

THE DIFFUSION OF INNOVATION IN THE MINING INDUSTRY:
AGENT-BASED MODELING AND SIMULATION

by
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ABSTRACT

The mining industry is a complex system in which diverse entities, called agents, with unique characteristics and adaptive behavior interact to reach their goals and often produce unexpected emergent phenomena. In an emergent phenomenon, the behavior of an individual agent is not reflected in the agents' aggregate behavior. This thesis highlights the importance of emergent phenomena since they can provide much insight into agents' ability to influence the future state of a complex system.

The main objective of this thesis is to provide and implement a framework for an agent-based model to demonstrate ways innovations can be adopted in the mining industry. The framework consists of three basic components: agents, objects and environment design. We provide an example of implementation of the framework by modeling the diffusion of the longwall mining method in the U.S.

The proposed model was capable of producing a diffusion pattern similar to the actual history; however, a similar diffusion pattern can also be produced through different combinations of parameter settings. The presented model can offer multiple scenarios that produce a similar diffusion pattern. The parameter setting and scenario used in the model is based on the author's interpretation of the actual diffusion process. One of the key findings of the model is that simple interaction rules between agents in the mining industry can explain collective behavior toward innovations. An emergent phenomenon in the model appeared when small mining companies were collectively persistent in utilizing an inferior mining method.

The agent-based model in this thesis can provide insight into how agents' diversity, adaptive behavior, and interaction influence the process of diffusion of innovation. Insights on the diffusion process will benefit any parties that wish to promote innovation in the mining industry. Suggestions for future work include more detailed studies and documentation of the behavior and interaction between agents in the mining industry with a special emphasis on their decision making process towards innovation as well as further research in establishing a standard validation technique that enables

integrated analysis of the trend of innovation diffusion, agents' internal condition, and interaction between agents.

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CHAPTER 1

INTRODUCTION

A complex adaptive system (also known as a complex system or CAS) is a system that consists of heterogeneous and interacting components with adaptation capability (Ahmed, Elgazzar, & Hegazi, 2005). Examples of CAS can be found in different fields of study, including biology, politics, and economics. The complexity of a system arises from the interaction and adaptive behavior of its diverse components, which may be living organisms, people, or organizations. This can be a physical interaction, an exchange of information, or both. The components of a CAS are called “agents” (Holland, 1996). Every agent has specific goals and rules of behavior. Because of the diversity and interaction between agents, the behavior of a CAS is not just a simple linear aggregation of the behavior of individual agents within the system (Holland, 1992). The collective behavior of agents in a complex system that is not specifically imposed on each individual agent is known as emergent phenomena.

The mining industry can be considered a complex system because consists of many interacting agents that participate in the activities of exploring, extracting, and processing coal and minerals. Mining companies, equipment manufacturers, government agencies, and mining contractors are examples of different agents that participate and interact in different activities and processes. Diversity can also be found within the same types of agents. For example, mining companies run different mining operations with unique geological characteristics, mineral types, and locations. Given the understanding that the behavior of a complex system cannot be simply derived from the behavior of individual agents in the system, it is essential to perform an analysis of the behavior of the industry from the perspective of complexity by observing how collective behavior of agents is altered when the modeling parameters are changed.

1.1. The Diffusion of Innovation

Innovation can be an idea, object, or practice that is perceived as new by the potential adopters (Rogers, 2003). Technological innovations include software, hardware, and process applications. Depending on how a technological innovation differs from previous technology, it can be categorized as either a revolutionary or an incremental innovation. Revolutionary innovations are fundamentally different from current existing technologies or practices; some examples from the mining industry are the longwall mining method for underground coal mines, rock bolts, and the load-haul-dump units in underground mining operation (Committee on Technologies for the Mining Industry, Committee on Earth Resources, 2002). On the other hand, incremental innovations are generally minor developmental changes such as additional capacities, new features of technology and tools, or different utilization of existing products or technologies that do not change the fundamental aspects of practice. The increased capacity of haul trucks is an example of this type of innovation.

This thesis is an attempt to model the process through which an innovation is widely adopted in the mining industry. The process of diffusing an innovation into the members of a social system through is known as the diffusion of innovation (Rogers, 2003). The speed of the diffusion of an innovation is usually measured by the rate of adoption of the innovation by the potential adopters in a specific time period.

Several researchers highlight the importance of the interaction among agents and agents' diversity in understanding the dynamics of the process of diffusion of innovation in the mining industry (e.g., Ala-Härkönen, 1993a; Barczak, 1992; Reid & Richardson, 1995; Souder & Palowitch, 1981; Tilton & Landsberg, 1999). Mining companies gain information about other mines through interaction in the form of informal discussion, observing their competitors (Ala-Härkönen, 1993b), and visiting other mines (Souder & Palowitch, 1981). Interaction is important in the diffusion process because it leads to exchange of information between agents that can lead to innovation adoption. For example, the early application of roof bolting at Consol's Mine no. 7 in Illinois was decided after the Chief Engineer of Consol visited a St. Joe Lead Company mine and observed its successful application there (Mark & Barczak, 2011). Interaction between equipment manufacturers and mining companies also contributes to the diffusion of

innovation. Reid and Richardson (1995) note that longwall equipment manufacturers helped diffuse the longwall mining method by providing training and consultation services to potential adopters that removed the barriers to adopting the method faced by inexperienced potential adopters.

Mining companies have different characteristics of mining operations, mineral deposits (e.g., size, mineral deposit type, ore grade, coal seam thickness), and strategies for adopting an innovation. These different characteristics influence how mining companies evaluate an innovation. Mining companies evaluate an innovation based on the attributes of the innovation. These perceived attributes are defined by Rogers (2003) as follows:

- a) Compatibility: the degree to which an innovation will match the needs, values, or specific characteristics of adopters.
- b) Relative advantage: the benefit of adopting an innovation compared to the current practice/technology.
- c) Trialability: the degree to which an innovation can be implemented on a smaller scale before fully adopting it.
- d) Complexity: the level of difficulty or complexity in adopting an innovation.
- e) Observability: the degree to which innovation results are visible for the adopters.

The perceived attributes of innovation for mining companies as potential adopters may change because mining companies and innovations both evolve. For example, a mining company may mine different types of mineral deposit, a thicker coal seam, or a deeper coal deposit and may value the compatibility of a specific innovation differently at different times. Mining companies may also adjust their strategies for innovation, such as becoming more open to adopt an innovation.

Bartos (2002, 2006) argues that diffusion of revolutionary innovation in the mining industry is typically slow. Using the case studies of mine lamp technology and solvent extraction and electrowinning (SX/EW) technology for copper ore processing, Bartos showed that a time lag of adoption occurs with both low-cost (mine lamp) and high-cost (SX/EW) technologies. Some possible reasons that cause for slow diffusion of revolutionary innovations include large investment requirement, lack of pressure from

competition, site-specific condition for innovation, and unproven performance of the innovation.

The development of infrastructures and facilities in the mining industry requires a large investment, which can be a barrier to adoption of innovation (Hitzman, 2002). It is difficult to justify a fundamental change or a new technology when the timing does not coincide with the capital life cycle of the current technology (Batterham, 2004). It is also difficult to justify a large investment for innovation. Large investment requirement can also be a barrier for potential adopters with limited resources.

The adoption of an innovation is also influenced by the level of competition. Bartos (2002) mentions that there was lag time in the diffusion of the SX-EW technology to copper mines in Chile because they were still low-cost mines. The situation changed after the SX-EW technology brought more competition.

Unique characteristics of a mining operation also influence the decision to adopt an innovation because an innovation may not be applicable to all types of mineral deposits and may not be feasibly implemented due to the unique characteristics of a mine. For example, SX-EW technology is only applicable to oxide copper deposits (Bartos, 2002; Tilton & Landsberg, 1999).¹

Mining companies tend to wait for proven results of innovations before they consider adopting them (Bartos, 2006). This strategy is chosen to reduce the risk of failure in adopting an innovation and reduce the cost in improving the innovation. Therefore, it is more challenging for unproven innovations to be adopted in the industry. The slow diffusion of the longwall mining method by the 1960s was due to its lack of performance in terms of productivity and safety compared to room and pillar mines. One of the key factors of rapid diffusion of this mining method between the mid-1960s and the late 1980s was improvement in roof support and coal cutting equipment. A series of improvements that follow the introduction of revolutionary innovation is critical for potential adopters.

In contrast to Bartos, Ala-Härkönen (1993) describes the diffusion of technological innovation in the mining industry as rapid because of unique characteristics of the industry including the innovativeness of equipment manufacturers, the possibility

¹ Bartos (2002) provides the history and the technology cycle of SX-EW.

of adopting technology from other mining sectors, technology standardization, preference for proven technologies, eagerness to market technologies, and openness in communicating technology. However, Ala-Härkönen did not specifically explain whether rapid diffusion occurs for both types of innovation (incremental or revolutionary) and how the speed of diffusion is determined. The author believes that the factors described by Ala-Härkönen only benefit the diffusion of proven innovations and that they are unlikely to contribute to the diffusion of unproven innovations.

The speed of diffusion can be examined by creating a model. However, most previous studies on the diffusion of innovation in the mining industry are qualitative studies. These studies describe diffusion by reconstructing the timeline of the diffusion and describe the rate of adoption as a combined effect of some or all of the following factors: specific events (e.g., rising commodity price, increase in demand), innovative efforts from various entities (e.g., joint research with government agency, the introduction of new technology from manufacturers), barriers to innovation (e.g., high failure rates, expensive equipment), key benefits from the innovation (e.g., higher productivity, better safety).

Examples of detailed studies on the diffusion of specific revolutionary innovation can be found in studies on the development of the longwall mining method (Barczak, 1992; Energy Information Administration [EIA], 1995; Souder & Palowitch, 1981) and studies on the development of SX/EW technology (Bartos, 2002; 2006).

1.2. Modeling the Diffusion of Innovation in the Mining Industry

Generally, modeling of the diffusion of innovation utilizes three approaches: the epidemic approach, the equilibrium diffusion approach, and the evolutionary approach (Silverberg, 1988). One of the main areas of interest in studying the diffusion of innovation is the time lag of adoption between the potential adopters, so these approaches will be described in the context of the time lag of adoption.

In the epidemic approach, the time lag occurs because potential adopters have imperfect or incomplete information about the innovation (Geroski, 2000). The key in this approach is to model the dissemination of information about innovation and its characteristics among potential adopters. The basic model in this approach is a

differential equation that determines the rate of adoption in a specific range of time (Mahajan & Peterson, 1985). The model is a function of time, the number of potential adopters in a specific time period, the cumulative adopters in a specific time period, and a diffusion coefficient. The diffusion coefficient is usually estimated from historical data. However, the epidemic approach does not take into account the possibility that innovation may have different benefits or impacts for different potential adopters. This flaw led to the development of the second approach: the equilibrium approach.

The equilibrium approach assumes that the time lag of adoption occurs due to different characteristics of potential adopters that affect the impact of adopting the innovation (Geroski, 2000). This approach highlights several factors that may influence the advantage of adopting an innovation for a particular potential adopter (e.g., cost of adoption, size of the adopting firm, market structure). However, this approach generally assumes that all potential adopters can have perfect information about the innovation. Therefore, the main focus of this approach is each potential adopter's adoption decision making process.

Using the evolutionary approach allows one to model diffusion of innovation under conditions of imperfect information, but still accommodate the possibility of diversity among the potential adopters. This approach also allows agents to be modeled in other roles than as potential adopters (e.g., producers) and to interact with each other. Because of imperfect information, potential adopters face uncertainty in making adoption decisions. Using the evolutionary approach, actors in the diffusion process make decisions based on procedural rationality instead of complex optimization equations (Dawid, 2006). Furthermore, this approach allows for the evolution of different actors (potential adopters and the suppliers) and the innovation itself during the diffusion process. The next section will introduce a modeling technique based on the evolutionary approach.

A review of the literature reveals that few researchers have attempted to model the diffusion of innovation in the mining industry. For example, Souder and Palowitch (1981), Souder and Quaddus (1982), and Barczak (1992) attempted to make predictions about longwall utilization in their models. Souder and Palowitch projected the trend of longwall utilization by extrapolating actual longwall utilization before 1978. Their model

predicted that the number of longwall utilization would rise to above 250 after 1985, but the number of longwall utilization actually started to decrease in the early 1980s. Similarly, Barczak estimated the trend of longwall utilization from 1992 to year 2000 based on trends in previous years, but excluded the steeply increasing trend of longwall utilization from 1969 to 1983, arguing that most mines might not have sufficient capacity to employ the longwall mining method. Barczak predicted that the number of mines using longwall methods would be close to 120 in 2000. Both of these models showed increasing trends of longwall utilization, but it has actually been declining since 1983, from 120 to about 50 mines in the late 1990s.

Souder and Quaddus (1982) developed a longwall diffusion model that utilized the epidemic approach to predict the upper limit of the market share of longwall mining technology in the year 2000. Specifically, they utilized historical data of longwall utilization, expert opinions, and user value judgment (Mahajan & Peterson, 1985). Their model uses a differential equation as a function of the upper limit of potential adopters at each time period, the perceived value of different underground mining methods in different time period, and the diffusion constants. The diffusion constants represent internal and external factors during the diffusion process, and historical data are used to estimate the diffusion constant and the upper limit in the equation. Expert opinions were used to determine the perceived value of different underground mining methods.² The differential equation model predicted that the market share of longwall mining technology would reach somewhere between 34% and 68% in 2000.

None of these attempts to model the diffusion of the longwall mining method considered the diversity of mining companies that could lead to different perceived values of different mining methods. The results from Souder and Quaddus (1982) are quite accurate if a market share of longwall means the proportion of coal produced from longwall compared to the total coal produced from underground coal mines.³ If market share is measured by the percentage of longwall mines among the total number of underground coal mines, then the results from Souder and Quaddus' model show a great

² The experts decided the performance score of different underground mining methods in seven categories: productivity, health and safety, percent recovery, depth of cover, roof support, cutting rate, and conveying rate.

³ Coal production from longwall mines has accounted for more than 50% of the total coal produced from underground coal mines since 2003.

discrepancy with the actual condition: the percentage of longwall mines was less than 10% in the 2000s. Given the limitation of previous attempts to model the diffusion of innovation in the mining industry, there is a need for a modeling approach that can capture the diversity and interaction between different agents during the diffusion of innovation.

1.3. Agent-Based Modeling and Simulation

Agent-based modeling and simulation (ABMS) is a computational simulation technique that can be used to analyze a complex system. In the context of modeling the diffusion of innovation, this approach is considered to be based on the evolutionary approach. This modeling technique focuses on the construction of each individual agent in the system. Each agent can be designed to have unique characteristics and behavior known as attributes. For example, when modeling a market that consists of consumers as agents, the modeler can assign different preferences toward product price, wealth, and utility functions to consumers. Furthermore, the modeler can also assign rules that govern agents' adaptive behavior based on agents' internal and external conditions. In the context of consumers as agents, the modeler can design behaviors such as purchasing cheaper products when their state of wealth is poor at a specific time during the simulation. External conditions can also be designed to stimulate specific agent behavior (e.g., imposing a higher tax). Furthermore, agents can be modeled to continuously interact with other agents during the simulation.

In the context of the diffusion of innovation in the mining industry, agents can represent different mining companies with different characteristics of mining operations. These agents can adjust their willingness to try an innovation when their performance is poor or when they see that other agents perform better after adopting an innovation. The agent-based modeler can also develop external factors in the adoption decision (e.g., the fluctuation of commodity price) to analyze how the system behaves during a specific time period. In addition, an agent-based model can have multiple types of agents with specific roles and individual characteristics (e.g., equipment manufacturers, contractors, consumers, producers). Agents that represent manufacturers can be modeled to be diverse in their sets of expertise, innovation strategy, and initial capital. This feature opens up the

possibility of modeling interaction between different types of agents in generating and diffusing an innovation.

In addition to the ability to model agents' adaptive behavior, the ABMS also allows for modeling the evolution of the innovation. Ma and Nakamori (2005) provide an example in their agent-based model in which producers can alter their products to find the best product design for the consumers in the model. In another application of ABMS, agents' learning process and collaboration during the generation and evolution of an innovation can be modeled. The Simulating Knowledge in Innovation Networks (SKIN) model presented by Ahrweiler, Pyka, and Gilbert (2004) is an example of this capability. In the SKIN model, agents collaborate to gain sets of knowledge and expertise required to produce innovations. The introductory theory, including examples of applications and several techniques that can be used in agent-based modeling such as the SKIN model, are described in more detail in Chapter 2.

1.4. Objective

Agent-based modeling provides many attractive features for exploring the complexity of the diffusion of innovation process in the mining industry. To the best knowledge of the author, this thesis is the first attempt to model the diffusion of innovation in the mining industry using ABMS. A main focus in studying a complex system such as the mining industry is the emergent phenomena. The emergent phenomena provide great insight into the future state of the complex system because they influence agents in the system. In the context of the mining industry, studying emergent phenomena would help to illuminate the key factors that can lead to the complexity of collective behavior toward innovation. Recognizing these key factors would be beneficial to the effort to promote innovation within the industry. Therefore, the objective of this thesis is to develop an ABMS-based framework to analyze critical phenomena that can emerge through interaction between interdependent agents during the diffusion of innovation in the mining industry.

1.5. Scope of Work

The framework of agent-based modeling in this research provides guidance to develop an agent-based model and perform a simulation. The framework defines three basic components (design of agents, objects, and the environment) and the important elements of these components in developing an agent-based model. Therefore, a specific description of each of these elements that can be translated to the model design is necessary. The framework does not suggest any specific technique or approach in designing the model, but some known techniques that have been used in agent-based modeling are introduced in this thesis in order to implement the framework.

As the first example of implementing the proposed framework, the author attempts to model the diffusion of the longwall mining method in the U.S. This particular innovation was chosen so that the construction of the model can utilize data from previous studies and the results from the simulation can be compared against the actual data. The agent-based model in this thesis simulates the evolution of both the agents and the longwall equipment technology.

The agent-based model in this research aims to replicate the regularities (stylized facts) of the diffusion of the longwall mining method in a qualitative way, especially related to changes in the trend of the rate of adoption. However, the model does not attempt to provide accurate quantitative results. The agent-based modeling approach requires a very detailed description of agents, especially their behavior. In previous studies on longwall development, the involved entities in the diffusion have been described qualitatively, so this model will be designed based on the author's interpretation of those qualitative descriptions. Quantitative data for the simulation (e.g., nominal coal price, number of mines) were obtained from government publications, journals, and various publications when they were available.

