, the whole unit is modeled by a **profit function**, which is simply the sum of the profit function of each store. A good example of how the structure of a firm may affect its behavior is in its reaction towards **innovation**. We give here some details on what we mean by this term.

3.2 Innovation as explanation of competitive landscape and as a process of information creation and communication.

Traditional methods usually ignore an organization's capacity to learn and change and to maintain diverse and varied strategies, assuring that a single "optimum" strategy is both possible and desirable. For an organization, such our firm, to survive and thrive it needs to explore its space of possibilities and to encourage variety. When markets were stable and growth was a constant, single optimum strategies based on extrapolation from historical data, were thought to be feasible. But as Ashby has shown (Ashby, 1964, 1969), unstable environments and rapidly changing markets require flexible approaches based on variety.

In our work we adopt the view of Radner (Radner, 1993) and Van Zandt (Van Zandt, 1998) of the innovation as the process of information creation and communication, as well as the views of Chang and Harrington (Chang and Harrington, 1998, Chang and Harrington, 2000) according to which **innovation** is regarded also as a **random search** carried out in a **fixed space of ideas**.

An **innovation (idea)** may be though of as a process that alters the policy of a store. In the model at hand, an idea may be though of as some process altering some of the entries of the policy vector z. The complexity of an idea is related to the number of entries of the policy vector, which are altered. An idea may originate either at store level or a headquarter level. An idea originating at headquarter level, may change some of the entries of the policy vector of some store. This number is related to the degree of centralization that a firm has. The smaller it is the grater the freedom that the headquarter allows the store managers towards innovation.

The modeling of innovation adoption will be as follows:

- An idea is randomly generated either at store level or at headquarter level.
- If an idea is generated at HQ level it is tested on whether it increases the potential profit of the chain and if it does it is adopted at a global level.
- If an idea is generated at store level, it is tested on whether it increases the profit of the store and then it is communicated to HQ where it is tested on whether it may increase profit at chain level. If the idea increases the profit of y store it is adopted, otherwise it is dropped. How easy the communication of an idea

to HQ is and how easy it is to adopt some idea or not is related to the **structure** of a firm and to the **degree of centralization**.

The markets may be stable (that is the agents preference distribution is independent of time) or fluctuating (the agents preference distribution may change stochastically in time).

3.3 A generalization of the Chang and Harrington model

The Chang and Harrington model is interesting and versatile enough to model decision making in a wide range of firms, even though it was originally proposed in the context of retail chains. However, we propose here some extra features that we feel may lead to a generalization of the model which may be used to shed even more light on the problem of interaction of the structure of a firm on decision making and its performance.

We begin by briefly describing the change we feel are major regarding the structural characteristics of the model and towards the end of this section mention some less important changes which will as well lead to more realistic features.

The major point in our generalization of the model of Chang and Harrington is the introduction of the notion of **firm topology** in the model. This notion is related to how different sub-units are connected and how they interact (e.g. how they exchange information). In the original CH model, the topology of the firm is extremely simple and essentially is the topology of a simple tree where we have a headquarters (HQ) and all stores (S) directly connected to it. While this may be a plausible structure, real life firms may display more complicated connections between their sub-units. For instance we may generalize this structure by introducing various levels of **sub-headquarters (S-HQ)** that will be responsible for decision-making and will only be responsible for the function of certain groups of stores. This will lead to a different firm topology, different connectivity properties etc. The idea of local management, as is clear intuitively may lead to effective management of local units so as the firm as a whole may be able to interact more efficiently to an **inhomogeneous** market. Furthermore, this structure may not be static. The topology and the structure of the firm may be made to vary depending on the performance and the long-time scale properties of the fluctuations of the market. This feature of the model may be used to model the **potential strategic restructuring** of a firm in the course of its function. This dynamic feature is built in our generalized model and it turns out that the simulation package we employ is well suited to deal with that. The structure proposed here is just one possibility. It is interesting to try and test different connection topologies (in this task ideas from **neural network** theory may be very useful) with regards to their performance and try to find the optical connection topology.

