Modeling an Innovation Ecosystem with Adaptive Agents*

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ABSTRACT
Agent-based modeling has proven effective in increasing the understanding of complex systems, including social-economical systems. A goal of modeling complex systems is to distill the system into simple agents with phenotypes guided by simple rules. The model then displays the emergent behavior of these agents interacting with each other and their environment. An agent-based model of innovation and its place in a global economy or ecosystem is presented. The model utilizes simple agents to represent innovating entities such as large corporations and small companies. The results produced by this model reveal the dynamics of innovation and its role in a global economy. The results indicate a large need for partnership in innovation for those entities working within rapidly changing domains. Domains, such as high technology, have constantly changing market expectations, which force innovating entities to seek external sources of assistance to meet these expectations in a timely enough fashion so as to incur benefit.

1. INTRODUCTION
The interest in complex systems has seen a marked increase over the past two decades. Various approaches have been developed to gain better understanding of these systems. Bandini et al. [4] and Chopard et al. [5] modeled complex systems as cellular automata. A cellular automaton, with its lattice of agent cells whose behavior is directly influenced by its neighbors, can be viewed as a hierarchical parent to the agent-based model discussed in this paper. Cellular automata can thus be considered as a more generalized conception of the full agent-based modeling approach.

An agent-based model utilizes simple agents interacting with their environment through sensors and actions [16]. The environment that the agents interact with is defined by the model that defines the interaction with other agents in the environment as well as external constraints or boundaries. The use of agent-based modeling to understand complex systems is well documented in the literature. For example, Koritarov [10] applied agent-based modeling to simulate electricity market scenarios and Tesfatsion [18] described an agent-based model of complex economic conditions.

The macro-behavior of a complex system cannot be described by the sum of the micro-behaviors of the interacting parts of the system alone [9]. Using complex systems theory to understand various issues related to innovation is also well documented in the literature. Albino et al. [1] related the interconnections of districts of industrial innovators to complex systems through an agent-based model. Similarly, Ma and Nakamori [12] presented an agent-based model of evolutionary processes at work in innovation.

As innovation is difficult to formalize and define, various surrogates have been offered in place of a definition, e.g., Stokic et al. [17] and [7]. This lack of a definition of innovation is partly due to a solid understanding of the interactions that take place during the innovation process. This paper seeks to illustrate some of these interactions and their results through agent-based modeling.

In this paper, an agent-based model of an innovation ecosystem is presented. The ecosystem is considered as an environment in which the individual agents (innovation entities) exist and interact. The interaction of the agents is with the other agents in the ecosystem as well as the dynamic environment itself. The model that is described in this paper seeks to understand the factors of importance with which innovating entities (e.g., corporations, smaller businesses) realize an optimization of their resources. The literature lacks such a model of an innovation ecosystem.

The remainder of this paper is organized as follows. Section 2 offers a brief introduction to agent-based modeling in the context of complex systems. The model utilized in this paper is presented in

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Section 3. Section 4 the results of this model are presented which illustrate that innovation entities operating within rapidly changing domains must seek innovation partners to cope with the rapidly changing market expectations. The results produced by the model and their contributions to innovation are discussed in Section 5. Finally, conclusions and suggestions for future research are presented in Section 6.

2. AGENT-BASED MODELING

An agent-based model includes a set of simple agents that interact with each other and their environment. The agent interaction mode and the resultant models vary. Both, simple message passing interfaces with which the agents communicate [8] and direct communication with various evolutionary processes to update the agents [3] has been researched.

Agents are often defined with an initial set of simple rules, which are updated at discrete time intervals based upon a history of actions and sensed environment [14]. The rules that define the agent initially define the response of the agent to specific conditions in the environment and trigger that response to these conditions. The updating of the rules proceeds in discrete time intervals, often synchronously with the other agents and the environment. The updating process varies, though most often it relies on the agents making decision based upon past experience. Therefore, agents tend to maintain a history of their experiences and update their rules adapting to this history.

A key aspect in agent-based models is the lack of a centralized control [19]. Rather each agent controls its own updating and actions. This lack of centralized control makes agent-based modeling well suited for simulation of ad hoc networks of entities such as an ecosystem of innovating companies. The lack of centralized control over a system ensures that the only possible means with which the system can be understood is through simulation, which is the case with many social and economic scenarios.

An agent-based model iteratively produces its emergent behavior (see Figure 1).