The main output of the model is the confirmation of the complexity of the diffusion of the longwall mining method, including how interaction between agents influences the outcome of the model. The model produced time series data on longwall utilization that can be compared with the actual data. Sensitivity analyses were performed to analyze different conditions during the diffusion and check the consistency of the results from the model.

1.6. Thesis Organization

Chapter 2 provides an introduction to the theory of agent-based modeling and the proposed agent-based modeling framework. This chapter covers the history, basic principles, and different types of agent-based models, requirements in developing agent-based models, and examples of previous applications of agent-based modeling in various research areas. Several techniques in agent-based modeling that are used in this thesis are also presented.

Chapter 3 provides the historical perspective on the diffusion of the longwall mining method in the U.S., highlighting the important incentives, barriers, entities, and events in the development of the longwall method. The information from this chapter is used to develop the agent-based model in chapter 4.

Chapter 4 presents the design of agents, objects, and the environment within the proposed framework and a description of the simulation parameters, initialization, and specific computation procedures for the model.

Chapter 5 starts with the verification and validation of agent-based modeling and continues with a discussion of the results of the implementation of the agent-based modeling framework, including the sensitivity analysis.

Chapter 6 contains the conclusion, including discussion about the strengths and limitations of the agent-based modeling framework and its implementation and suggestions for further development in utilizing agent-based modeling.

CHAPTER 2

AGENT-BASED MODELING AND SIMULATION

The focus of agent-based modeling and simulation is to model and simulate the behavior of a complex system. Agent-based modeling emphasizes the detailed description of agents in the complex system. Several researchers (Epstein, 1999; Goldstone & Janssen, 2005; Yilmaz & Ören, 2009) list the general characteristics of agent-based model and simulation as heterogeneous and autonomous agents, explicit environmental representation, local interaction between agents, and bounded rationality.⁴

The agent-based modeling technique allows the modeler to design a system that consists of agents with unique characteristics (e.g., preferences, options, strategy, size). These agents behave and perform actions based on sets of rules that can be influenced by the aggregate behavior of the system. Agents also interact with other agents either physically or through exchanges of information. Agents have limited computational capability and do not have global information (bounded rationality), and they create perceptions about their environment and choose to perform specific actions based on this limited information.

Agents in agent-based modeling are autonomous discrete entities whose behavior depends on their own set of rules instead of a central authority and who also have the capability to change and adapt their behavior over time. The main activities of agents in agent-based modeling can be described as a cycle of three processes (Michel, Ferber, & Drogoul, 2009) as shown in Figure 2.1. Agents gather or receive information and create a perception about the environment (e.g., other agents, events) through interactions and observations. Agents then use the information to evaluate their internal and external conditions to decide for their actions. Because agents are interacting with other agents, the action of one agent can affect other agents' behavior and may change the state of the environment.

⁴ Goldstone and Janssen (2005) and Epstein (1999) provide similar description about the characteristics of ABMS.

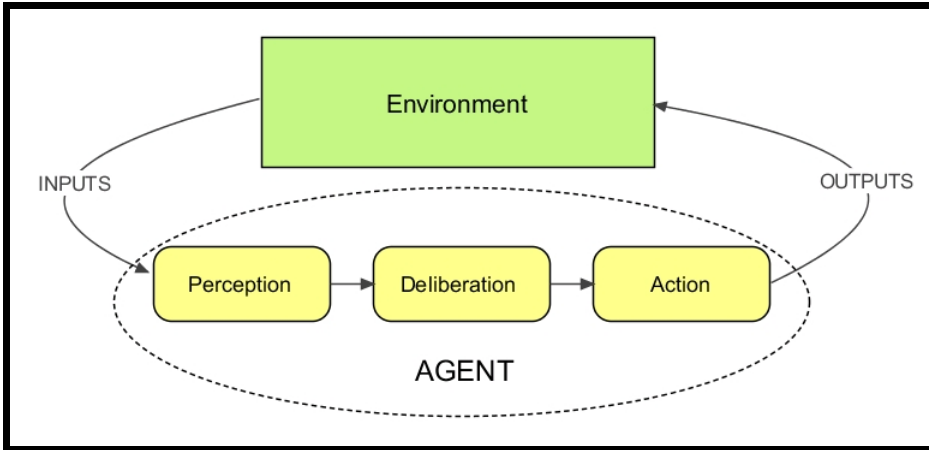


Figure 2.1 The agent's cycle of activities (Michel, Ferber, & Drogoul, 2009)

The main properties of agents in the agent-based model are their unique characteristics and their rules of behaviors. The unique characteristics of agents are called agents' attributes; rules of behavior are the set of rules that dictates how agents select and perform specific actions in the complex system given their perception of their internal and external conditions. Yilmaz and Ören (2009) list the following essential elements of modeling agents' behavior in agent-based modeling:

a) Input and knowledge processing

An agent will have exogenous and endogenous inputs. Inputs can be actively perceived (forced or imposed) or passively accepted. Some examples of actively perceived inputs are the perception about agent's internal condition and the interpretation of event/data. Some examples of passively accepted inputs are facts and forced events.

b) Agent's goal-directed behavior

Every agent in the agent-based model has specific goals, and their behaviors are directed to reach these goals.

c) Agent's interaction

Agent's interaction implies exchange of information with other agents.

d) Strategic action

Agents can select the best strategy and actions for their best interest.

e) Cognitive and deliberative decision making process

Agents' actions are determined through specific decision making processes.

The development of an agent-based model heavily depends on the detailed development of agents in a complex system. The goal of the modeling is usually related to specific regularities/phenomena in the complex system. The steps in developing an agent-based model are as follows:

- a) Identify the complex system and the phenomena in the system that are the focus of interest.
- b) Define the objective of performing agent-based modeling.
- c) Specifically identify and describe agents in the complex system, including their characteristics, behavior, decision making process, and interaction and relationships with other agents.
- d) Define the agents' environment and all processes/events that influence agents' behavior.
- e) Choose an ABMS platform to develop the model.
- f) Develop the agent-based model.
- g) Verify the model design.
- h) Run the model and validate the result.
- i) Analyze the output.

Based on its objective, an agent-based model can be an abstract, middle range, or facsimile model (Gilbert, 2008). An abstract model shows the basic process in a complex system as part of theory development. This type of model is very generic, but the results from the model should already show regularities, behaviors, or patterns of a system that can be interpreted but cannot be validated with empirical data. Schelling's segregation model (which will be explained in sub-chapter 2.1) is an example of an abstract model. The middle range model is developed based on available data on existing phenomena. The result from this model can be compared qualitatively with empirical data (Gilbert, 2008). One application of this type of model is to replicate specific regularities observed in a specific system, such as historical events in a particular industry. This type of modeling is also known as the "history-friendly model." Some examples of the history-friendly modeling approach are studies on the evolution of the computer industry and the pharmaceutical industry. The facsimile model aims to reproduce social phenomena accurately, sometimes with the intention to make a future prediction.

2.1. Agent-Based Models and Emergent Phenomena

Even though the development of an agent-based model mainly focuses on the agents' characteristics, behavior, and interaction, this modeling approach has the capability to capture the behavior of complex systems which is not explicitly imposed on individual agents in the system, known as emergent phenomena (Bonabeau, 2002; Holland & Miller, 1991). An example of emergent phenomena can be found in Schelling's segregation model (1971), which simulates neighborhood segregation. Agents in the Schelling model represent households; each agent in the model interacts with other agents on a regular grid. Each cell on the grid represents an area where a household can live, and each cell can only hold one agent. The total number of agents is less than the total number of cells, so that agents can move to empty cells during the simulation.

There are two types of agents in the Schelling model: type A and B. In the initial condition, all agents are placed randomly on the regular grid (Figure 2.2). Every agent then surveys its eight neighboring cells and looks for other agents with similar type. The goal for each agent is to live in a cell whose eight neighboring cells contain agents that are similar in type. The minimum number of neighbors with the same type that can make an agent comfortable living in a particular cell is called the *tolerance threshold*. The tolerance threshold is set to be equal for all agents. When an agent observes that the proportion of other agents of the same type in the neighboring cells is less than the tolerance threshold, the agent will move to another empty cell.

The simulation runs until all agents are satisfied with their condition (i.e., the tolerance threshold is met; see Figure 2.3). The simulation result from the Schelling model in Figure 2.3 was obtained when the tolerance threshold was set to 30%. The neighborhood segregation that occurred despite agents' willingness to live as a minority in their neighborhood is an example of emergent phenomena that agent-based modeling and simulation can capture.

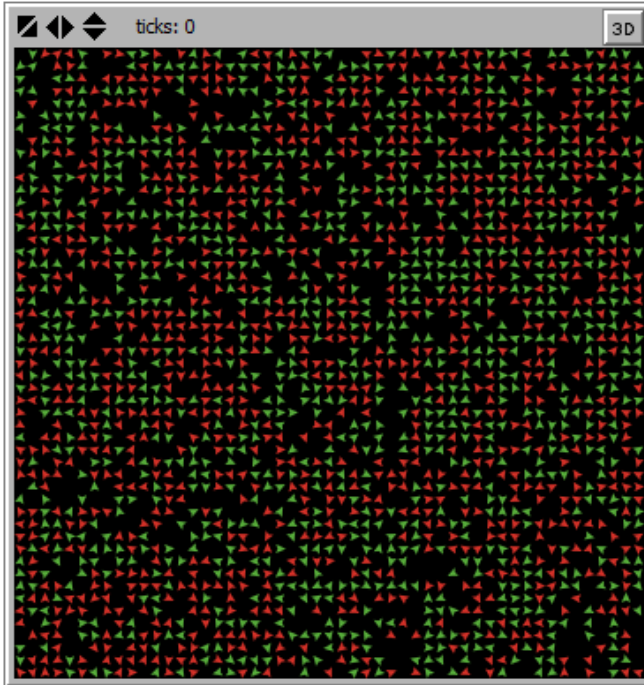


Figure 2.2 Initial agent distributions in Schelling's segregation model. The model is from Wilensky (1997) and was developed with Netlogo software (Wilensky, 1999).

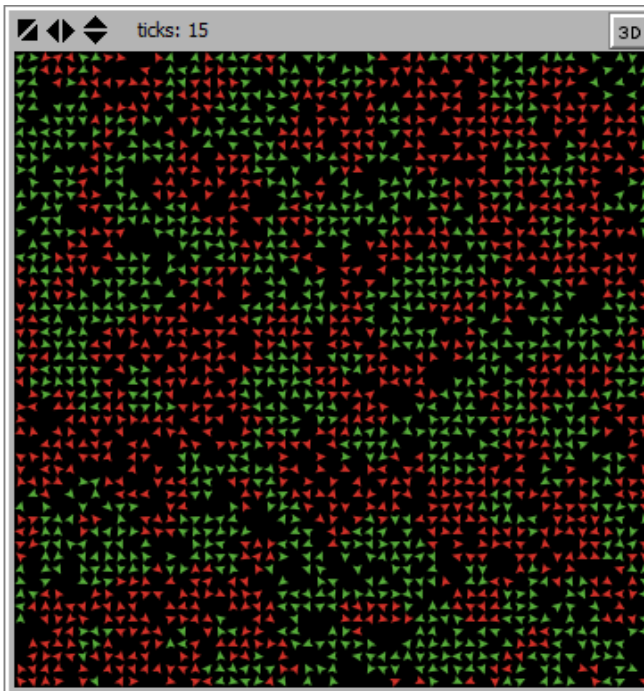


Figure 2.3 Distribution of agents in Schelling's model at the end of simulation (tolerance threshold = 30%). The model is from Wilensky (1997) and was developed with Netlogo (Wilensky, 1999).

2.2. General Applications of Agent-Based Modeling and Simulation (ABMS)

ABMS can be applied in various research fields in which a complex adaptive system can be identified. Other than the biological research field,⁵ it can also be applied to fields of study in which main agents are individual humans or organizations, such as politics, economics, business management,⁶ public policy, military, operations research, traffic simulation, geographic systems,⁷ and anthropology⁸ as presented in Table 2.1.

Table 2.1 ABMS Applications in Various Research Fields

Research Fields	Examples of ABMS Applications
Politics	Modeling adaptive parties in spatial elections (Kollman, Miller, & Page, 1992)
Anthropology	Study about the evolution of Plio-Pleistocene hominid food sharing in East Africa (Premo, 2006)
Economics	Agent-based computational economics (Tsfatsion, 2002; 2006), multi-agent social and organizational modeling of electric power and natural gas markets (North, 2001)
Public Policy	Evaluation of government policy on promoting smart metering in retail electricity markets (T. Zhang & Nuttall, 2011)
Military	Evaluation of the U.S. Army's network-based Future Force to perform with degraded communications, observing how unmanned surface vehicles can be used in force protection missions, evaluation of standard Army squad size (Cioppa, Lucas, & Sanchez, 2004)
Traffic Simulation	Air traffic management system, the effect of advanced driver assistance systems on road traffic accidents (Yuhara & Tajima, 2006)
Operations Research	The optimization of supply chain configurations (Akanle & Zhang, 2008), scheduling problems with two competing agents (Agnētis, Mirchandani, Pacciarelli, & Pacifici, 2004)
Business & Management	Evaluation of corporate strategy (Caldart & Ricart, 2007), the impact of market interventions on the strategic evolution of electricity markets (Bunn & Oliveira, 2008)
Biology	Adaptive immune simulator (Folcik, An, & Orosz, 2007)
Geographical System	Constructing and implementing an agent-based model of residential segregation through vector GIS (Crooks, 2010)

⁵ For example, modeling of the immune system shows how antibodies adapt to various antigens that invade human body (Holland, 1992).

⁶ The potential for using the ABMS approach in management research is discussed by Robertson and Caldart (2008).

⁷ The potential for using the ABMS approach in geographical systems research is discussed by Torrens (2010).

⁸ The potential for using the ABMS approach in anthropology is discussed by Premo (2006).

In addition to its potential applications in various research fields, ABMS provides opportunities for multi-disciplinary collaboration (Axelrod, 2006). For instance, Axelrod and Bennett (1993) applied agent-based modeling of alliance formation of nations in World War II to the business field. ABMS also provides opportunities to implement various modeling techniques from different research fields, such as agents' decision making process, agents' learning and adaptation mechanism, and agents' interaction.

The modeling of agents' decision making capability can utilize different techniques. Agents generally only use one rule to determine their behavior. Agents with more complex rules activate multiple rules (sometimes including nested rules) in making decisions. Advanced techniques in modeling agents' behavior include statistical methods (e.g., multinomial logit modeling to forecast the likelihood of future events based on historical data), artificial intelligence (e.g., neural networks, swarm intelligence), and optimization methods (e.g., genetic algorithm, linear programming) (North & Macal, 2007).

Some of the techniques for modeling agents' learning and adaptation mechanisms are the genetic algorithm (GA) and the classifier system (CS). Holland and Miller (1991) propose these techniques to simulate the learning and adaptation mechanisms of economic agents based on the agents' attributes (e.g., risk aversion, expectations) and market forces.⁹ The GA is a programming technique that mimics the evolution of a biological system. It utilizes a series of binary numbers as a unique identity for individuals and their characteristics. Individuals learn and adapt their behavior by changing (through selection and reproduction) their binary numbers. CS is based on machine learning algorithm (Bull, 2004). Rejeb and Guessoum (2006) provide an example of CS being used to model firm adaptation in dynamic economic systems.

ABMS models different types of real-world interactions. Interaction not only represents the transfer of information, but may also depict competition and collaboration between agents. Competition and collaboration between different entities are important research topics in various research fields (e.g., politics, economy, business, military). A game theory algorithm from applied mathematics can be used to model the competition

⁹ Holland and Miller (1991) named their model the artificial adaptive agents (AAA) model.

among agents, while network models from operations research can be used to simulate collaboration.

2.3. Agent-Based Modeling of the Diffusion of Innovation

Kiesling, Gunther, Stummer, and Wakolbinger (2011), Dawid (2006), and Garcia (2005) conducted extensive reviews of the application of agent-based modeling in the study of the diffusion of innovation. The key feature of this modeling approach that attracts applications related to the diffusion of innovation is its ability to model population heterogeneity, including interactions between agents in the population.

Garcia (2005) identifies three potential research areas for ABMS applications related to the complexity in the generation and diffusion of innovation: the diffusion of innovations, knowledge/information flow, and organization structure. Studies on diffusion of innovation mainly focus on agents' internal and external adoption factors (e.g., risk preference, adoption strategy, policy, network structure, opinion leaders) and their influence on the rate of innovation adoption. Of interest in this study, ABMS has been applied in studies of the influence of tax policy (Schwoon, 2006), opinion leaders (van Eck, Jager, & Leeflang, 2011; Valente & R. L. Davis, 1999), and government policy (T. Zhang & Nuttall, 2011) on the diffusion of specific innovations.

Applications of ABMS in the area of knowledge/information flow aim to model how knowledge and information can be transferred between agents. Knowledge is an important factor in the generation of innovation. When agents have limited time and knowledge to develop innovations, they may need to collaborate with other agents. In this case, agents have the incentive to form innovation networks with other agents in order to gain complementary resources in developing new products or innovations.

Organization research mainly focuses on agents' organizational structures and strategy in generating innovation. ABMS is a potential tool for modeling agents' decisions to innovate or to imitate innovation (e.g., Bullnheimer, Dawid, & Zeller, 1998; Debenham & Wilkinson, 2006) as well as their strategies for collaboration. Axelrod (1997) provides a brief discussion about competition and collaboration in a complex system including some related examples of ABMS applications. Using the ABMS approach to study innovation networks (e.g., Ahrweiler, Pyka, & Gilbert, 2011) shows

how knowledge can be an important part of agents' strategies in selecting their research partners.

Different types of agents have different roles in the diffusion of innovation (e.g., producers of innovation, potential adopters). Every agent has its own individual attributes that influence its decision to generate or adopt an innovation, such as knowledge, innovation strategy, capital resources, and risk preference. Some examples of different types of agents featured in studies on diffusion of innovation using ABMS are presented in Table 2.2.