We now describe some less major, but all the same interesting changes in the original model.

- In the model of Chang and Harrington, ideas are **randomly** generated. To make the model realistic, we have to introduce at store level a **search policy** to increase profit at store level.
- We have to take into account **interaction** of agents and store, in what the agents' preferred practice may not be considered as given and unchanged in time, but will change according to what the store offers. In other words there will be some sort of **feedback** between the store and the consumers that will affect the consumers taste.
- **The policy of HQ may not be** uniform towards the whole chain but may change from store to store. For instance the HQ may put more weight in certain markets neglecting others, or may allow more freedom in certain stores depending on store managers abilities etc.

3.4 Description of the implementation

For the implementation of the simulation software we used **Swarm** (see section 2.3). The basic architecture of Swarm is the simulation of collections of concurrently interacting agents: with this architecture, we can implement a large variety of agent-based models. Swarm is a collection of object oriented software libraries, which provide support for simulation programming (see Langton, C., 1995). We build simulations by incorporating Swarm library objects in our programs. **Figure 1** shows the main objects that Swarm provides and their interactions in a simulation application.

One can define agents (either independent or belonging to a group) and their behavior (actions and schedule). This is the model of the simulation. The observer object monitors the model execution and provides methods to output the results (to a GUI or to files on the hard disk) (Benedic S., et al, 2000, Daniels M., 2000).