In an agent-based model, a population of agents is initialized with their defining rules, often randomly generated. The agents then sense their environment and interact with one another and record this information as a history. The agents update their rules based upon this history and begin the process of sensing and updating all over again.

During the iterative model development, it is often desirable to record the states of the environment and the agents to facilitate the observation of the emergent behavior of the system. Observing the complete system at discrete time intervals allows the user to understand more fully the behaviors

Figure 1. Iterative agent-based model.
emerging within the system and to possibly abstract rules based upon these behaviors. It is the emergent behaviors of the set of agents that makes agent-based modeling so appealing for understanding complex system.

Various methodologies are used for rule updating of agents. Some models utilize a simple look up tables of rules that the agents can choose from based upon their history. Other models utilize evolutionary concepts, such as genetic algorithms [2] or even a simple mutation to update the rules of each agent. Regardless of the updating methodology, the rule updates are critical to the evolving of an optimal system and to agent survival within that system.

3. AGENT-BASED MODEL OF AN INNOVATION ECOSYSTEM

This section describes the model built in this paper to simulate an innovation ecosystem. An innovation ecosystem is described here as a set of innovation entities (e.g., small businesses, governments, corporations) all functioning in a dynamic environment. Each of these entities (agents) offers a single product at any given time. Each of the agents in the ecosystem communicates with one another and decides whether or not to form a partnership to generate new products or not. Agents of the ecosystem also have the opportunities to retool their processes and produce a new product without a partnership arrangement.

3.1 Agent Description

The innovation ecosystem model built here uses a standard population of 1000 agents. This population size is given as a parameter to the system and could be changed based upon the user’s desire. As previously mentioned, each agent in the ecosystem produces a single product at any given time. These products fall into one of thirty domain categories, which is a system parameter that can be changed by the user. Each product that is produced by the agents of the system consists of properties. The number of these properties is a user selected system parameter and it is the same number for all agents’ products. For the model built in this paper, the value of this parameter is 100, i.e., equal the number of properties for each product in the model.

Each product of the agents is represented by a bit string. Each bit string is made up of the product domain as well as the properties of the product being produced by the agents. Fig. 2 illustrates a bit string that represents a sample product with the first 5 bits representing the domain of the product and the remaining 10 bits represent the properties of that product. The representation of the agents’ products as bit strings is utilized to compare that product with dynamic market requirements.

In addition to product type and product properties, each agent is defined by a number of variables. Often in models of complex adaptive systems, such as the innovation ecosystem under consideration here, agents maintain resources (e.g., [13], [15]). In this model the resources that each agent maintains, and attempts to maximize, is a set of assets (e.g., capital) and is given as a single variable. Agents also contain variables for market share that is described in Section 3.3. Additionally, agents have variables to represent the amount of interaction to be performed with other agents, the minimum market share required of an interacting agent before interaction will take place, and a variable to indicate the rate at which each agent learns from other agents.

Innovation may be realized in practice by retooling of a product where certain characteristics of the product are altered in an attempt to offer it a new life in the market place. The innovation ecosystem presented here allows agents to retool their product as well. This retooling if governed by a retool rate parameter and a retool amount parameter that is maintained by the agent and can be adjusted as needed by the agent.

As stated previously, agents often maintain a history of their interactions with the environment and other agents. In the model built here agents maintain a resource history as well as an interaction history that provides the agent with information about the environment and the other agents. These histories are utilized by the agents during their updating process which will be illustrated in Section 3.3.

Figure 2. Product bit string representation.
3.2 Environment Description

In the innovation ecosystem model, each product domain is assigned a randomly generated set of properties which represented as a bit string form the market requirements for the given product domain. In this simulation, as in the real world domain, these market requirements are constantly changing. The rate of change (the range (0, 1)) of a domain changes is established by a random number generator. In the example, domain $A$ may have a rate of change 0.0125 while domain $B$ may have a rate of change of 0.627. Once at each generation run, a rate of change is randomly generated for each domain. If that number is less than the given domain’s rate of change then the properties are randomly modified for that domain’s market requirements. While the actual market conditions may not change randomly, the random change in this model are well within rational reason for representing a changing market. In neither the real world, nor this model, can market requirements be fully predicted.

The environment of the innovation ecosystem model contains user defined parameters for the cost of interaction and the payoff of each generation. At each generation, agents decide whether or not to interact with other agents. If an agent decides to interact with another agent then the agents exchange information. Included in this information is some of the resources of the agent whose market share is greatest of the two. The exchange of resources as discussed here is often referred in the literature [11] as the flow. The agent with the largest market share is compelled to pay, or flow to, the other agent a portion of its resources for the interaction. The portion of payment transferred in the model is given by the cost of interaction parameter. The payoff parameter illustrates another example of flows and indicates the amount of resources each agent gains at each generation based upon their fitness to the market requirements. Both the cost of interaction parameter and the payoff parameter are discussed in Section 3.3 when updating is described.