Table 2.2 Different Types of Agents in ABMS Applications related to the Diffusion of Innovation

Agent-Based Model	Agents	Agents' Attributes
The diffusion of agricultural technology (Berger, 2001)	Farm households	Farms with biophysical and economic attributes (e.g., soil quality, land use, water supply, internal transport costs)
The diffusion of medical innovation (Ratna, Dray, Perez, Grafton, & Kompas, 2008)	Doctors	Adoption thresholds, locations of practice, innovativeness level
New product diffusion of novel biomass fuel	Consumers	Capacity of fuel tanks, consumer types (price sensitive, environmentally conscious, quality seeking, exclusivity seeking), travel behavior, refueling behavior.

As mentioned earlier, one of the key properties of agents is their rules of behavior. In the context of agent-based modeling of the diffusion of innovation, these rules dictate agents' activities in searching for an innovation (e.g., agents act as producers that always seek for a better product, a better idea, and a better practice) and in making decisions to adopt a specific innovation. The next two sections explain several techniques that can be used to model agents' activities in searching for and adopting an innovation.

2.3.1. Modeling Agents' Activities in Searching for Innovation

In 1993, Kauffman introduced a modeling technique to study the evolution of a biological system that is driven by mutation of its elements. In Kauffman's model, the

term “fitness value” is used to denote a well-defined property (e.g., performance, ability, capacity) of a system. The modeling starts by determining the number of elements in the system (N) and how these elements interact in the system (K).¹⁰ Therefore, this modeling technique is known as the NK model. Each element in the system can be assigned A number of variants, resulting in A^N possible system designs.¹¹ For example, consider a system X with 3 elements ($N = 3$); each element in the system can have a binary value 0 or 1 ($A = 2$). This system can have eight possible system designs (000, 001, 010, 100, 011, 101, 110, 111). These possible system designs can then be plotted in a design space (Figure 2.4). The evolution of system X is the movements from one system design to another system design (e.g., from 000 to 001).

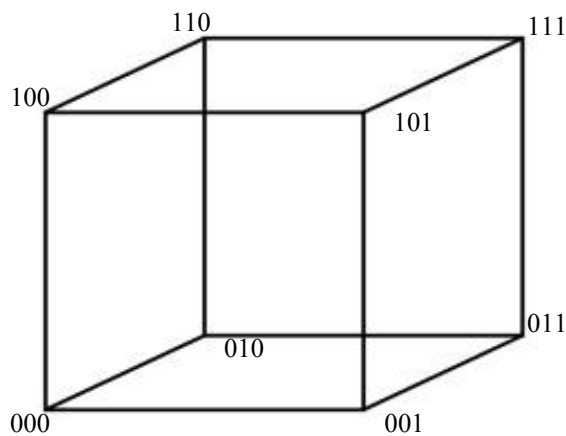


Figure 2.4 Example of a design space with $N = 3$ and $A = 2$ in NK model.

In the NK model, every possible system design is assigned a fitness value that indicates the performance of that particular system design. The fitness value is also used to determine if an evolution from one design to another design improves system performance. Changing the system design to another design with a higher fitness value improves the performance of the system. Evolution of the system occurs when one element of the system mutates. As shown in Figure 2.4, an example of system evolution is the movement from system design 000 to system design 001.

¹⁰ Kauffman introduced this model in a biology research field. The N represents the number of *genotype loci* in a chromosome.

¹¹ In Kauffman's genetics NK model, each *genotype locus* can have A number of *alleles*.

If we plot the fitness value of all possible system designs, we will get a “fitness landscape.” Evolution then can be seen as movement on the fitness landscape. The process to reach a point with higher fitness value on the fitness landscape can be used to simulate the search for innovation in agent-based modeling. The mutation can be seen as changing some aspects of an existing technology to produce a better technology.

In the NK model, the fitness value is a number between 0.0 and 1.0. The fitness value of a system design (W) is simply the average of fitness value contribution from each component (w_n) where $n \in (1, \dots, N)$.

$$W = \frac{1}{N} \sum_{n=1}^N w_n \quad (2.1)$$

where

W : The fitness of the system

w_n : The fitness value contribution of component n in the system

With a single component mutation rule, the system can only change one component. This means that movement in the fitness landscape is restricted to the adjacent neighbors from the current point. The movement stops when there is no adjacent point with higher fitness value than the current one.

In a system with multiple components, modifications to one component may affect the fitness value contribution not only to the modified component, but also from other components. The NK model introduces the concept of “epistatic relations” to capture this relation. The epistatic relation is determined by setting up the value of K , $K \in \{0, 1, \dots, N-1\}$, which indicates the number of components affected by a modification of a single component other than the modified one. If $K = 0$, then a modification of a single component in a system will not change the fitness contribution from other components. If $K \neq 0$, then the fitness contribution of each component depends on the component itself and K other components. An example of the epistatic relations in the NK model with $N = 3$, $A = 2$, and $K = 1$ is presented in Table 2.3.

Based on the epistatic relations in Table 2.3, the influence of mutation on one component to the fitness value contribution from other components can be described as follows:

- a) Mutation of component 1 will influence the fitness value contribution from components 1 and 2, but not component 3.
- b) Mutation of component 2 will influence the fitness value contribution from components 2 and 3, but not component 1.
- c) Mutation of component 3 will influence the fitness value contribution from components 1 and 3, but not component 2.

Table 2.4 provides an example of fitness values for each system design based on the epistatic relations in Table 2.3, assuming the initial system design is 000 with $w_1 = 0.2$, $w_2 = 0.2$, and $w_3 = 0.4$. Based on the fitness value in Table 2.4, we can generate a fitness landscape in Figure 2.5.

Table 2.3 Epistatic Relations with $N = 3$, $A = 2$, and $K = 1$

Fitness Contribution	Component 1	Component 2	Component 3
w_1	yes	-	yes
w_2	yes	yes	-
w_3	-	yes	yes

Table 2.4 Example of Fitness Landscape based on the Epistatic Relations in Table 2.3

Element Configuration	w_1	w_2	w_3	W
000	0.2	0.2	0.4	0.27
001	0.1	0.2	0.7	0.33
010	0.2	0.3	0.8	0.43
011	0.1	0.3	0.2	0.20
100	0.5	0.6	0.4	0.50
101	0.9	0.6	0.7	0.73
110	0.5	0.7	0.8	0.67
111	0.9	0.7	0.2	0.60

In the innovation context, Figure 2.5 shows different designs of innovation and their performance. When an agent starts with system design 000, it can choose to switch to system 100, 010, or 001 because they all have a higher fitness value than system design 000. With the NK model, the innovation can be seen as a result of an agent's selection of several alternative solutions. Figure 2.5 also shows that an agent may reach

the local optima of performance instead of the global optima. An agent will stop searching for a better system design upon reaching system design 110 because there is no adjacent system design with a higher fitness value.

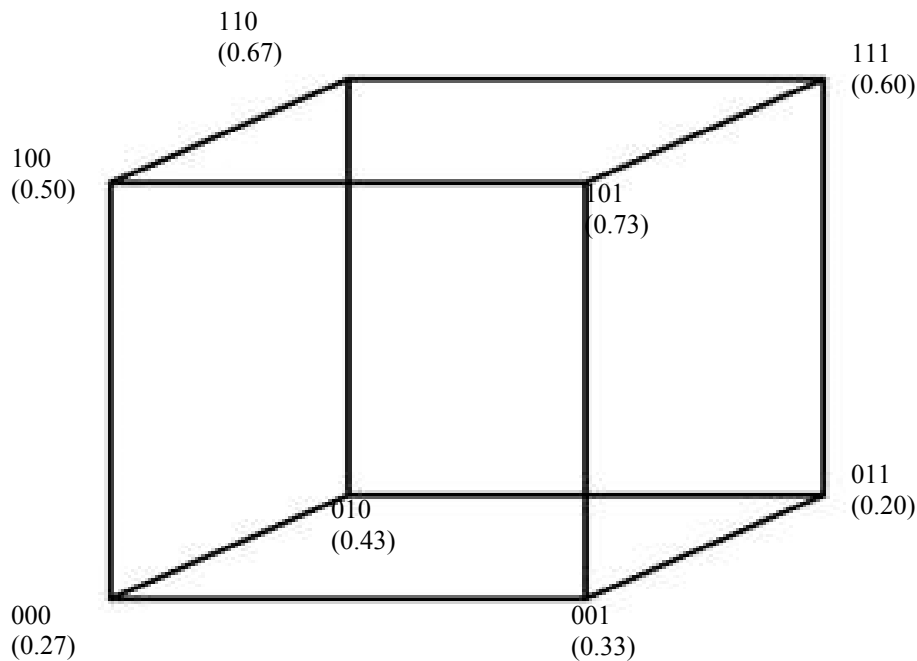


Figure 2.5 Example of a fitness landscape with $N = 3$, $A = 2$, and $K = 1$.

Altenberg (1997) generalizes the NK model and makes it more realistic for modeling the process of searching for innovation. The generalized NK model removes the identification between a component of a system and its fitness contribution (w_n). In the generalized NK model, w_n is defined as different criteria of performance for a system. Altenberg (1997) defines a set of N components and a set of fitness functions (f). The fitness functions measure the performance of the whole system based on several criteria. The number of criteria and the number of components do not necessarily have to be equal. For example, a laptop system that consists of four components (screen, processor, camera, and memory) may only be measured using three criteria (Internet browsing speed, lightness, and portability). The generalized NK model has been used to model the evolution of an organization (Jacoby, 2001) and the evolution of an organization's strategy (e.g., Gavetti, Levinthal, & Rivkin, 2005; Levinthal, 1997; Rivkin, 2000). More

specific discussions about the utilization and advancement of the NK model in the context of organization strategy can be found in the work of Ganco and Hoetker (2009). Another possible application of the NK model related to innovation is in modeling innovation networks. Frenken (2000) adopted the NK model to evaluate the pattern of collaboration between producers, consumers, and government (countries) in the aircraft industry.

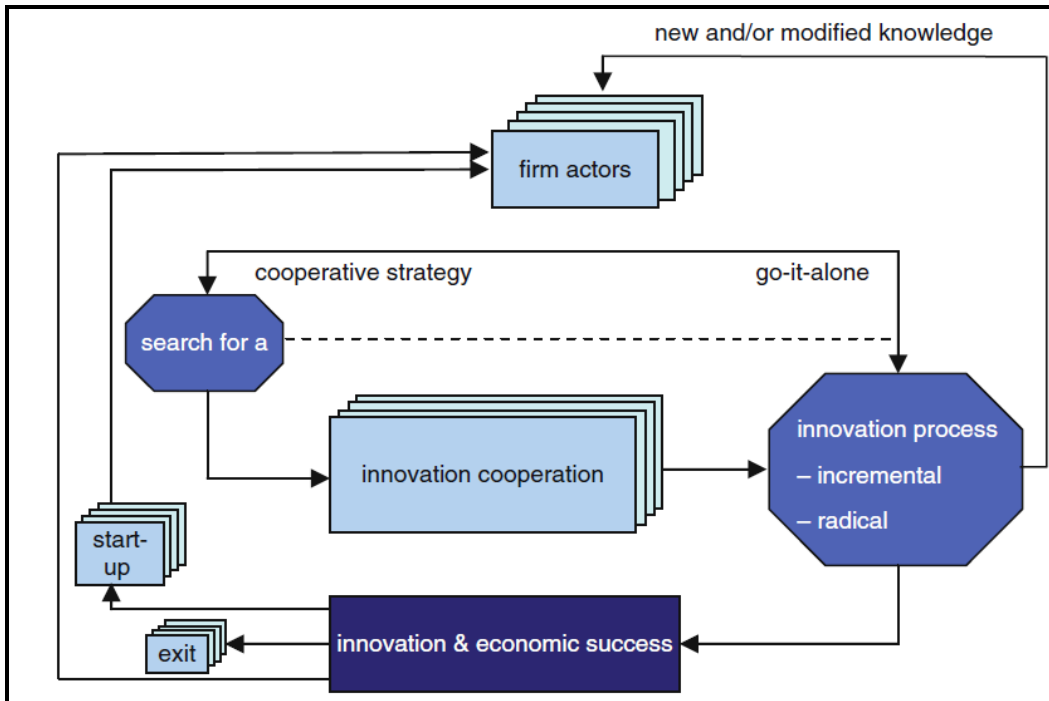
2.3.2. Modeling Agents' Collaboration in the Search for Innovation

In the innovation search process, an agent may interact and collaborate with other agents. In this case, agents have the incentive to form innovation networks with other agents in order to gain complementary resources to develop a new product or innovation.

Pyka and Küppers (2002) define innovation networks as “interaction processes between a set of heterogeneous actors producing innovations at any possible aggregation level (regional, national, supranational)” (p. 7). Members of innovation networks can be firms, universities, R&D contractors, government research entities, manufacturers, and other types of entities with the capability to produce innovations. Frenken (2000) includes users in the innovation network considering the importance of mutual feedback among producers and users in shaping the development of an innovation.

ABMS has been used in studies about innovation networks. One example is the Simulating Knowledge dynamics in Innovation Networks (SKIN) model, which is a knowledge-based approach model that was specifically developed for innovation networks studies by Gilbert. The concept of this model was introduced by Gilbert, Pyka, and Ahrweiler (2001).¹² In the SKIN model, agents collaborate with other agents based on their knowledge set. Knowledge flow between agents occurs after agents agree to collaborate to generate innovations. Successful innovations benefit those agents that are involved in the collaboration (member of the innovation networks), but the innovation network dissolves when innovation processes do not succeed. The basic structure of the SKIN model is presented in Figure 2.6.

¹² The introduction and explanation about the SKIN model can also be found in series of publications from the same authors (Ahrweiler, Pyka, & Gilbert, 2004; Gilbert, Ahrweiler, & Pyka, 2007; Pyka et al., 2009)



Source: Pyka, Gilbert, & Ahrweiler (2009)

Figure 2.6 The basic structure of the SKIN model.¹³

Every agent in the SKIN model is designed to have a “kene” that represents that agent’s sets of knowledge. A kene is a list of triplets that consist of agent’s capability (C) in a specific area of knowledge, specific ability (A) related to capability, and level of expertise (E). For example, an agent may have the capability to produce roof support technology for underground mines. Some of that agent’s ability may include expertise about hydraulic machinery and control system. Figure 2.7 illustrates the kene of an agent in the SKIN model where i is an index for agent’s capability and j is an index for agent’s ability (i and j are integers).

$$\left\{ \begin{bmatrix} C_i \\ A_i^j \\ E_i^j \end{bmatrix}, \begin{bmatrix} C_i \\ A_i^{j+1} \\ E_i^{j+1} \end{bmatrix}, \begin{bmatrix} C_{i+1} \\ A_{i+1}^{j+3} \\ E_{i+1}^{j+3} \end{bmatrix}, \begin{bmatrix} C_{i+n} \\ A_{i+n}^{j+m} \\ E_{i+n}^{j+m} \end{bmatrix} \right\}$$

Figure 2.7 The kene in the SKIN model.

¹³ The agents in a SKIN model can be other types of entities with sets of knowledge that can be used in innovation generation processes. Ahrweiler, Pyka, and Gilbert (2011) use SKIN to model universities and firms in the innovation network.

Different agents may have different types and numbers of triplets in their kene. They develop their kene by performing research (independent/collaborative). Agents can use some of the triplets in their kene to perform a research. The selected triplets implies the direction of the research project and in the SKIN model is called the agent's *innovation hypothesis*. The illustration of innovation hypothesis (IH) is presented in Figure 2.8.

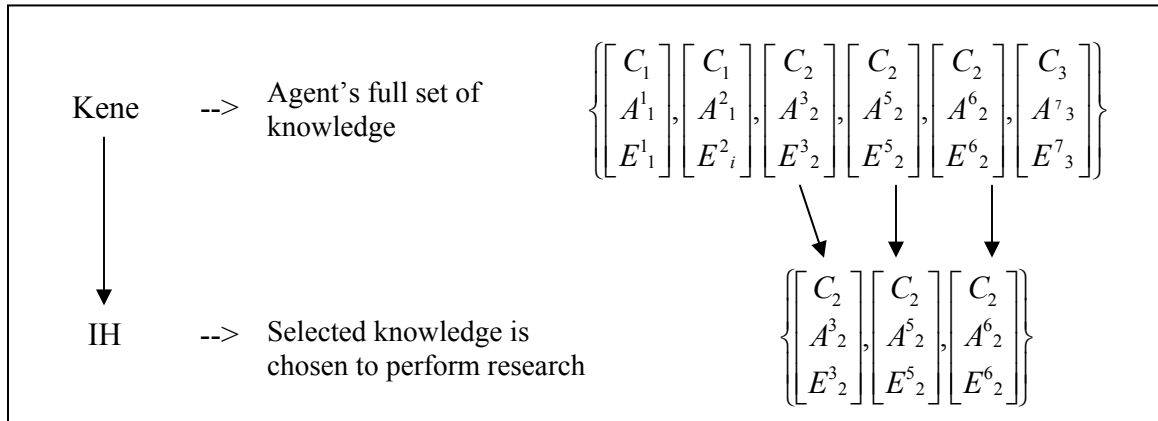


Figure 2.8 Kene and innovation hypothesis. Agents choose to use only three sets of knowledge from their kene.

Agents increase their level of expertise in the abilities and capabilities included in the IH. In the SKIN model, agents drop their level of expertise in other abilities and capabilities that are not included in the IH. Agents adapt their innovation strategy by changing the IH for their research activities.

Agents choose their potential partners based on several criteria such as knowledge similarities/dissimilarities and previous partnership experiences. Agents will copy new capabilities from the IH of their partners. Agents can then use the new sets of knowledge in their kene to produce new types of products on their own.

2.3.3. The Process of Adopting an Innovation

The previous sections presented some techniques in ABMS that can be used to model different adaptive behaviors in the generation of innovation. Another important aspect of modeling the innovation process is designing the adoption decision making process. The model has to define internal and external adoption factors that will influence agents' decisions to adopt. Some internal adoption factors include preference, experience,

knowledge, risk aversion, available capital, and strategy, while the external factors include government policy and social network condition. ABMS also allows for the implementation of different techniques and procedures in modeling the decision making process. The most common technique is to use the concept of adoption threshold, which is the minimum number of current adopters that can trigger another agent to adopt an innovation. This mechanism captures the influence of social networks on agents' decisions to adopt.¹⁴ This concept can be used to model the adaptor strategy that mining companies use in considering an innovation. The adaptor strategy is mentioned by Bartos (2006). Another technique that can be employed is modeling an agent as a potential adopter that can perform multi-criteria decision making analysis in evaluating an innovation. For instance, in the innovation adoption model developed by Ma, Chi, Chen, and Shi (2009), agents evaluate technology for adoption based on its efficiency and initial investment costs.