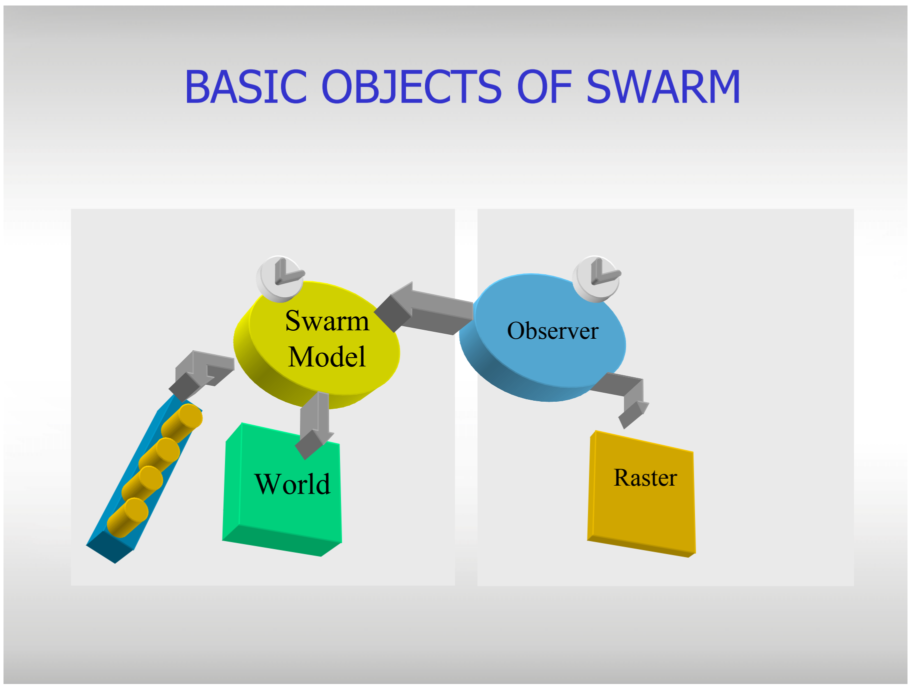

Figure 1a Main Objects of Swarm environment

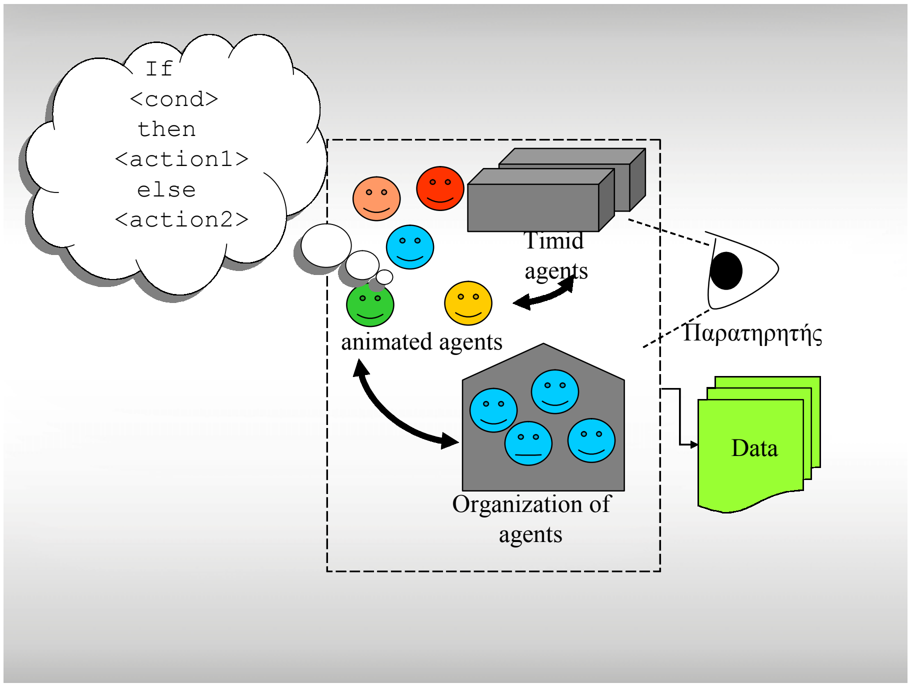

Figure 1b

3.4.1. Definition of categories of Agents

For the implementation of a simulation with Swarm, the first step is to define the agents of the simulation. In the case of our simulation of a retail chain, we defined the agents, as shown in **figure 2.**

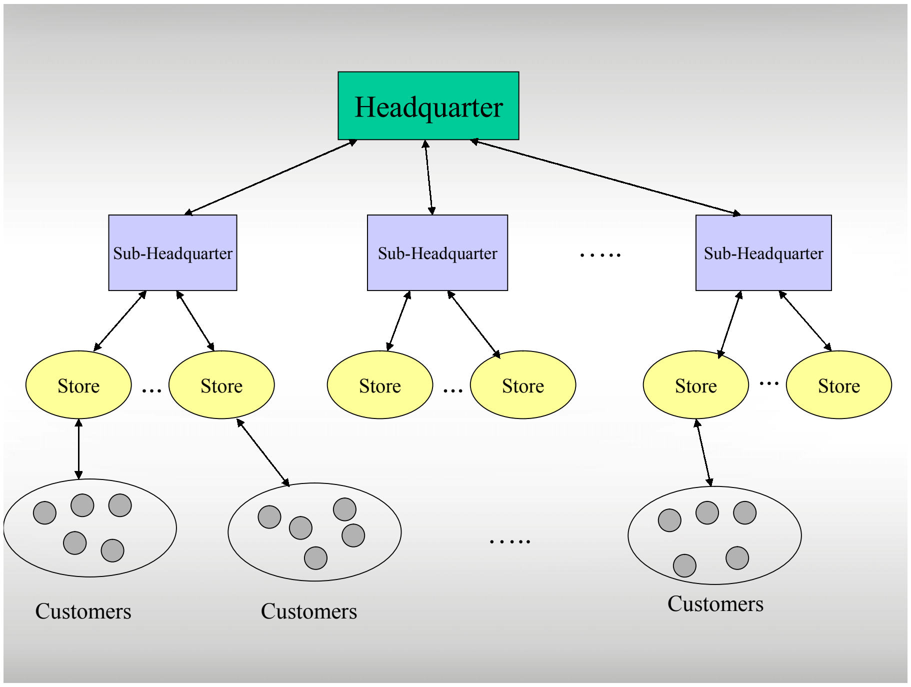

Figure 2 : The agents of the simulation

The main agent is the Store. Each store has a number of Customer agents and it belongs to a Headquarter or a Sub-Headquarter agent, depending on the structure of the Retail chain. As one can see, stores and headquarters are modeled as a whole, without being analyzed to sub-agents (for example, employees of the store).