3.3 Updating

At each generation the resources of the agents are updated to reflect their adherence to the market requirements. This update is preformed as a percentage of the agent’s resources and is defined in (1).

$$\varphi_{t+1} = \varphi_t f(a_t) \rho$$  \hspace{1cm} (1)

where $\rho \in (0, 1]$ is a payoff parameter set by the user, $\varphi$ is the resources of the agent at time $t$ and time $t + 1$, and $f$ is the fitness function of each agent given by (2) where $r_j$ is the allele at the $j$th loci of the requirement string $r$ with $N$ properties.

$$f(a_t) = \frac{1}{N} \sum_{j=1}^{N} \varphi_j$$  \hspace{1cm} (2)

The resources of the agents are also used in determining the market share each agent holds in the domain of their given product. This market share is given by the agent’s resources in relation to the total resources of all agents in the given domain as described by (3).

$$m_i = \frac{\varphi_i}{\sum_{j=1}^{K} \varphi_i}$$  \hspace{1cm} (3)

where $m$ is the market share of agent $i$, $\varphi$ is the resources of agent $i$, and $K$ is the number of agents whose products are in the given domain.

The market share of each agent is then utilized in each generation to determine if any agent will interact with a selected agent. Each agent maintains a minimum market share variable that indicates the required market share of each agent that the given agent will interact with. In the interaction, an agent chooses another agent to interact with. If the chosen agent’s market share is below the threshold of the first agent then that agent will not be accepted for interaction. Upon interaction acceptance the agent with the larger market share is compelled to pay a portion of its resources to the other agent. The amount of resources paid, $\mu$, is given as a product of the paying agent’s resource and the cost of interaction parameter, $\theta$, as shown in (4).

$$\mu = \varphi_i \theta$$  \hspace{1cm} (4)
The interaction of the two agents is performed using crossover. The properties of each agent are used as the parents for the crossover process. A random point within the bit strings of the properties is selected and the values are exchanged to form two new products. These new products replace the existing products of the agents. This form of crossover interaction encourages diversity within the population of agents and allows for more fit agents to exchange information with less fit agents.

During the interaction the interacting agents have the opportunity to learn from one another. This learning is governed by each agent’s learning rate. A random number is chosen and if it this number is less than the agent’s learning rate, then that agent may learn from the other agent in the interaction. Learning takes place utilizing the evolutionary operation of cross-over similar to the product property exchange discussed above. Vectors of each agent’s interaction rate, interaction minimum value, retool rate, amount of retool, learning rate, and the rates at which the agents adjust their own parameters are formed for each agent. A random loci within the parameter is selected and the alleles of the loci proceeding the swap point of one of the vectors is combined with the alleles of the loci following the swap point of the other vector. In this manner agents are able to learn from more successful agents in the population.

At each generation agents are given the opportunity to retool their products. A random number is selected and if that number is smaller than the agent’s retooling rate, the agent may retool its product. Retooling proceeds with the use of the mutation operator from evolutionary computation. Each loci of the property string of the agent’s product is selected for mutation if a randomly selected number is less than the agent’s retooling amount parameter. Retooling in the real world incurs a cost (e.g. new machinery, new production methodologies). In the innovation ecosystem, retooling costs the agent a portion of its resources as a simulation of the real world costs. For the purposes of this model the retooling cost was fixed at 15% of the agent’s resources. Future models may set this as a parameter for user input.

With each generation the agents are given the opportunity to change their rate of interaction. If the history of the agent’s interactions indicates a downward trend in resources the agent may decrease their rate of interaction. Should the agent observe an upward trend in its resources over the course of the given history, that agent may decide to increase its interaction rate. This evaluation of the history and subsequent alteration of the rate of interaction allows the agents to adapt to conditions present in the market place.

Finally, agents whose resources have fallen below a specified threshold for more than 5 generations are allowed to parish. These agents are then replaced with new agents. All agents in the model are generated with their parameters randomly initialized. Thus, the agents replacing the extinct agents incur the same initialization procedure as the initial population, irrespectively of the generation number. In this model the population size is maintained at 1000 agents and therefore the number of extinct agents is replaced by the same number of randomly generated agents.