2.4. The ABMS Framework

The author developed an agent-based model framework for studying the diffusion of innovation in the mining industry (see Figure 2.9). The framework consists of three basic components: agents, objects, and environment. The core of each circle in the framework represents the three basic components. The second layer represents the category of each component, while the third layer shows different elements/attributes and behaviors/mechanisms that a modeler needs to define. The connecting lines between the three basic components show the relationship between the components.

2.4.1. The Design of Agents

Typically, there are two main roles for agents in agent-based modeling of the diffusion of innovation: the role of potential adopter and the role of innovation generator (technology provider, researcher). A model can be designed in which one type of agent can play one or both roles during the simulation (e.g., mining companies can adopt an innovation as well as participate in a research program). The important elements in

¹⁴ Lamieri and Ietri (2004) explain the influence of social networks in the generation and diffusion of innovation with the ABMS approach.

designing agents for both roles are agents' goals, attributes, decision making process, interaction mechanism, and adaptive behavior.

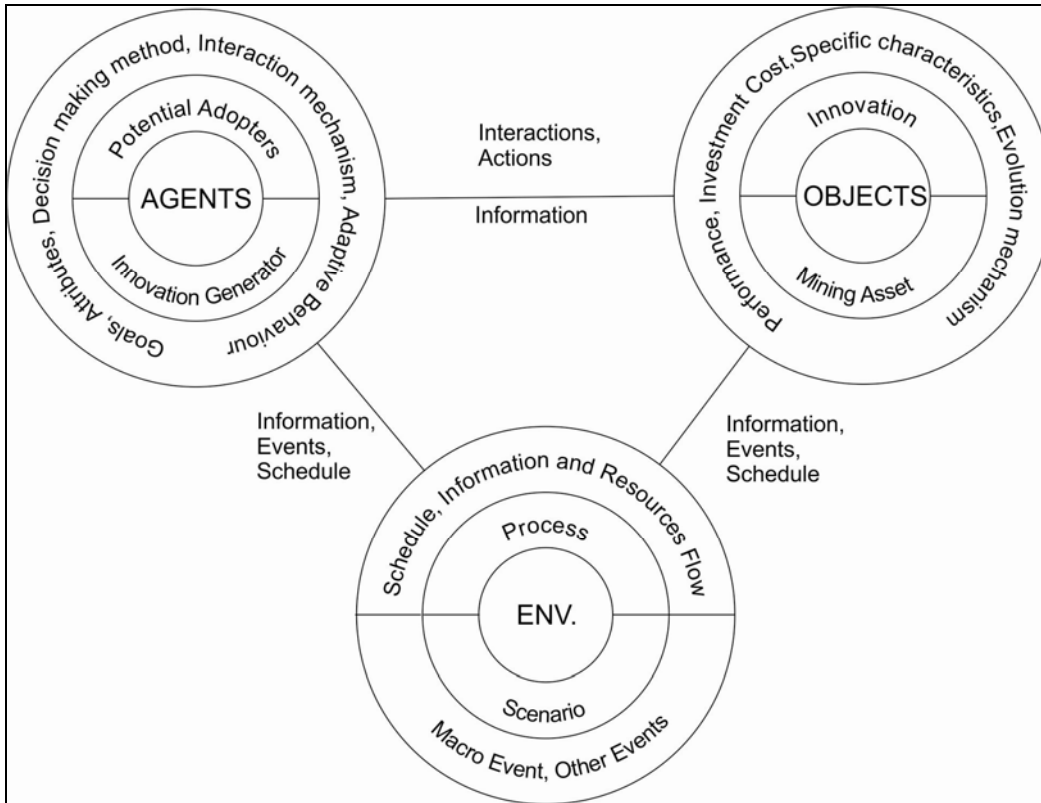


Figure 2.9 The ABMS framework for modeling the diffusion of innovation in the mining industry.

Agents' goals are critical in designing agents because agents' actions have to be driven by goals. For instance, a goal for an agent in the potential adopter role is to become the lowest-cost mine among its competitors, while a goal for an innovation generator is to produce a better technology than other producers. With a specific goal, the modeler can design the agents' behavior including the internal and external information that agents need to evaluate their goals.

Agents' attributes are their unique characteristics that can be used by the agent-based modeler to control the diversity of agents. Some examples of agents' attributes in the context of the diffusion of innovation in the mining industry are mine size, strategy, location, mining depth, and deposit type.

Agents' decision making process describes how agents select the best action for themselves in the model, including the important factors that influence the process. In the context of diffusion of innovation, potential adopters make a decision to adopt an innovation, while innovation generators make a decision to search for and produce innovation. The agent-based modeler has to define the situation and condition that lead to the decision making process, the information that agents need to make these decisions, the process to get the information, and the process and criteria used in selecting the possible actions. For example, an agent-based modeler can set the model such that agents will consider an innovation if their profit is low, and in order to make the decision, the agents need information about the cost of adopting the innovation. Using the same example, the modeler can also design the model so that agents get information about the innovation from their neighboring agents and use the information to calculate the benefit of adopting the innovation. Agents will adopt the innovation if the benefit outweighs the cost.

The key feature of interaction is exchange of information. Agents obtain information about other agents through interaction. The interaction between agents can be designed as physical interaction or simple observation. Agents can also be set to move to meet other agents to gain information.

Agents' adaptive behavior is defined by imposing sets of rules that can change how agents decide about their actions. For example, consider agents that represent equipment manufacturers in the mining industry. At the beginning of the simulation, these agents are set to improve their product by invention. As the simulation progresses, the agents can be set to improve their products by imitation if their effort in invention fails.

2.4.2. The Design of Objects

Objects in this framework are physical/virtual entities that are used by agents in their behavior. There are two main objects in the diffusion of innovation in the mining industry: the innovation and the mining asset. An innovation object can be a new type of equipment, practice, or method; a mining asset object can be a mining operation or processing plant that agents will use to implement the innovation. The important

elements for defining objects in the proposed framework are performance, investment cost, specific characteristics, and evolution mechanism.

The performance element of an object includes information that potential adopters can use to evaluate the perceived value of an innovation (e.g., compatibility, relative advantage), such as its productivity, safety, and capacity. This element also describes the criteria that agents use in evaluating the condition of their mining asset (e.g., mining cost).

The investment cost element of an object is the cost of adopting an innovation, the cost of searching for innovation, and the cost of using the current technology. The cost of adopting an innovation is used by potential adopters to evaluate the possibility of adopting the innovation. The cost of searching for innovation is used by the innovation generator in making the decision to improve their product. The cost of using the current technology is used by the potential adopter to evaluate if it is economically feasible to replace the current technology with the innovation.

The specific characteristics element of an object include the unique characteristics of a mining asset, such as mineral deposit type, mining depth, scale of the mine, mineral reserves, and the production capacity that can be used to assess the benefit of adopting an innovation.

Both the innovation object and the mining asset object can be designed to evolve during the simulation. For example, innovation can be set to improve (e.g., by becoming cheaper or more reliable) and mining operation can get deeper during the simulation. Some of the techniques that can be used to model the evolution of an innovation are the NK model (Kauffman, 1993; 2000), genetic algorithm (Holland, 1992, 1996; Holland & Miller, 1991), and the learning classifier system (Bull, 2004; Drugowitsch, 2008).

2.4.3. The Design of the Environment

Environment design is the design of processes and scenarios that control agents' behavior during the simulation. The elements of process design are process scheduling and the flow of information and resources. Process scheduling comprises the sequence of agents' actions: gathering and processing information, selecting actions, and finally performing actions. The agent-based modeler has to clearly define a plausible cycle of

this sequence. The information and resources flow element is the type of information and resources that an agent can access during the simulation and the mechanism of information and resource flow from and to an agent.

The elements of scenario design are macro events and other events. Macro events are any external events that generate external information for agents. The information is available for agents to access. Examples of macro events that an agent-based modeler can impose are commodity market dynamics (e.g., commodity price fluctuation, market demand) and government regulation. Other events are events during the simulation that generate external information for agents but may not be available for all agents to access, such as a failure in trying an innovation in a mining operation. An agent-based modeler can design a model in which a small failure in one mine is known only by agents that interact with the mine.

An agent-based modeler can control the level of complexity of the agent-based model by limiting some elements in the framework. For example, the agent-based model can have only a potential adopter agent instead of both potential adopters and innovation generators. An agent-based modeler can also assume that the innovation does not evolve during the simulation so that the agent-based model does not have to include the evolution mechanism described in the framework.

CHAPTER 3

THE HISTORICAL PERSPECTIVE ON THE DIFFUSION OF THE LONGWALL MINING METHOD IN THE U.S.

The longwall mining method was introduced in U.S. in the late 1800s (Barczak, 1992; Souder & Palowitch, 1981).¹⁵ The longwall mining method was a revolutionary innovation in the U.S coal mining industry (Committee on Technologies for the Mining Industry, Committee on Earth Resources National Research Council, 2002) because its basic mining principles are significantly different from those of the conventional room and pillar mining method.

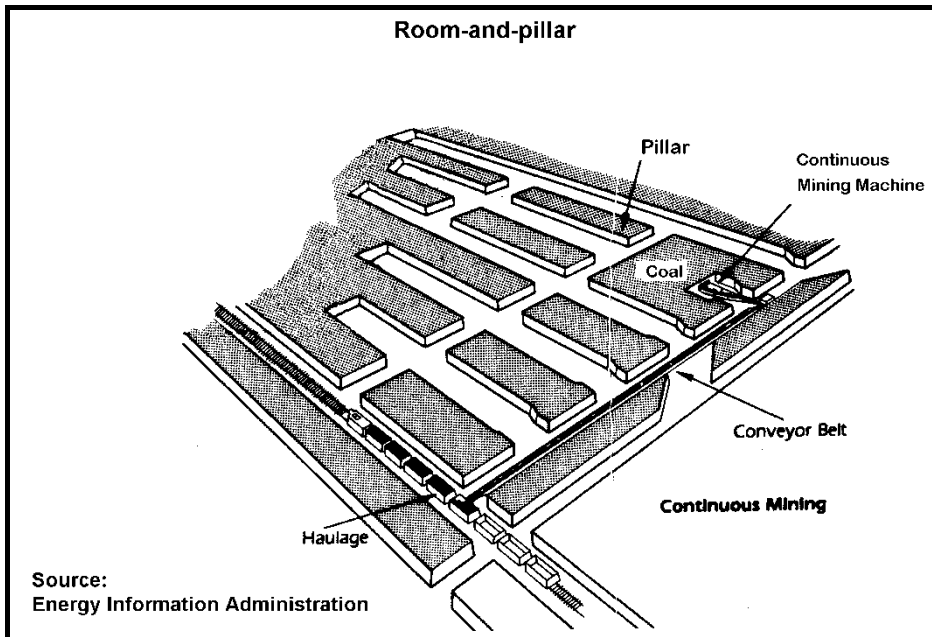
In the room and pillar mining method, the mined area is laid out like a chess board, with the empty spaces after the coal has been mined called “rooms” and the blocks of coal that are left to support the roof called “pillars” (Figure 3.1). In conventional room and pillar mines, there are five cyclical steps in the mining process: cutting a small section at the bottom of the coal seam (undercutting), drilling to place explosives, blasting, loading the coal onto the haulage equipment, and supporting the roof of the mined area. These mining cycles can occur simultaneously in different rooms.

By contrast, the longwall mining method allows for continuous extraction of a large coal block without having to leave some of the coal for roof support (Figure 3.2).¹⁶ In longwall mines, roof support equipment provides support along the extraction face. After the full length of the coal face is mined, the coal extraction process advances. Current longwall mines utilize mobile roof supports that can also be moved when the mine advances.¹⁷ Figure 3.2 illustrates the layout of a typical longwall mine.

¹⁵ The earliest publications about longwall mines date from 1914 and 1936 and describe longwall mines in Illinois (Easton et al., 1914; Toenges, 1936).

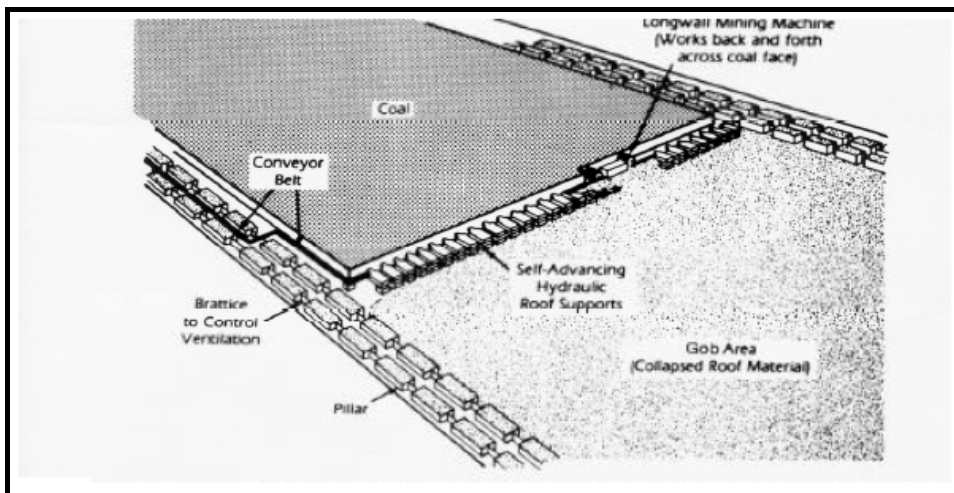
¹⁶ Current application of the retreating room and pillar allows for pillar extraction to get additional coal (Energy Information Administration, 1995).

¹⁷ When roof support equipment is not movable, new roof support equipment is installed closer to the coal face every time coal extraction advances.



Source: EIA (1995)

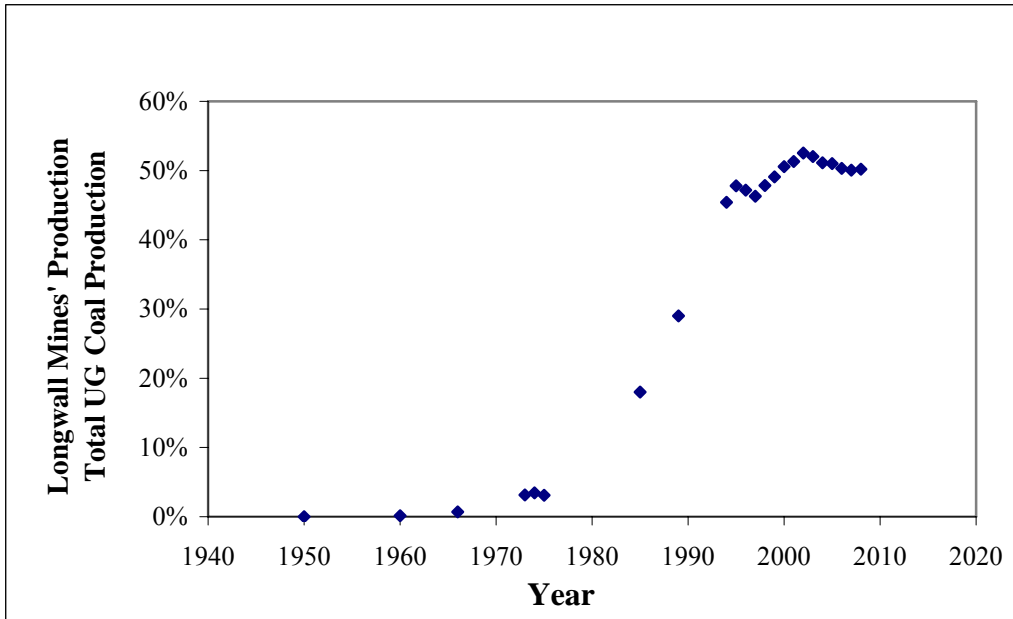
Figure 3.1 Typical layout of a room and pillar mine.



Source: EIA (1995)

Figure 3.2 Typical layout of a longwall mine.

The longwall mining method is important for the U.S. coal mining industry because it has been used to produce more than 50% of the coal obtained from underground mines since 2003. The proportion of coal produced from longwall mines increased rapidly from the mid 1970s until the mid 1990s and has leveled off since then (Figure 3.3).



Sources: Longwall Census from the magazines *Coal Mining* (1984-1988), *Coal Magazine* (1989-1996), and *Coal Age* (1997-2010).

Figure 3.3 The percentage of coal production from longwall mines compared to total coal production from underground coal mines.

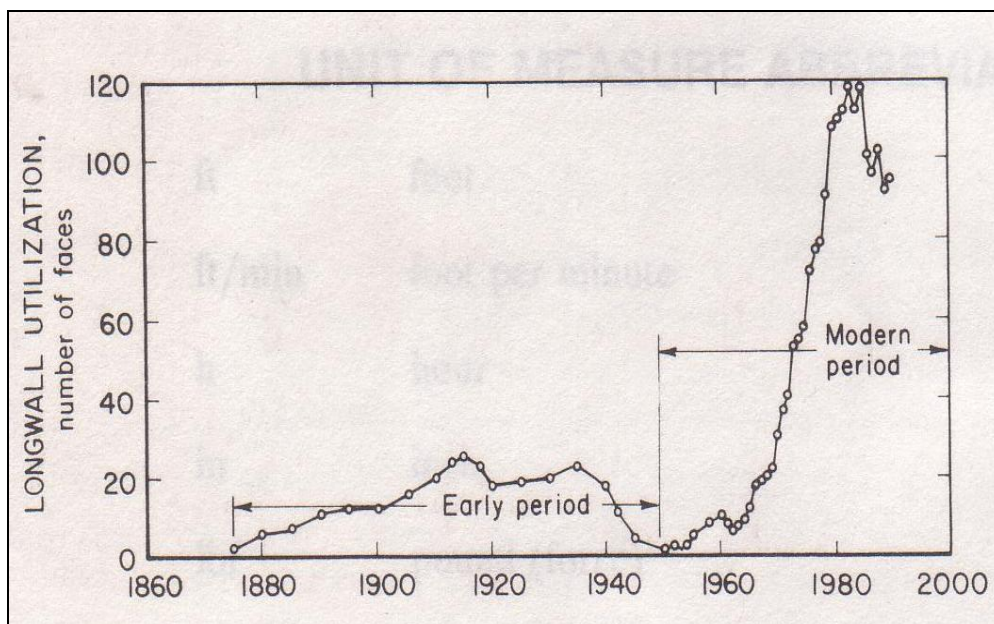
Figure 3.4 shows that the trend of longwall utilization increased until 1983. At that point, despite the increasing proportion of coal produced from longwall mines, the number of mines utilizing longwall began to decrease (Figure 3.5).¹⁸ The declining trend occurred due to the combined effect of the increasing size and productivity of longwall mines and the decreasing coal price.¹⁹ Mining companies could still meet demand while idling or closing their inefficient mines when the coal price was declining.²⁰ By letting their mines idle, mining companies also reduced their excess capacity. Furthermore, larger mines require more capital investment and thus larger coal reserves to justify the investment. This condition has created a barrier to utilizing the longwall mining method for mining companies with small coal reserves.