3.4.2. Agent characteristics

Customers: Each customer belongs to one store for the whole simulation period. Each one has a set of preferences, which is described by a vector of arithmetic values. Depending on the simulation parameters, the preferences of a customer may remain the same or change during the simulation period.

Stores: Each store has a set of practices, which is described by a vector of arithmetic values. The store's market consists of a number of customer agents. The profit of the store is maximized when its practices are closer to its customers' preferences. The markets can be the same for all the stores, or may vary from store to store. This is accomplished with differently distribution of the customers (actually the customer preferences). The stores generate new ideas at every repetition of the simulation. These ideas are evaluated and are accepted if they result in raising the profit of the store and the retail chain.

Sub-Headquarters: The Sub-Headquarters agents introduce another level of complexity to the simulation. Each Sub-Headquarter has a number of stores under its authority. Depending on the mode of simulation selected by the user, the Sub-Headquarter either takes part in the evaluation of new ideas generated by their stores, or they just act as a carrier, in order to transfer information among the stores.

Headquarter: It is the central point of the model. It gives the total profit of the Retail chain. Depending on the structure of the chain, which was selected by the user, it has a number of stores or sub-headquarters under its authority.

3.4.3. Model flow

The simulation starts by building the different agents. The creation of the agents starts from the bottom. First, we create the customer agents. Then the stores are created and the customers are assigned to them. The next step is the creation of the sub-headquarters, if the user has selected a three-level simulation. The stores are then assigned to the sub-headquarters, in an equal manner. That means that if we have 4 stores and 2 sub-headquarters, the first two stores are assigned to the first sub-headquarter and the other two to the second. Finally, the headquarter agent is constructed. Depending on the structure of the Retail chain (two or three levels), the Headquarter agent is connected either to the sub-headquarter agents or to the store agents.

When the creation of the agents is completed, the simulation starts executing. In each iteration of the simulation, we have the following steps:

Each store has a new idea (innovation). The new idea is a change in one of the practices of the store. The store then calculates its profit with the new idea and compares it with its previous profit (before the emergence of the innovation). If the new profit is lower, then the idea is discarded. Otherwise, it is passed to the next level of the retail chain structure for further evaluation (headquarter or sub-headquarter). The Headquarter or sub-headquarter then passes the idea to the stores that are under its authority. If the mode of operation of the retail chain is the decentralization, then the idea is considered independently by each store. If it raises its profit it is realized, otherwise it is discarded. If the mode of operation of the retail chain is the centralization, the idea is mandated to all the stores, if more than y stores (y can be determined by the user) profit from it.

3.4.4. User Interface

The user interface of the application was designed with the principle to facilitate the use of the software. We have combined GUI elements that are provided by the Swarm with custom-made frames.

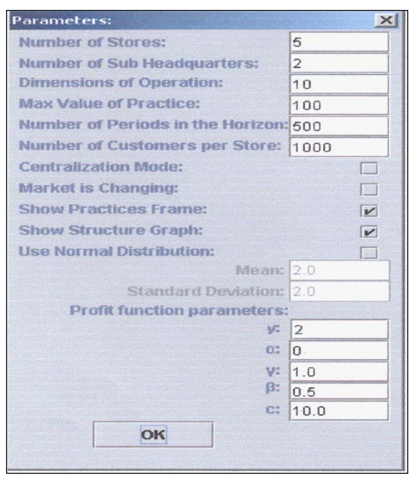

Figure 3: The screen where the user enters the simulation parameters.