4. MODEL RESULTS
For the purposes of exploration the model described in section 3 was ran with 125 different sets of parameters. The model maintained the constant parameters of:

- Population size = 1000,
- Number of product domains = 30, and
- Number of properties per product = 100.

The parameters of fitness change rate, cost of interaction and payoff were accounted for with values from (0.01, 0.05, 0.10, 0.20, 0.50). Each run of a set of parameters was repeated 10 times and the average of the ten runs was recorded. This allowed for the randomness of the model to be discounted in the results of the runs. During each run results were recorded for:

- The mean fitness of the population,
- The fitness value of the fittest individual,
- The mean interaction rate of the population,
- The mean market share of the population,
- The maximum market share of an agent in the population, and
- The mean resources of the population.
The results discussed above were recorded at each generation to preserve a historic representation of the system for each parameter combination. These results were averaged over the ten repeated runs of each parameter combination as previously discussed. The results of these averaged runs are now presented.

All the runs of this model were limited to 1000 generations to ensure accurate comparison ability. Fig. 1 - Fig 3 illustrate the results of a single averaged run of the model, showing mean fitness, mean interaction rate and mean resources respectfully.

As can be seen from Fig. 1 through Fig. 3 the mean interaction rate trends downward throughout most of the run with sharp declines in the first 100 generations. Similarly, the mean resources of the population take a sharp decline in the first 100 generation but then they appear to stabilize for the remainder of the run. The mean fitness of the population fluctuates constantly throughout the run but remains within a bounded region.

The initial hypothesis of this model was that the mean interaction rate would increase as the cost of interaction remained low and the payoff for each generation increased. Unfortunately, this hypothesis was proven to be faulty. Fig. 4 – Fig. 8 show that the mean interaction rate remains within a bounded constant region regardless of the cost of interaction and the amount of payoff. The results for runs where the fitness change rate remained constant at 0.05 are presented in Fig. 4 – Fig. 8.

![Mean Fitness graph](image1)

**Figure 1.** Mean fitness for an average run of the model with the fitness change rate = 0.01, the cost of interaction = 0.01, and the payoff = 0.01.

![Mean Interaction Rate graph](image2)

**Mean Interaction Rate graph**

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Figure 3. Mean agent resource for an average run of the model with the fitness change rate = 0.01, the cost of interaction = 0.01, and the payoff = 0.01.

Figure 4. Mean interaction for an average run with cost of interaction = 0.01 and the payoff = 0.01.

Figure 5. Mean interaction for an average run with the interaction cost = 0.01 and payoff = 0.05.
Figure 6. Mean interaction for an average run with the interaction cost = 0.01 and the payoff = 0.0.10.

Figure 7. Mean interaction for an average run with the interaction cost = 0.01 and payoff = 0.20.

Figure 8. Mean interaction for an average run with the interaction cost = 0.01 and the payoff = 0.50.
As illustrated in Fig. 4 – Fig. 8, the mean interaction rate continued to trend low for all of the runs which is contrary to the initial hypothesis. In fact, the trend appears to be just the opposite, the higher the payoff the less likely the agents were to interact. Fig. 9 and Fig. 10 illustrate that in the same runs the mean resources of the population changed little from a payoff of 0.01 to a payoff of 0.50, ruling out the thought that resources increase as payoff increases.

The simulation has shown that the cost of interaction and the payoff rate had little, if any, impact on the change in the system behavior. The only factor that weighed heavily on the behavior of the system was the rate at which the market requirements (fitness) changed. It was discovered that if the rate of change of the market requirements increased that the mean interaction rate and the mean resources of the population increased as well. In the case of the resources they began to increase in an exponential fashion. This fact is illustrated in Fig. 11 – Fig. 14 where the cost of interaction and payoff parameters were set to 0.10.

The mean interaction rate increases dramatically as the rate at which the market requirements change increases (see Fig. 11–Fig. 14). In addition, the mean resources of the population experience exponential growth with the frequent changes of the market requirements. This type of emergent behavior cannot be accounted for through considering the agent definitions alone. Rather, this behavior

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Figure 9. Mean resources for an average run with the interaction cost = 0.01 and the payoff = 0.01.

Figure 10. Mean resources for an average run with the interaction cost = 0.01 and the payoff = 0.50.
Figure 11. Mean interaction for an average run with the fitness rate of change = 0.01.

Figure 12. Mean resources for an average run with the fitness rate of change = 0.01.