¹⁸ Longwall mines accounted for 8.15% of total underground coal mines in 2009.

¹⁹ EIA (1995) and Merritt (1991) show that between the early 1980s and the early 1990s, the size of longwall mines (in terms of panel length and face width) grew more than 20%.

²⁰ Longwall census figures from *Coal Mining*, *Coal Age*, and *Coal Magazine* from 1984 to the present show that some longwall mines had to be closed due to declining coal prices in the early 1990s. For example in 1995, Consol and Peabody idled some of their mines to save costs.

Several studies indicate that innovations in longwall equipment technology both influence the diffusion of this method and change the characteristics of longwall utilization (Barczak, 1992; EIA, 1995; Souder & Palowitch, 1981).²¹ Innovations in longwall equipment technology have increased the average mining depth, mine height, and size of longwall mines. According to the EIA, Barczak, and Haycocks and Karmis (1997), in addition to longwall equipment improvement, government regulation and innovative efforts from government agencies and equipment manufacturers have also contributed to the diffusion of the longwall mining method.



Source: Barczak (1992)

Figure 3.4 Longwall utilization in the United States.

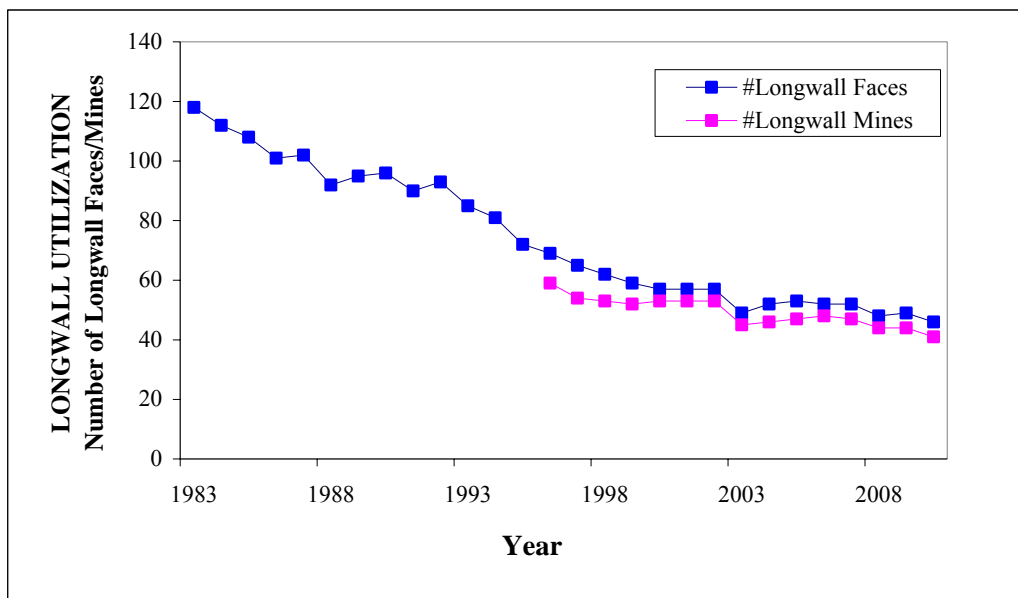
3.1. The Influence of Innovations and Regulation on Longwall Utilization

Before the mid 1950s, the main advantages of longwall mines over room and pillar mines were the quick return on investment and higher coal recovery.²² Longwall equipment had evolved during this period. Roof support equipment evolved from timber

²¹ The important innovations have occurred in the three main pieces of equipment in a longwall mine: the coal mining equipment, the roof support equipment, and the coal haulage equipment.

²² Most longwall mines until the late 1940s were the advancing type. In the advancing longwall method, the coal extraction process starts from the mine entry instead of from the end of mining block like in the retreating longwall method. Therefore, the coal extraction process does not have to wait for the development stage to be fully completed.

to steel friction jacks to mechanical I-beam friction props and wood cribs. Coal haulage equipment evolved from slushers and scraper boxes to belt conveyors. Coal cutting equipment evolved from manual undercutting equipment to mechanized undercutting equipment; mechanized coal cutting technology from Europe was eventually introduced and widely used (i.e., the German coal plow).²³ Despite these improvements, longwall mines still could not compete with room and pillar mines in terms of productivity and safety.²⁴ The main drawback for a wider application of this method was the labor and time requirement in moving and installing the roof support equipment. In addition, the early coal plow technology only worked well with a soft coal seam.²⁵



Sources: 1984-1996 Longwall Census from *Coal Mining*, 1997-2009 Longwall Census from *Coal Age*

Figure 3.5 Longwall utilization in the United States since 1983.

²³ The utilization of a coal plow omits the labor-intensive mechanized undercutting process. The first coal plow was tried at Statesbury Mine in West Virginia, owned by Eastern Gas and Fuel Associates, now Peabody

²⁴ The average productivity of longwall mines was about 3 tons per worker per shift by the 1950s. Assuming 8 hours per shift, the average productivity was .375 tons per worker per hour. This number is approximately 45% lower than the average productivity of underground coal mines in the late 1940s. In terms of safety, the main concerns with longwall mining were unexpected rock falls and the low resistance and reliability of the available roof support equipment.

²⁵ The failure rate in longwall mines between 1950 and 1960 was still high (approximately 75%) due to the incompatibility between the coal plow and the coal deposit, poor roof control, and lower profitability compared to room and pillar mines (Barczak, 1992).

Another barrier for longwall utilization was the complexity of its implementation. Longwall implementation is an integrated system of coal mining, coal haulage, and roof support sub-system. The continuous production process requires teamwork and trained labor because any disruption in one of the sub-systems would disrupt the whole mining process. Therefore, given the lack of significant relative advantage and the difficulty of implementing the longwall mining method, it was difficult to justify adopting this method until the 1960s, when the relative advantage in productivity and safety of longwall mines increased. Roof support equipment started to have a bigger capacity and could be moved hydraulically, so it required less labor to operate.²⁶ It continued to improve with the introduction of the chock and shield support. These innovations led to more longwall utilization in deeper mines in the Western United States. Mining equipment also improved because of innovations to the coal plow and the introduction of the coal shearer.

In addition to the innovations, the longwall mining method gained attention from the industry after the Federal Coal Mine Health and Safety Act of 1969, also known as The Coal Act of 1969, was enacted. This regulation emphasizes safety in coal mines and has been considered a significant factor in the decline of underground coal mining productivity in the early 1970s (U.S. General Accounting Office [GAO], 1981). One of the key points in the regulation that affected mining practice in underground coal mines was the requirement that miners should always work under a supported roof. With this requirement, the coal-cutting machines in room and pillar coal mines had to be withdrawn for every 20 feet advanced in order to allow for roof bolting activities. Prior to the Coal Act of 1969, some mines allowed movement of 90 to 105 feet before installing the roof bolts (GAO, 1981). After this regulation, the productivity of underground coal mines decreased approximately 20% annually.

The longwall mining method was very appealing because it helped the operator to comply with safety requirements while maintaining the opportunity to increase productivity. A survey of 64 mines in 1970 showed that the productivity of longwall mines with production of more than 2 million tons per year actually increased (Straton,

²⁶ The first hydraulic roof support was installed in a West Virginia mine in 1960.

1972).²⁷ This was in contrast to the general condition of underground coal mines after the Coal Act of 1969.

The lack of successful implementation had been a reason why many mining companies were reluctant to try the longwall mining method before the 1960s. In fact, most mines had stopped using the longwall method due to disappointing results (Souder & Palowitch, 1981).²⁸ However, innovations in the 1970s led to wider utilization of the longwall method. Successful longwall implementation reduced the perceived risk of adopting longwall for other potential adopters.

In addition to the relative advantage and visible implementations for many mining companies, many mines were willing to try the longwall method in the 1970s and early 1980s because it could be implemented on a small scale (i.e., in a section of the mine). This encouraged potential longwall adopters to try the longwall method and observe its result at their mines. Therefore, the significant longwall adopters during the late 1960s and 1970s were small coal operators (Souder & Palowitch, 1981).

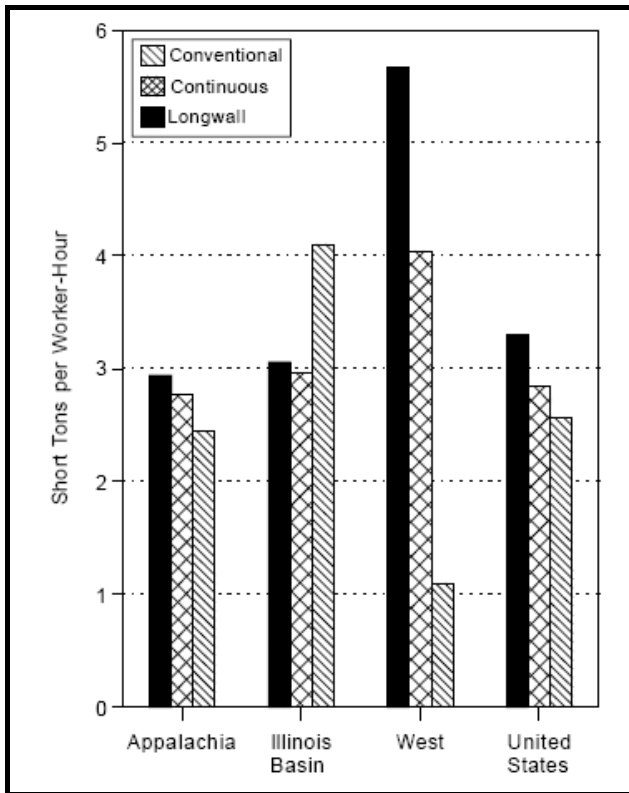
After the 1980s, longwall innovators focused on automation as well as more reliable and powerful equipment to attain the potential of the longwall method for higher productivity and safety. More reliable and powerful equipment enabled continuous extraction along the panel without any major maintenance work or replacement necessary (Peng, 2006), while other improvements created equipment with more capacity, size, power, and speed. Longwall mines have been becoming larger in size and more productive. However, to ensure continuous production, the application of this method requires large coal reserves and extensive capital cost. These requirements create barriers for the development of new longwall faces, especially for smaller mining companies.

The perceived relative advantages of longwall to mining companies depended not only on the technology, but also on the compatibility of the available longwall equipment technology with the coal deposit. Despite the known productivity leverage of longwall mines since the late 1970s, Figure 3.6 shows that the productivity leverage varied for different types of coal deposits. The longwall mines in the Appalachian region had the lowest productivity because they produced metallurgical coal that requires further

²⁷ These mines represent 77 million tons of coal production from deep mining.

²⁸ Souder and Palowitch (1981) showed that the rate of discontinuance from the earlier longwall mines was higher for older longwall equipment technology.

processing (EIA, 1995), which increased the labor input and reduced the total final product.



Source: Energy Information Administration (EIA), 1995

Figure 3.6 The productivity of underground coal mines in 1993.

In addition, the longwall mining method cannot be implemented in all types of coal deposits. The general requirements for longwall utilization are a fairly flat coal deposit that is free from discontinuities and has a uniform seam thickness and immediate roof strata that cave easily (EIA, 1995; Peng, 1987). Other than these general requirements, there are other geological conditions (e.g., seam thickness and depth, reserve size) that influence the dynamics of how mining companies determine whether a coal deposit is favorable for use of the longwall mining method.

3.2. The Role of the U.S. Bureau of Mines and Equipment Manufacturers

The U.S. Bureau of Mines (USBM) had been the driver for the development of longwall mining practice in the U.S. by sponsoring research and development projects

using longwall technology and providing the mining industry with more information through its publications, workshops, and technology transfer seminars. The USBM also reviewed some foreign technologies and applications in using the longwall mining method and spread the information through its Information Circular Bulletin (e.g., Olson & Tandanand, 1977).

The USBM also took an active role in responding to the decline in coal mine productivity in the 1970s. Seventy percent of the USBM's budget for the 1975-1980 periods went to improve mining technology; 75% of that funding was for underground mining technology (Yancik, 1975). One of the major goals of improving mining technology was to "accelerate the use of longwall mining to increase the percentage of coal recovered and to mine efficiently and safely coal deposits at greater depths and under difficult strata conditions" (Yancik, 1975, p. 101). Participation and support from the USBM reduced the financial risk and uncertainties faced by coal mining companies when they wanted to develop longwall. For example, the USBM sponsored approximately \$67 million in various research projects between 1975 and 1985 (Barczak, 1992), including four full-scale longwall coal mining demonstration projects in 1975 (Wade, 1986). One of these was at the York Canyon Coal Mine, where shield support systems were demonstrated and tested under different mining conditions. The results from the demonstration project were disseminated by the USBM to encourage further longwall implementation in other mines.

Other USBM demonstration projects displayed longwall effectiveness in areas with difficult mining conditions, as in a cost-sharing contract between the USBM and the Old Ben Coal Company in 1975. The goal of this project was to demonstrate that the Herrin no. 6 Coalbed in Southern Illinois could be mined safely by the longwall method (Curth, 1978). Before the project started, there had been several failed attempts to use the longwall method in this region (Curth, 1978; Wade, 1986).²⁹

Equipment manufacturers have also contributed significantly to the growth and development of longwall utilization. They are the suppliers as well as the consulting firms for coal mining companies. Their roles have been greater for mining companies

²⁹ The failed attempts were 6 faces at the Old Ben's no. 21 between 1962 and 1971 and Orient no. 5 and 6 mines owned by the Freeman Coal Co.

without previous experience with the longwall mining method,³⁰ providing them with technical appraisals and services before and during mining operations, such as the training provided for employees at Emery Mining Corp., which decided to use the longwall method in 1980 (Jackson, 1980). Manufacturers have also contributed to innovation for faster, bigger, more reliable, more powerful, and more automated longwall equipment that have led to more productive, safer, and larger longwall mines.

3.3. The Coal Industry and Market

In addition to innovations, regulations, and the efforts from the USBM and manufacturers, coal price has also influenced longwall utilization. Rising coal prices from the mid-1970s to the early 1980s contributed to the increased amount of longwall utilization³¹ because it allowed for wider margins that provided incentive and flexibility for mining companies to try the longwall mining method. Higher prices also led to the opening of new mines (sometimes higher-cost mines). When the price of coal began to decline in the mid-1980s, these mines had to be closed.³² Sprouls (1986) explains that many closed mines in 1985 were mines with high cost and without markets with average age of 8 years.

Mergers and acquisitions (M&A) in the coal mining industry are also important for the diffusion of the longwall mining method because the M&A process can contribute to the transfer of longwall knowledge between mine operators and provide access to more resources to fund innovation projects as well as allow for the implementation of longwall on a larger scale. However, annual surveys on longwall mines since the mid 1980s have shown that several longwall systems were shut down after mergers and acquisitions (Sprouls, 1989). One of the reasons for the closures was the excessive production capacity of the mining company.

Another characteristic of the coal mining industry that is important for diffusion of longwall methods is open personal communication (Souder & Palowitch, 1981). This

³⁰ One important period in longwall development was in the early 1980s. During that time, the numbers of inexperienced adopters were significant, making up 86% of adopters (Souder & Palowitch, 1981).

³¹ Coal price was increasing approximately 7% annually from 1974-1982 due to the oil embargo (Energy Information Administration, 1992).

³² Coal price was decreasing approximately 2.8% from 1982-1990 (Energy Information Administration, 1992).

industry is relatively open about technological innovations compared to other industries. It is common to gain information about other companies' innovations and adoption through personal communication and company visits. This characteristic benefits the knowledge transfer about the longwall mining method, but may also inhibit diffusion due to the lack of leverage as innovators for the early adopters.

3.4. Summary

The diffusion of the longwall mining method in the United States has been driven by innovations in underground mining equipment technology, the Coal Act of 1969, and changes in coal price. Mining companies make adoption decisions based on the investment cost required for adoption, perceived attributes and risks of the innovation, and their familiarity with the innovation. The perceived risk of adopting the longwall mining method was mainly assessed by mining companies through observation of longwall mining method implementations in other mines and through interaction with current users and longwall equipment manufacturers. Mining companies seek for significant relative advantage in terms of productivity, mining cost, and equipment reliability that provides a safer working environment. As a result, the most dominant attributes of innovation in influencing the adoption decision are the innovation's relative advantage and compatibility with the coal deposit.

CHAPTER 4

AGENT-BASED MODELING OF THE DIFFUSION OF THE LONGWALL MINING METHOD IN THE U.S.

An agent-based model was developed by the author based on the historical perspectives in the previous chapter and run on Netlogo software (Wilensky, 1999) to simulate the diffusion of the longwall mining method from 1914 to 1989.³³ The simulation runs in 900 time steps to represent the period of interest (1 time step = 1 month). Details of the agent-based model will be described in this chapter.

4.1. General Description of the Model

The proposed agent-based model defines two types of agents for the simulation: mining companies and equipment manufacturers. Mining companies in the model represent coal mining companies with underground mining operations, while equipment manufacturers represent producers of underground mining equipment. Mining companies in the model are the potential adopters of longwall mining methods, and equipment manufacturers are the innovators that always seek to improve underground mining equipment technologies. In the agent-based model, mining companies have only two alternatives for their mining method: longwall or room and pillar. During the simulation, each mining company has one mining operation and constantly observes several other mines for performance benchmarking. This thesis introduces the term *observation network* to denote a group of mines that a mining company observes during the simulation. The goals for the companies during the simulation are as follows:

- a) Reach higher productivity compared to other mines in the observation network.
- b) Obtain lower mining cost compared to other mines in the observation network.
- c) Avoid failures at their mine. Failure in this agent-based model is defined as disruption in mining activities due to the unreliability of the mining equipment.

³³ The Netlogo model in this thesis can be found on the CD available with the hard copy of this thesis.