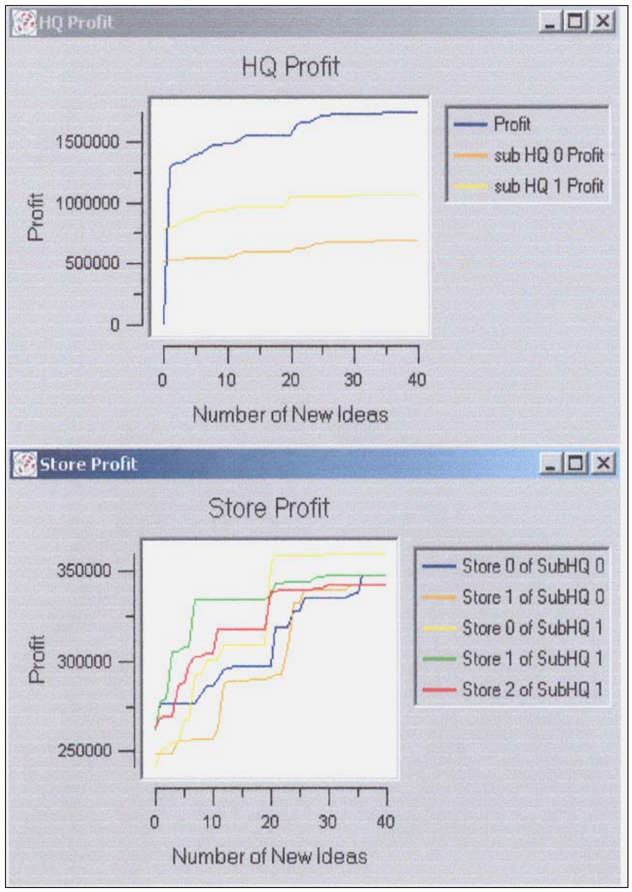

Figure 4: The graphs that present the profit of the stores and the headquarters

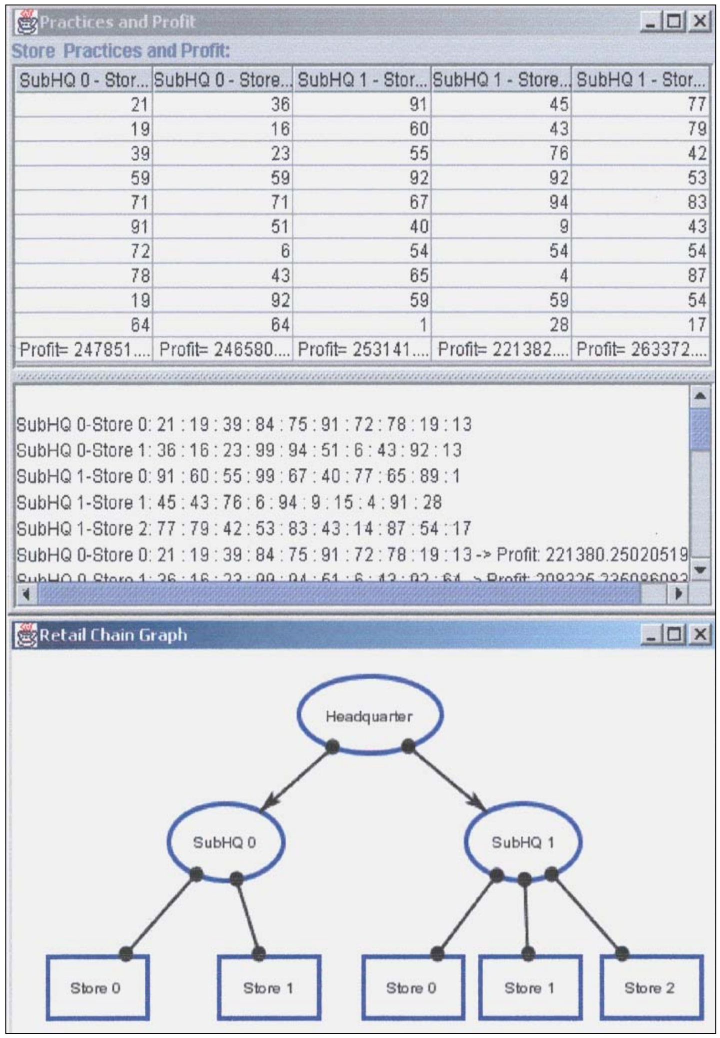

Figure 5: Custom made screens for showing the practices of the stores and the structure of the Retail chain.