Figure 13. Mean interaction for an average run with the fitness rate of change = 0.50.
is truly complex and can only be understood from the creation of a model such as the innovation ecosystem given here.

5. A SEMICONDUCTOR CASE STUDY

The innovation ecosystem model built in this paper has provided some startling insights into the emergent behavior of complex systems. The results presented in Section 4 where unexpected and point to some useful principles related to innovation and the global market place.

The amount of interaction between innovating entities is directly related to the rate at which the market changes. The model shown in Section 4 illustrates that a rapidly changing marketplace calls for greater interaction between companies to ensure success. The model illustrates that a rapidly changing market requirement offers a great opportunity for investment and resource gain. When considering the rapidly changing technological markets, the increase in resources indicated by the model is justified.

It has been shown that in the real world market with rapidly changing technology, partnerships increase the chances of innovation success. Companies such as Microsoft, which initially concentrated on software production, have teamed with other entities to produce entertainment devices and communications ability as seen in the Sync product in which Microsoft teamed with Ford Motors [6]. The technology of communications and entertainment is rapidly changing therefore innovation entities must seek partners to keep up with the rapidly changing market expectations. With technologies that change rapidly it is doubtful that a single innovation entity can retool fast enough to maintain a market lead.

A search of the internet shows that there is prolific use of the concepts presented in this paper in the semiconductor industry. Siemens and Infineon teamed together in 2007 to produce power semiconductors for use in the power generation fields [20]. Quimonda, a German semiconductor supplier of memory products, in 2008 teamed with Centrosolar Group, to produce crystalline solar cells [21]. In 2006 Ball Semiconductor joined forces with K.K. Dai-Nippon Kaken, a displays company, to produce maskless exposure equipment [22]. These are but a few of the many examples of semiconducting firms teaming with extra-domain entities to produce new innovations. Fields with rapid technological growth such as the semiconductor industry experience some of the highest change in innovation requirements. Therefore, it is essential for the survival of these companies to partner with other companies to keep up with the changing requirements.

Macher et al [23] stated while the number of technology-development alliances in the global semiconductor industry declined during the 1990s, alliances among foreign firms appeared to show more sustainable growth. This statement illustrates that even during times of economic turmoil, such as was seen in the early 1990s, the semiconductor industry witnessed growth through the formation of alliances. This growth is attributable directly to the innovation entity alliances that were formed in this ever-changing domain.

An interesting behavior that was discovered in the innovation ecosystem was that of niche creation and filling. It was discovered that product domains with lower rate of change in requirements
experienced agents whose interaction rates remained extremely low but whose resources would trend upwards. These markets can be viewed in similarity to the market for grandfather clocks. This market has changed little over the last 100 years in terms of its requirements, yet companies perform relatively well in this market if they are established. The model showed that it took time for an agent to gain a large market share in these types of markets but once it had that larger share it was difficult for the agent to lose it. The niche creation was discussed in [9].

Therefore, it can be concluded that if an innovation entity is working within a rapidly changing domain, such as high-end technology, it is beneficial for that entity to work in partnership with another innovation entity in order to meet market demands. Further, if an innovation entity is in a market domain in which requirements change very little, that entity should seek to maximize their longevity in the market and minimize their innovation interactions with external entities.

6. CONCLUSION

An agent-based model of an innovation ecosystem was presented. While the model reduced the number of active variables, (e.g. product description representation, market requirement representation, removal of geo-political parameters) to a minimum, it fully represents the emergent behavior of innovation entities working within an innovation environment. This form of innovation ecosystem is novel.

Agent-based modeling has been utilized to discover emergent behavior in many systems (e.g. the economy, stock trading, disease spread). The novel contribution of the work discussed here is to represent an ecosystem of innovation. This paper illustrated the influence of market expectations on innovating entities. This concept is also novel as most previous research has been centered on the diffusion of innovation rather than its ontology.

This paper showed that innovation entities within rapidly changing market domains benefit from the partnership with external entities. Furthermore, the paper proved that innovation entities benefit from resource and/or knowledge acquisition if the market domain they operate in is rapidly changing. Niche creation within slower changing markets was also discussed.

Future research in this area includes expanding the model to allow the user to define more agent parameters. Additionally, coevolutionary modeling may illustrate a deeper dependence on external entities than what is initially given in this model. Lever points, defined as small interactions which cause directed lasting changes, are present in all complex adaptive systems although they remain without a solid understanding of how they occur. Lever points in the innovation ecosystem are yet another area for future research.

REFERENCES