During the simulation, mining companies evaluate these goals annually. When their goals are not achieved, mining companies can perform the following actions:

- a) Perform internal research.
- b) Update their equipment.
- c) Switch to an alternative mining method (from longwall to room and pillar and vice versa).
- d) Seek solutions by visiting other mines.

The general illustration of mining companies' behavior in the agent-based model is presented in Figure 4.1. Mining companies evaluate their goals after getting information about the performance of their mine and other mines. During the simulation, mining companies are always connected to one equipment manufacturer as their supplier for underground mining equipment. The oval node contains information that mining companies receive from their suppliers about the latest equipment technology. Mining companies then decide the best actions based on this internal and external information.

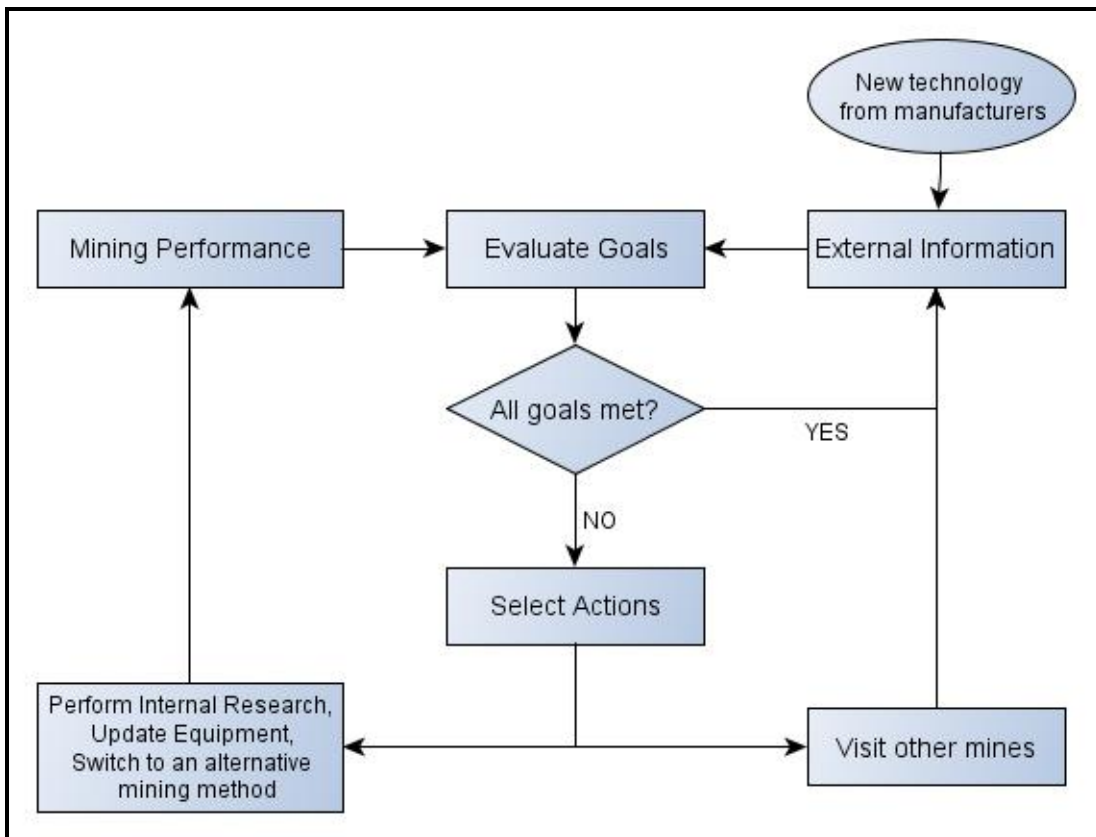


Figure 4.1 Mining companies' behavior in the agent-based model.

The goal of equipment manufacturers in this agent-based model is to maintain the number of clients by continuously improving their products. This goal of keeping the number of clients is used rather than the goal of profit maximization goal for the purpose of simplification. Using monetary values during the simulation would make the model more complicated because modeling goal-related profit maximization requires the modeler to simulate the fluctuation of cost in producing equipment and the fluctuation of the price of the equipment.

Equipment manufacturers can choose if they want to innovate or imitate other manufacturers' technology in improving their product. Innovating means that manufacturers attempt to produce a new variant of underground mining equipment that does not exist yet in the market, while imitating means they just copy products made by other manufacturers. They make this decision after observing underground equipment made by other manufacturers. The general illustration of equipment manufacturers' behavior in this agent-based model is presented in Figure 4.2.

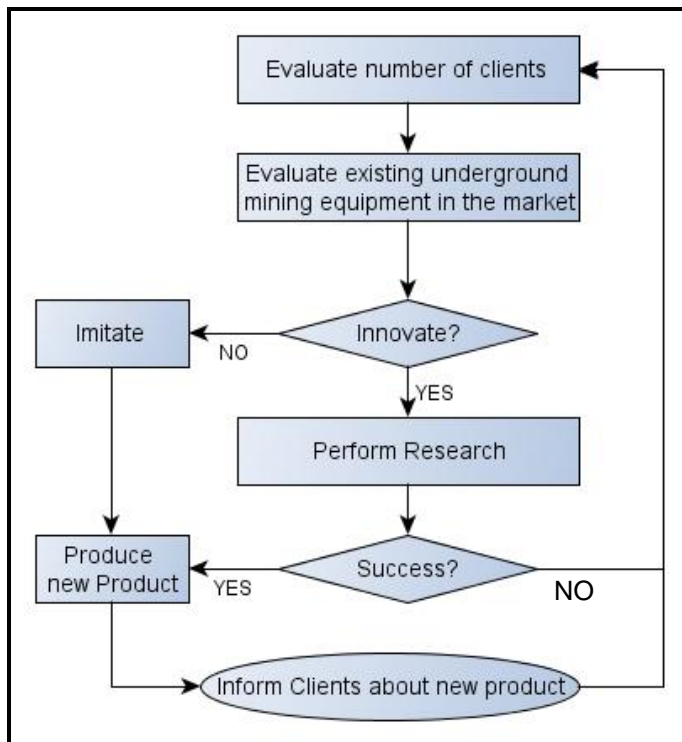


Figure 4.2 Equipment manufacturers' behavior in the agent-based model.

4.2. Design of Agents: Agents' Attributes

In order to implement the behavior of agents in Figures 4.1 and 4.2, the model defines specific characteristics for each individual agent. These specific characteristics are called agents' attributes. The key attributes of mining companies in this model are adoption threshold, strategy, and payback period threshold.

The adoption threshold is the minimum number of other mines that have successfully adopted an innovation before a mining company is willing to consider the innovation. Successful applications in other mines are defined as experiencing no failures and generating lower mining cost or higher productivity. After evaluating their goals, mining companies determine if they want to reduce their adoption threshold (*progressive strategy*) or maintain their adoption threshold (*conservative strategy*).

Mining companies evaluate the cost of adopting an innovation by calculating its payback period. Each mining company has a maximum payback period (payback period threshold) in adopting an innovation that is based on the size of the mining operation. Mining companies will not adopt an innovation if the payback period exceeds their payback period threshold.

In addition to these attributes, each mining company is also assumed to have one mining operation. Every mining operation has the following key attributes:

- a) size
- b) mining depth (feet)
- c) seam thickness (inches)
- d) mining cost (\$/ton)

Mining companies inherit the attributes of their mining operation, and these attributes influence their behavior. For example, mining companies take into account the mining depth and seam thickness at their mining operation in deciding the most appropriate mining method for their mine.

As for equipment manufacturers, their main attributes are as follows:

- a) Sets of knowledge (kene)

This attribute indicates the specific skills and expertise a manufacturer has and is described by utilizing the kene concept from the SKIN model.

b) Innovation strategy

Innovation strategy is defined as either innovation or imitation.

c) Research type

Research type is defined as either incremental or step-change research.

4.2.1. Mining Companies' Activities

In agent-based modeling, agents' activities in the simulation can be shown using an activity diagram. The diagram shows the sequence of actions that agents can take during a given period. The activity diagram in Figure 4.3 shows mining activities during the simulation. The filled black circle represents the initial step in the activity while the hollow circle with filled a black circle inside represents the end condition. The oval-shaped boxes in the activity diagram represent mining companies' actions. The thick black horizontal line in the diagram is a synchronization bar that represents parallel actions that mining companies can perform.

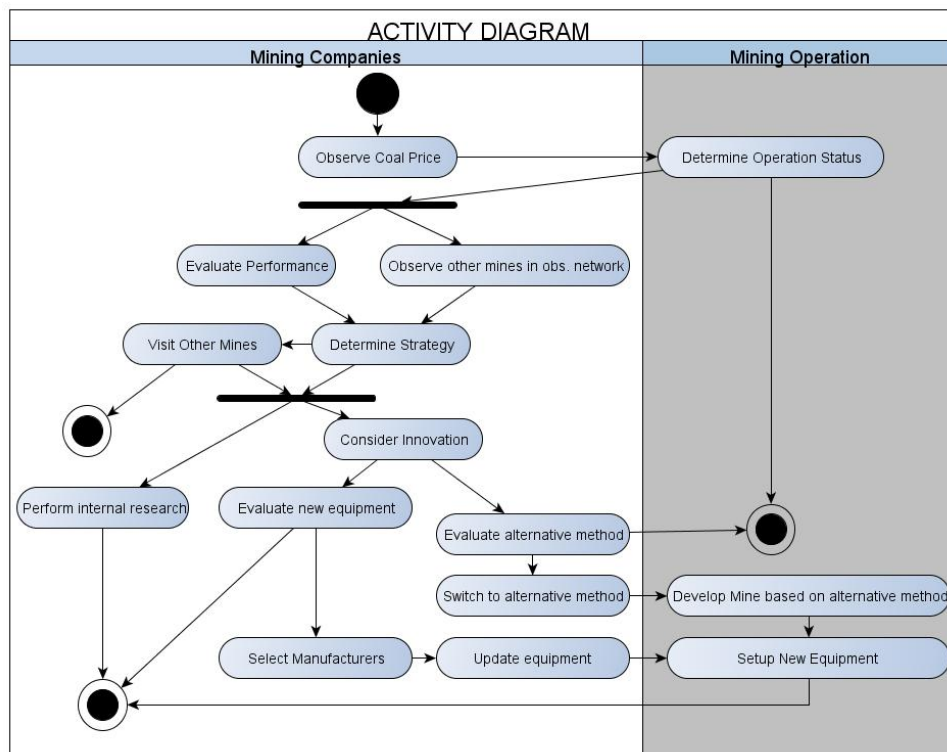


Figure 4.3 Activity diagram for mining companies.

Mining companies' activities start with observing the price of coal and comparing it to their mining cost. They will put their mining operations on idle status when the coal price is less than their mining cost. If they decide to continue mining operations, they will proceed to evaluate their mining operation performance by comparing their productivity and cost with those of other mines in the observation network and checking if failure occurs at their mine. After evaluating their performance, mining companies determine their strategy for the given year by following these rules:

- a) If mining productivity is the lowest or if mining cost is the highest compared to the mines in the observation network, the company will use a progressive strategy (lower adoption threshold) and plan to visit other mines.
- b) If mining productivity is below the average of productivity of mines in the observation network or mining cost is above the average, the company will plan to visit other mines and still use a conservative strategy.
- c) If mining cost is above the average, the company will plan to perform internal research.
- d) If failure occurs, the company will consider adopting an innovation (update equipment or switch to alternative mining method), use progressive strategy (lower adoption threshold), and plan to visit other mines.

When mining companies plan to visit other mines, they randomly choose the mines to visit. The rules in visiting other mines are as follows:

- a) If the visited mine performs significantly better (e.g., does not experience failure and has higher productivity or lower mining cost), the company will add the visited mine to its observation network.
- b) If the visited mine performs better and utilizes the same mining method, the company will check if the visited mine is using the same equipment. If the equipment is different, the company will consider updating its equipment.
- c) If the visited mine performs better and utilizes a different mining method, the company will consider switching to that mining method.

In terms of choosing their actions, mining companies use the following rules:

- a) Mining companies can simultaneously perform internal research and evaluate whether to update equipment.

- b) Mining companies consider the payback period for updating their equipment and prioritize getting equipment from their current suppliers. The general flowchart for evaluating the option of updating equipment is presented in Figure 4.4.
- c) Evaluating an alternative mining method is the last priority for mining companies and is executed only if updating mining equipment is not feasible.
- d) The important factors in evaluating an alternative mining method are compatibility, relative advantage, and payback period. The flow chart for evaluating an alternative mining method is presented in Figure 4.5.

More details on how mining companies evaluate the option of updating equipment and alternative mining methods are presented in sections 4.6 and 4.8 of this chapter.

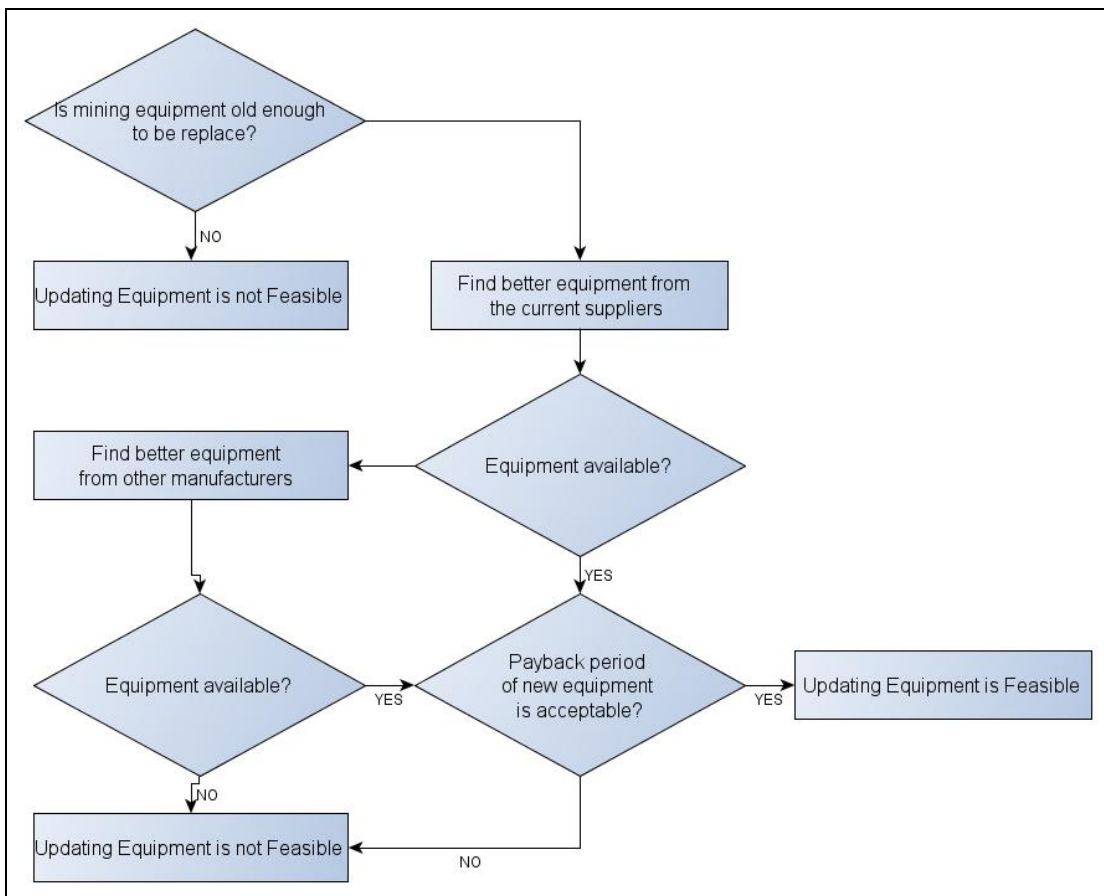


Figure 4.4 Flowchart for updating equipment.