4. Results

4a. Description of the simulation procedure

The software developed permits to conduct simulation runs with different parameters. Some of them are mentioned here:

- The structure of the Retail chain may vary. The number of stores and the existence (or not) of sub-headquarters can be defined by the user.
- The number of customers that are the market of a store may vary. The preferences of the customers are distributed over the type space either according to an uniform distribution, or according to a normal distribution with given mean and standard deviation. The distribution of customers may be either the same for all the stores (homogeneous markets) or different for each store (heterogeneous markets).
- Many parameters of the profit function may be changed by the user.
- The duration of the simulation runs can also change, in order to simulate over short or long horizons.

In order to perform the evaluation and compare the different models of operation, we have to keep some parameters fixed:

- The number of customers for each store was set to 1000.
- The number of preferences for each customer is set to 10, each having a value from 1 to 100. So, each store also has a set of 10 store practices, each having a value from 1 to 100.
- The parameters of the profit function for each store have remained unchanged for all the simulation runs.
- The maximum duration of the simulations was set to 500 repetitions. Results were gathered for 100 repetitions (short horizon) and 500 repetitions (long horizon).

The simulation runs were conducted on the following retail chain structures:

- 2,4,6 and 8 stores without Sub-Headquarters.
- 5 stores with 2 Sub-Headquarters, where the first Sub-Headquarter has 2 stores and the second 3.
- 8 stores with 2 Sub-Headquarters, each having 4 stores.

For each of the above configurations, runs were performed to compare the results among centralization and decentralization with different market conditions (heterogeneous vs. homogeneous markets, markets that are stable vs. markets that change during time etc). A total of 1000 runs were performed.

4b. Description of results

The results show that generally decentralization outperforms centralization in the majority of cases. Partial centralization gives better results when the retail chain has a three-level organization (it includes sub-headquarters). The best solution in that case seems to be a combination of centralization (sub-headquarter over stores) and decentralization (headquarter over sub-headquarters).

In more details, we can say the following:

- **Centralization** is more likely to outperform decentralization when the stores have similar markets, while decentralization is more likely to outperform centralization when markets are different. Since centralization imposes uniformity of practices, these results are not surprising. When the markets are different, it is better to let each store change its practices according to the needs of its local market. On the other hand, when markets are similar, common practices can be imposes and can give better results. Centralization gives better results in this case, especially when we have a large number of stores and long horizons of simulation. The presence of sub-headquarters does not have an impact when markets are similar. However, if markets are different, the presence of sub-headquarters can flavor centralization, if markets are grouped by similarity (sub-headquarters have under their authority stores with sufficiently similar markets).

- **Decentralization** outperforms centralization, almost in every case, when the markets are not stable (customer preferences change over time). Centralization does not seem to be able to follow the changes of the market of every store. On the other hand, decentralization gives the ability to each store to better adjust its practices, according to its customers needs. The presence of sub-headquarters does not change the situation very much in this case.