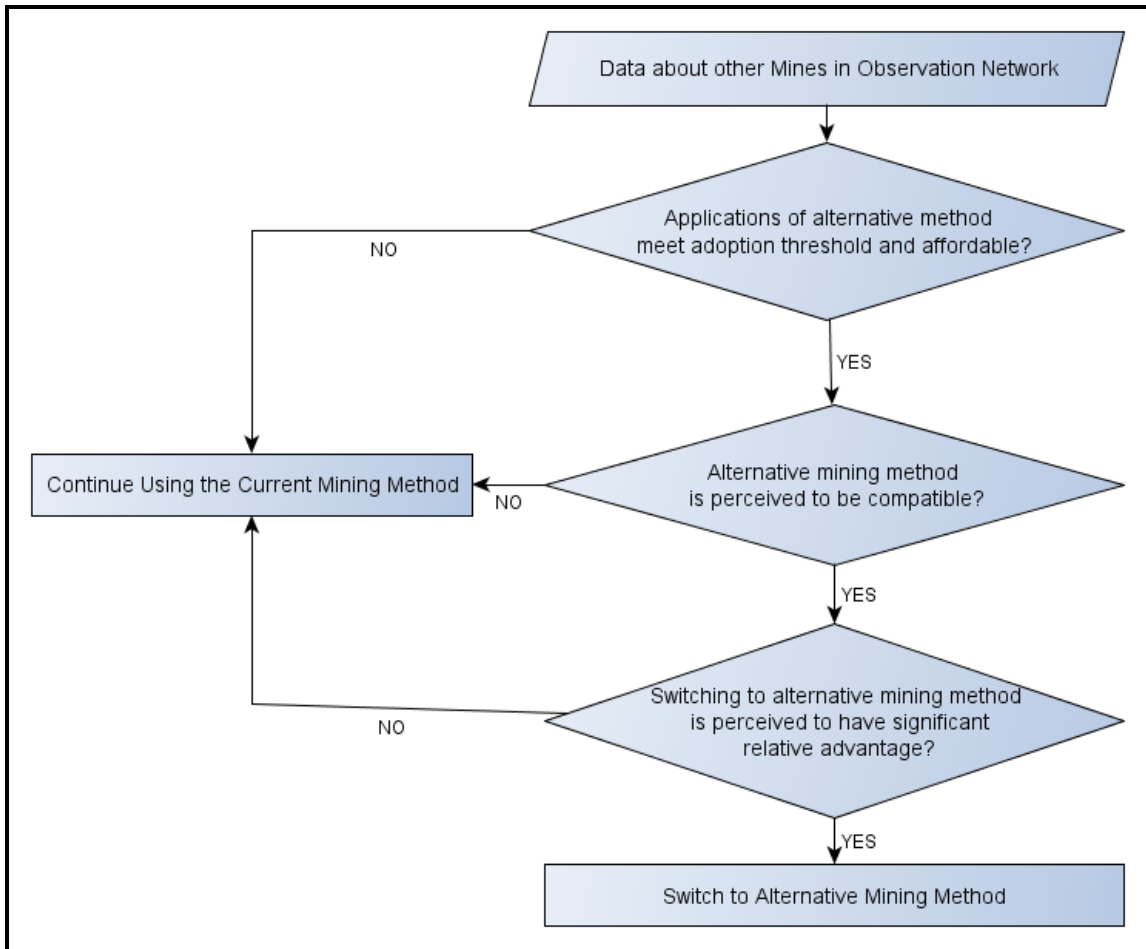
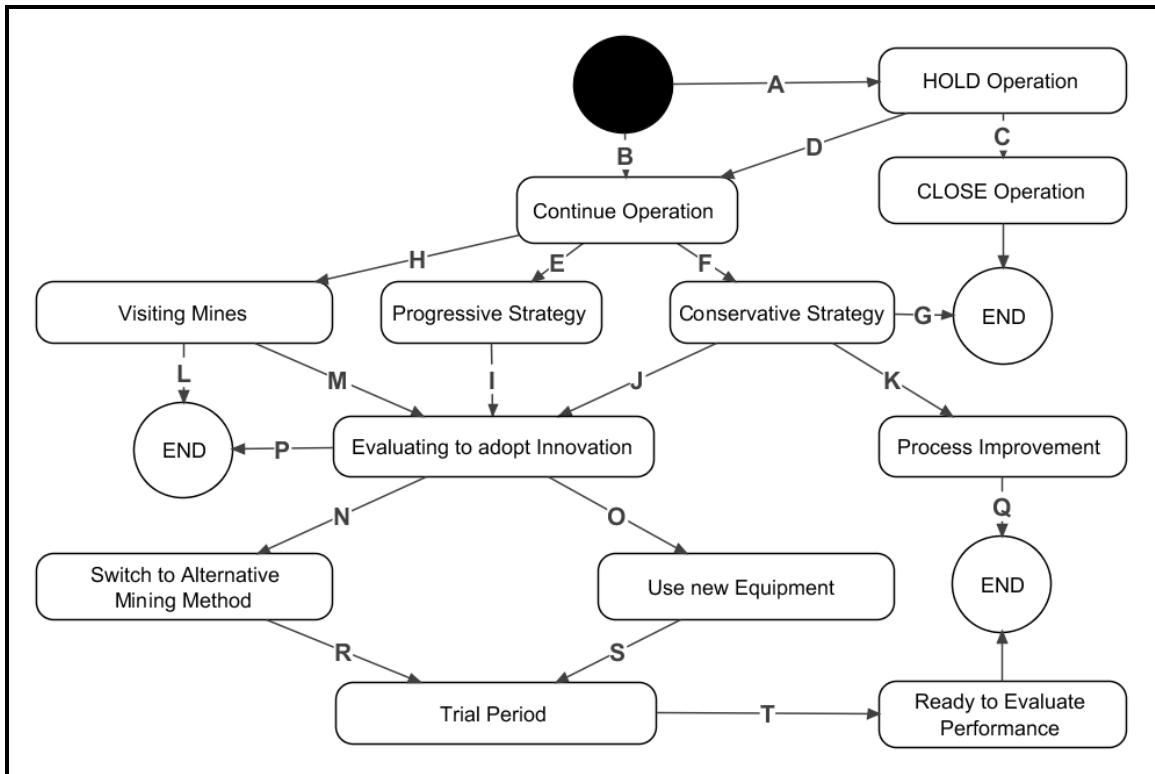


Figure 4.5 Flowchart for evaluating an alternative mining method.

The behavior of mining companies during the simulation can be presented in a state diagram (Figure 4.6). A state diagram shows agents' behavior, including the internal and/or external events that stimulate their specific actions. The black circle in a state diagram represents the initial status, and the labeled rounded rectangles represent the intermediate states. Arrowed lines show the flow of state progression and their labels explain the factors or events that stimulate state transition. During the simulation, after observing the coal price and mining cost, mining companies can choose to continue, idle or even close their mines. If they decide to continue operating their mine, they will then evaluate their competitiveness compared to other mines and decide for the best strategy to maintain or increase their competitiveness.



- A. Coal price is below mining cost.
- B. Coal price is higher than mining costs.
- C. Coal price has been less than mining cost for five consecutive years.
- D. Coal price is higher than mining costs.
- E. Poor performance and/or failure occurrence and/or significant declining profitability and/or low profitability.
- F. Good performance, no failure, and acceptable profitability.
- G. No successful applications of alternative method or new equipment.
- H. Profitability is low and/or significantly declining and/or poor performance.
- I. After lowering the adoption threshold, successful applications of alternative method in the observation network meet the adoption threshold OR equipment with new technology is available.
- J. Successful applications of alternative method in observation network meet the adoption threshold OR equipment with new technology is available.
- K. Mining cost is higher than competitor, but not the highest.
- L. Performance is better than visited mines.
- M. Visited mines have similar characteristics and perform better.
- N. Updating equipment is not feasible. Alternative method is perceived to be compatible with the coal deposit and switching to it will bring significant relative advantage.
- O. Updating equipment is feasible.
- P. Switching to alternative method AND updating equipment are not feasible.
- Q. Results of internal research.
- R. Select new equipment and new suppliers
- S. New equipment purchase.

Figure 4.6 State diagram for mining companies.

4.2.2. Equipment Manufacturers' Activities

The main activity of equipment manufacturers is the improvement of their products. Equipment manufacturers can consider two strategies in improving their products: innovation or imitation. When choosing an innovation strategy, manufacturers aim to produce a new variant of equipment other than those already available in the market. In an imitation strategy, manufacturers seek to copy other manufacturers' products.

With an innovation strategy, manufacturers can plan for a step-change or incremental research program. In a step-change research program, a manufacturer seeks to find and develop the next generation of mining equipment compared to what is available and what they are producing. On the other hand, an incremental research program aims to develop better equipment in the same generation of the current available equipment or technology. The process for deciding which strategy and research type to use is presented in Figure 4.7.

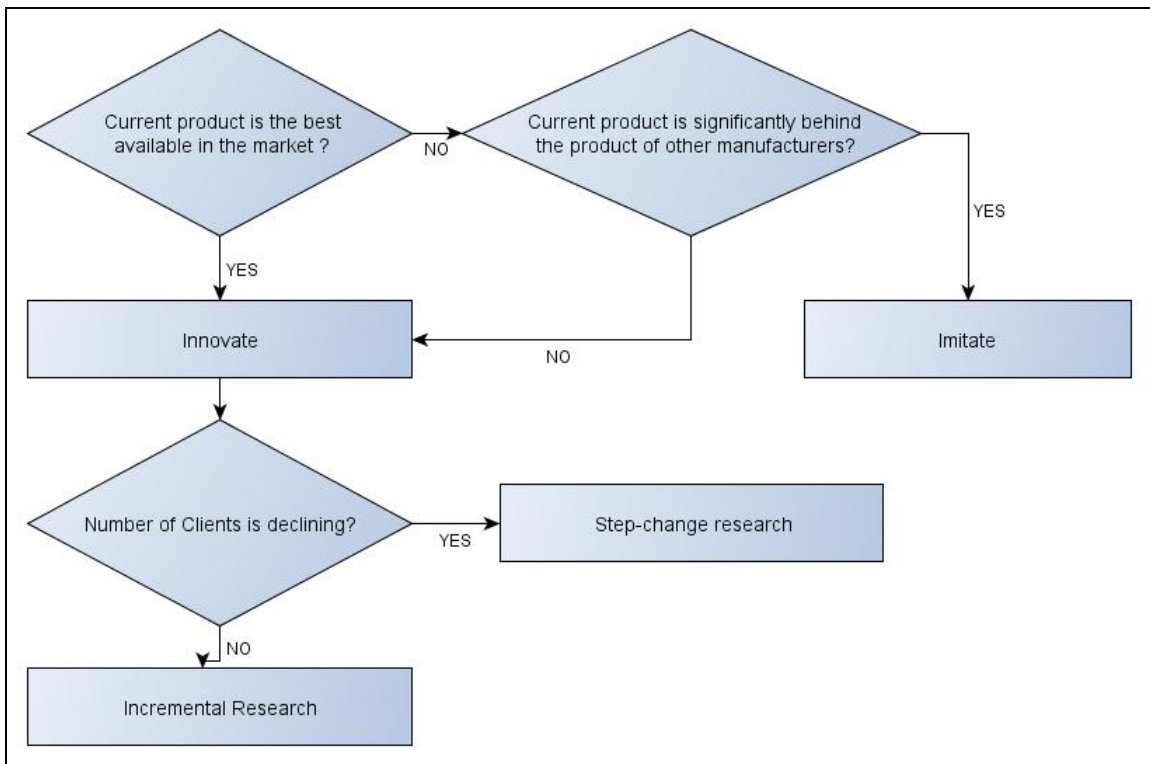


Figure 4.7 Flowchart for deciding innovation strategy and research type.

In order to execute the flowchart in Figure 4.7, equipment manufacturers perform activities that are presented in the activity diagram in Figure 4.8. The behaviors of equipment manufacturers during the simulation are presented in the state diagram in Figure 4.9.

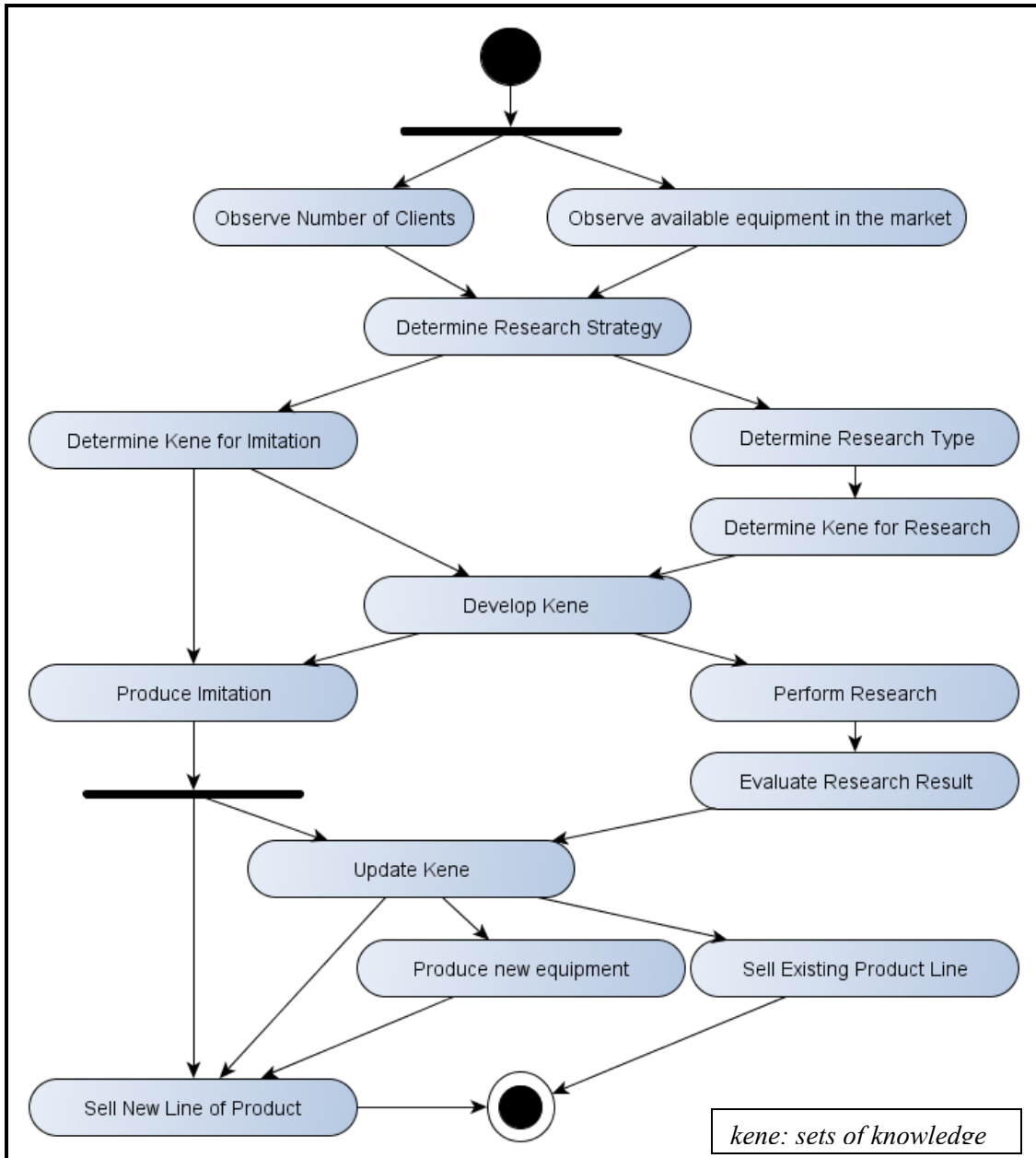
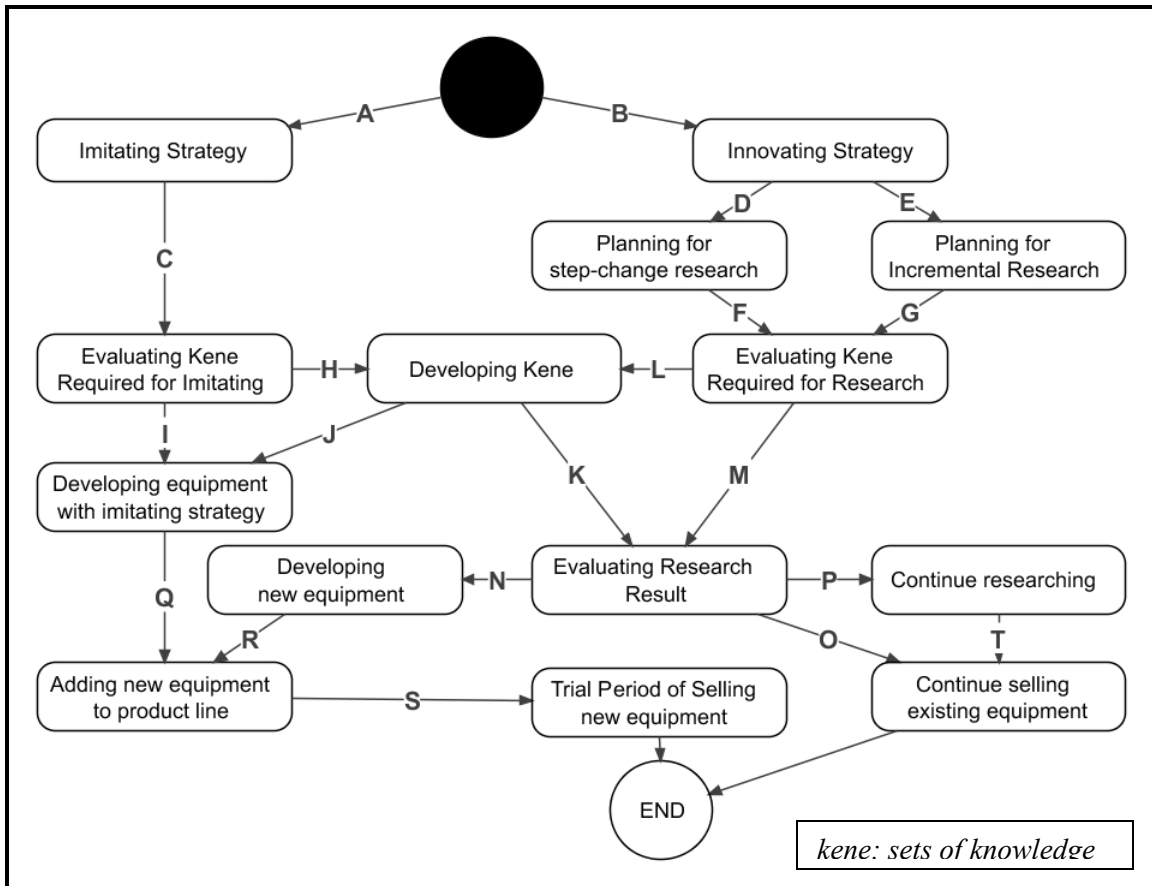


Figure 4.8 Activity diagram for equipment manufacturers.



- A. Current product sold is not the best on the market and is significantly behind the products from other manufacturers.
- B. Current product sold is the best in the market OR the best product in the market is not significantly better than the current product sold.
- C. Determine the required kene for imitating.
- D. Declining number of clients OR the current available technology has already reached its potential.
- E. Steady or increasing number of clients OR the current available technology is still not mature.
- F, G. Required kene for innovating is determined.
- H, L. Do not have the required kene to perform research/imitation.
- I, J. Required kene to perform imitation process has been developed.
- K, M. Required kene to perform research has been developed. Research has been done.
- N. New equipment technology is better than current one and ready for production.
- O. New technology is not better than current one AND update the kene after research process.
- P. New technology is better than current one, but not ready for production
- Q, R. Production process is done.
- S. Update kene after imitating process.
- T. Continue with current research program AND updating kene after the research process.

Figure 4.9 State diagram for equipment manufacturers.

The proposed model assumes that one manufacturer can only produce equipment for one mining method. Therefore, manufacturers have capability (C) to produce equipment for a specific mining method, specific ability (A) related to capability, and level of expertise (E) in their knowledge set (kene). Figure 4.10 illustrates the kene of a manufacturer that produces longwall mining equipment (LW), where j is an index for manufacturer's ability (j and m are integers). A^j_{LW} and E^j_{LW} are integers.

$$\left\{ \begin{bmatrix} C_{LW} \\ A^j_{LW} \\ E^j_{LW} \end{bmatrix}, \begin{bmatrix} C_{LW} \\ A^{j+1}_{LW} \\ E^{j+1}_{LW} \end{bmatrix}, \dots, \begin{bmatrix} C_{LW} \\ A^{j+m}_{LW} \\ E^{j+m}_{LW} \end{bmatrix} \right\}$$

Figure 4.10 Illustration of kene of longwall equipment manufacturers.

4.3. Design of Objects

The proposed agent-based model defines two objects: equipment and mining operation. Equipment is produced by equipment manufacturers and used by mining companies in their mining operation, while a mining operation is operated by a mining company.