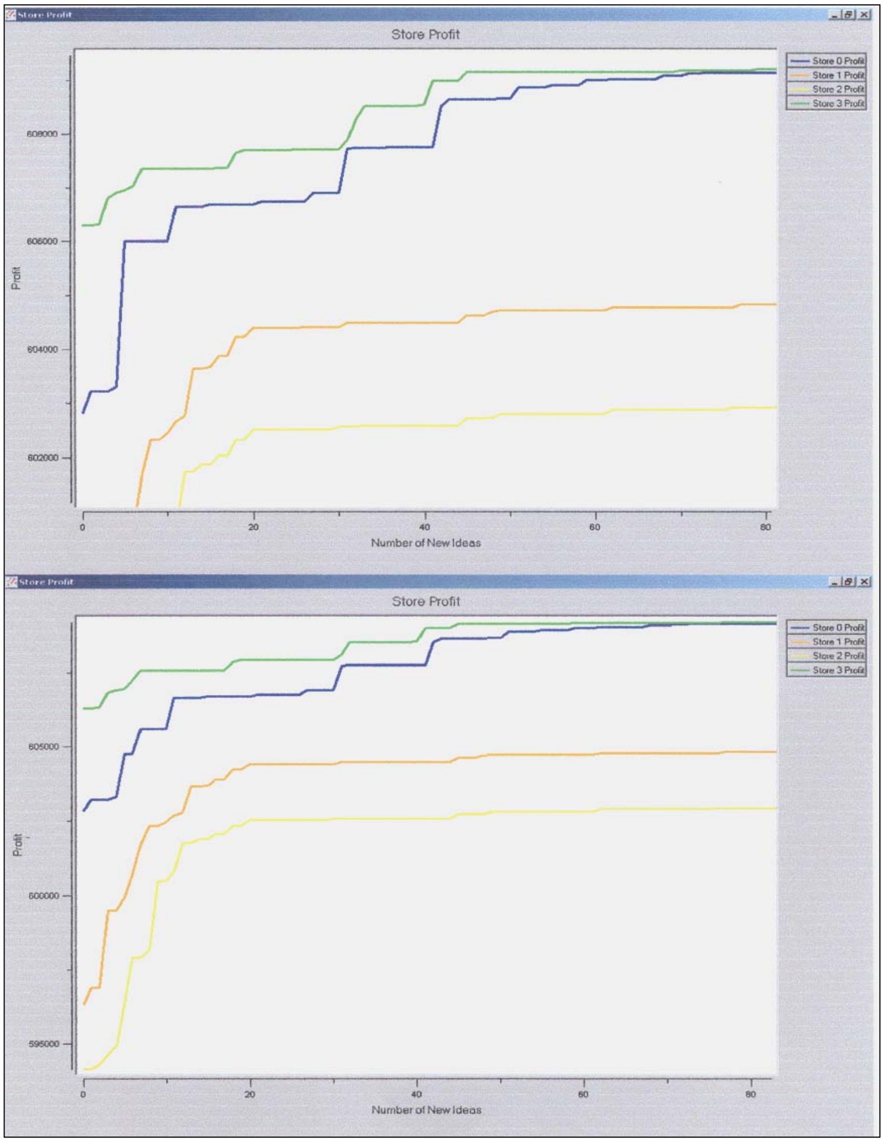

Figure 6: Store profit evolution example for 4 stores with different markets, for decentralization (up) and centralization (down).

Decentralization gives better results, especially for two of the 4 stores. The reason is that the similar practices enforced by centralization keep the two stores away from their optimum practices.

We have of course to comment that, in our simulation, the communication and transfer of ideas among stores is always perfect, in both modes of operation, centralization and decentralization. In the real world, that may not happen every time, so decentralization would probably have worse results, since the information about a new idea may never (or very late) reach all the stores of the retail chain.

5. Future improvements – Conclusion

One important improvement that will be made to the initial model is the introduction of the ability of customers to move. In that way, a customer that is not satisfied with one store's practices will be able to move to another store in his vicinity.

Another important step in enriching the model would be the introduction of rival businesses. In that scenario, a customer will also be able not only to move from store to store of the same retail chain, but also, if he is not satisfied by the retail chain in general, to move to a rival's store in the region.

Finally, improvements can be made in the user interface of the software. In future versions, the user will be able to design the structure of the retail chain in a graph. The software will then read the graph and construct the simulation for the specified structure. As a result, even more complicated structures will be supported.

- The model of Chang and Harrington, does not take into account competition at all. We intend to introduce into the model a competing firm B that will complete for the same market trying to adopt policies to approximate better the agents preferences. The stores of the rival firm, may observe the firm's A practice and learn from its experience.
- Finally, a detailed study of the agents' utility function has to be made. This will give us the characteristics of the market. We also need to introduce inhomogeneity of the markets (i.e. different preference distribution from market to market).

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