4.3.1. Equipment

Underground mining equipment is represented in the model as a series of integers $[a_1 a_2 a_3 \dots a_n]$ in which $a_n \in \{1, 2, \dots, m\}$ with m and n as integers. The value of n corresponds to the number of knowledge sets required to build the equipment. Equipment with more digits in the serial number is more sophisticated because it has more technological features in its design. For example, the early generation of roof support equipment (timber) is modeled to have a one-digit serial number ($n = 1$) while the last generation (shield support) is modeled to have five digits ($n = 5$). This arrangement implies that newer generation equipment provides more alternatives for improvement than older equipment. This setup aims to mimic the evolution of underground mining equipment technology that has resulted in different generations of underground mining equipment (e.g., from timber to shield support for roof support equipment). The equipment serial number also shows specific types of ability required of manufacturers to

produce specific equipment. This design aims to simulate how manufacturers put their skills and knowledge in their product.

Each variant of underground mining equipment has a “fitness value” that measures its relative quality compared to other variants of the equipment. Plotting the fitness value of each variant of equipment generates a technology landscape. The technology landscape is randomly pre-determined before running the simulation. It is assumed that every technology landscape has only one pre-determined peak point, meaning that every equipment generation has only one best variant (the variant with highest fitness value: $fitness_{max}$). If an n dimension of the technological landscape has a peak point $a_{max} = (a_{1max}, a_{2max}, \dots, a_{nmax})$, then the fitness value of other points in the landscape $a = (a_1, a_2, \dots, a_n)$ is determined by Equation 4.1.

$$fitness_a = \frac{fitness_{max}}{1 + \sum_{j=1}^n \left| \frac{a_j - a_{jmax}}{10} \right|} \quad (4.1)$$

In order to illustrate the process for creating the technology landscape, let us assume a two dimensional technological landscape ($n = 2$) with $fitness_{max} = 1$ and peak point $a_{max} = [4 \ 3]$. If $m = 5$ and $j \in \{1, 2\}$ then $a_j \in \{1, 2, \dots, 5\}$, the technology landscape for this example can be constructed by using Equation 4.1; this is presented in Figure 4.11. There can be different variants of equipment technology with the same fitness value. This is a plausible condition because in reality different manufacturers may put different features and technology in their product that in the end may offer a similar result.

The horizontal axes (A1 and A2) in the technology landscape in Figure 4.11 indicate the specific ability required to develop any variant of equipment on that landscape. For example, the technology landscape in Figure 4.11 represents a generation of longwall mining equipment. Therefore, in order to be able to produce longwall equipment [4 3], equipment manufacturers need to have capability in producing longwall equipment and ability 4 and 3 in their kene as shown in Figure 4.12.

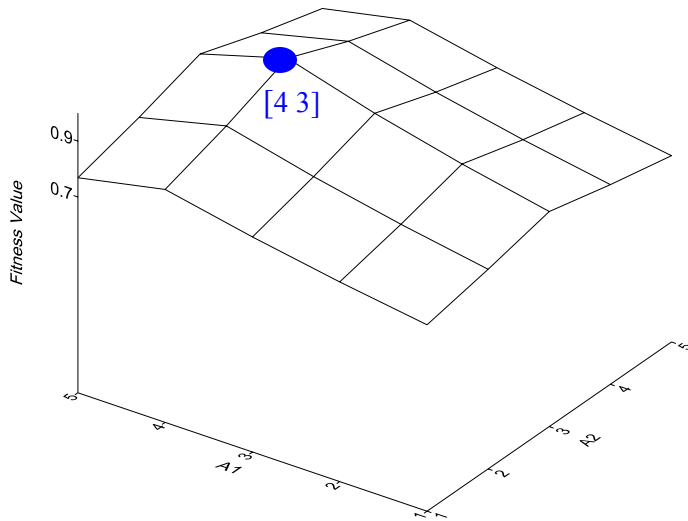


Figure 4.11 The technological landscape constructed from the example.

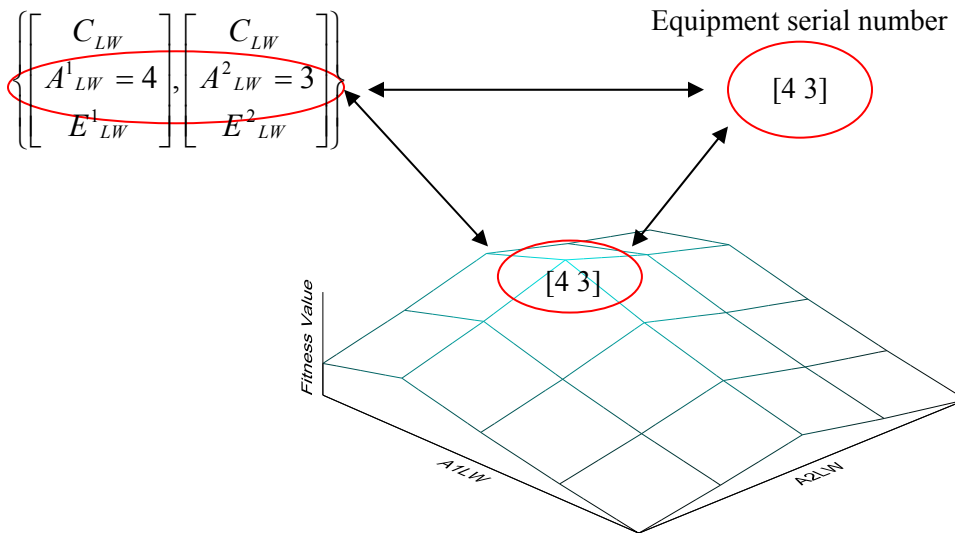


Figure 4.12 The relationship between kene, equipment serial number, and technology landscape.

4.3.1.1. The Performance of Underground Mining Equipment

Every generation of underground mining equipment offers a maximum performance potential in terms of productivity, safety, and coal recovery as well as the associated investment cost. The maximum performance potential and level of investment are measured on a scale from 1 to 10 and are determined based on the findings of Souder

and Quaddus (1982; see Table 4.1). A higher score for productivity, safety, and coal recovery means a better performance. As for the investment cost score, a higher score means cheaper equipment. The notation for potential performance of each generation of equipment mining technology is α_{nk} , where n indicates the generation of underground equipment technology and k is the performance category ($k = 1 =$ productivity, $k = 2 =$ safety, $k = 3 =$ coal recovery, and $k = 4 =$ investment cost). It is assumed that there are five advancements in room and pillar technology. It is noted that historically, significant improvement in room and pillar mines did not necessarily occur due to improvements in specific room and pillar equipment. The model also assumes that there are five generations of roof support equipment technology and four generations of haulage and coal mining (coal cutting machine) equipment technology for longwall.

Since this model assumes a single peak point of the technology landscape, there is only one variant of equipment in every generation of equipment technology that can offer the maximum performance potential as shown in Table 4.1. The performance potential of other variants is determined by their fitness value relative to the maximum. For example, a generation of underground mining equipment can offer a maximum productivity score of 10 with a maximum fitness value of 1. If specific equipment x is a variant of equipment in the same generation and has a fitness value equal to .8, then the maximum productivity score that equipment x can offer is only 8.

4.3.1.2. The Cost of Adopting Innovations

The score for investment cost in Table 4.1 is then used to determine the payback period for a particular item of underground mining equipment. Assuming that the payback period increases exponentially as the score of investment cost decreases (Figure 4.13), the payback period can be computed by using Equation 4.2.

$$PB_{ia} = \text{ceiling}(\beta_1 \times e^{(-\beta_2 \alpha_{ia4})}) \quad (4.2)$$

where

PB_{ia} = payback period of utilizing equipment a in mine i (in years)

β_1 = a real number constant

β_2 = a constant

α_{ia4} = the investment cost score of installing equipment a in mine i

Table 4.1 Potential Performance for Each Generation of Underground Mining Equipment

Generation of LW Roof Support Equipment	Potential Performance Score			
	Productivity	Safety	Recovery	Investment
1	1	1	2	7
2	1	1	2	5
3	3	2	2	4
4	7	7	6	2
5	9	9	9	1
Generation of LW Haulage Equipment	Potential Performance Score			
	Productivity	Safety	Recovery	Investment
1	1	1	1	8
2	1	2	2	6
3	7	7	6	4
4	9	9	9	1
Generation of LW Coal Mining Equipment	Potential Performance Score			
	Productivity	Safety	Recovery	Investment
1	1	1	1	7
2	1	2	2	5
3	6	4	6	4
4	9	9	9	1
Generation of Room and Pillar Equipment	Potential Performance Score			
	Productivity	Safety	Recovery	Investment
1	3	3	2	5
2	3	3	2	4
3	4	4	3	4
4	5	5	5	4
5	6	6	6	3

LW= Longwall.

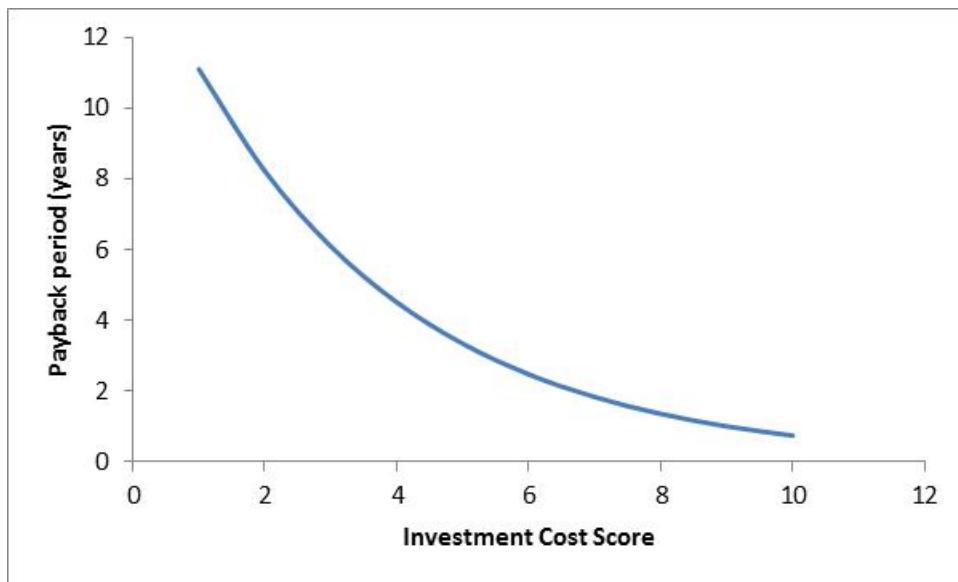


Figure 4.13 Illustration of the relationship between investment cost score and payback period.

Equation 4.2 determines the payback period of using one piece of equipment. When mining companies are looking at switching to an alternative mining method, the payback period should be higher because they also have to consider the cost of developing the infrastructure and the time required for development. This model defines the payback period of switching to an alternative mining method in Equation 4.3.

$$PB_{li} = \text{ceiling}(\beta_3 e^{(-\beta_4 \alpha_{il4})}) \quad (4.3)$$

where

- PB_{li} = payback period of switching to mining method l in mine i
- β_3 = a real number constant, $\beta_3 > \beta_1$
- β_4 = a constant between 0 and 1
- α_{il4} = the investment cost of setting up mining method l in mine i .

4.3.2. Mining Operations

The deposit characteristics of a mining operation in the proposed model are defined in terms of deposit type, seam thickness, and coal deposit depth. There are two types of deposits: a thick and deep or a thinner and shallow coal deposit. In addition to the deposit characteristics, mining operations are also characterized by their scale. The model defines three different sizes of mining operation: large, medium, and small. Different sized mining operations have different maximum payback periods.

The size, seam thickness, and deposit type of a mining operation are assumed to be constant during the simulation, but the depth may change according to a simple rule. Mining companies can increase the mining depth at their mine when they evaluate that the current mining equipment is compatible with their coal deposit. This rule is designed to simulate the increasing depth of a mining operation.

All mining operations have a limited mine life in the model: 15 years for small mines, 25 for medium mines, and 30 for large mines. The expected years of mine life left is used by mining companies in evaluating the possibility of updating their equipment or switching to an alternative mining method. If the payback period for performing these activities is longer than the expected mine life that is left, companies will not consider updating their equipment or switching to an alternative mining method. Three years

before they reach their maximum life expectancy, mines try to extend their mine life with α probability of success. Mining companies that have successfully extended their mine life will lower their adoption threshold, which means they are willing to consider the possibility of using an alternative mining method.

4.4. Design of the Environment

The design of the environment includes the process and scenario design. The process design covers the schedule of processes/procedures in the model, the design of information flow, and data collection. The scenario design in this model includes failure event, the fluctuation of commodity price and mining cost, and the influence of government regulation.

4.4.1. Process Design

During the simulation, mining companies define their strategy at the beginning of each year (time step 1, 13, . . . , 889). They evaluate the performance of their mine toward the end of each year (time step 11, 23, . . . , 899). Between those time steps, mining companies interact with other mines (observe mines in the observation network and visit other mines) and perform their actions (conduct internal research, evaluate alternative mining methods, or update their equipment).

Equipment manufacturers can only perform one research project at a given time. The length of a research project varies due to the time required to develop the necessary skill. They determine their research strategy after they complete one research project. More details on the research process are presented in section 4.7.

In terms of information flow, mining companies are assumed to know the performance and the mining cost of mines in their observation network. This mechanism is an interpretation of open communication between mining companies (Ala-Härkönen, 1993b; Souder & Palowitch, 1981). Mining companies use the results of their observation to estimate the compatibility and potential relative advantage of an alternative technology. They can only know the actual performance of the alternative technology after they try it at their own mine. Mining companies are also assumed to know all

equipment manufacturers as well as their product lines. They use this knowledge to select a manufacturer that can provide the best equipment for their mines.

Equipment manufacturers are assumed to have knowledge about the performance potential of all equipment available in the market. They use this knowledge for benchmarking the potential performance of their own products. Manufacturers cannot predict the outcome of their research. They do not know the form of the technological landscape, but they have memory, so they do not search for better technology in directions that previously failed. It is also assumed that equipment manufacturers can only produce one type of equipment: longwall or room and pillar equipment.

Agents' interaction is defined as information flow. Mining companies gain information about the performance of other companies by visiting other mines and observing the mines in their observation network. This type of interaction mimics the flow of information between mining companies through mine visits. Mining companies interact with equipment manufacturers through the equipment that they use in their mining operation.

In order to analyze the results of the simulation, the model records the following data during the simulation:

- a) The number of longwall mines at the end of each year.
- b) The productivity score of mines during the simulation.
- c) The number of failed mines.
- d) The average mining cost of mines.

4.4.2. Scenario Design

This model uses historical nominal coal price for bituminous coal and inflation rate data from 1914 until 1989.³⁴ Coal price data are used to help mining companies determine their profitability. The model uses inflation rate to model the increasing mining cost through time. When inflation rate is negative, mining cost is assumed to be equal with the mining cost in the previous year.

³⁴ The inflation rate is determined by using the average Consumer Price Index for Urban Consumers (CPI-U).

The model imposes a rule that mining companies can reduce their mining cost up to 10% when performing internal research. They can also reduce their costs by switching to an alternative mining method when the new mining method is compatible with their coal deposit.

In order to observe the influence of regulation, the proposed model reduces the productivity score of room and pillar mines in year 55 in the simulation. This arrangement is aimed to mimic the impact of the Coal Act of 1969 that reduced the productivity of room and pillar mines up to 20% as described in a 1981 publication by the U.S. General Accounting Office.

The failure occurrence at a mine is determined based on its safety score. We assume that as the safety score increases, the probability of failure decreases exponentially (Figure 4.11). In this case, the probability of failure in mine i can be computed by Equation 4.4.

$$prob_{failure} = e^{(-k_1\alpha_{ia1})} \quad (4.4)$$

where

k_1 = a constant between 0 and 1

α_{ia1} = the safety performance score of mine i when using equipment a

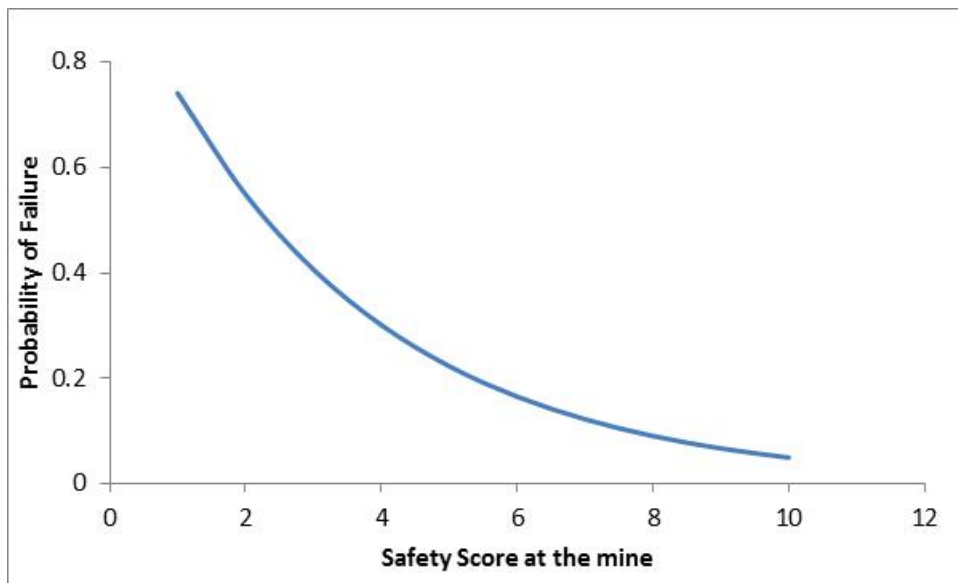


Figure 4.14 Illustration of the relationship between safety score and the probability of failure in a mine.

4.5. Simulation Initialization and Parameters

Based on the design of agents, objects, and environment, we define the parameters for the agent-based model and set them to be constant during the simulation. The default parameters are as follows:

a) comp-threshold

The minimum compatibility score between mining method and the coal deposit. The value for this parameter is between 0 and 1. If mining companies see that the compatibility between the mining method and their coal deposit is below this threshold, they will rate the performance of the mining method as poor and seek an alternative mining method.

b) depth-increase

Incremental increase of mining depth in feet when equipment is successfully implemented in a mine.

c) profit-threshold

The minimum profit margins sought by mining companies. If the profit margin in a given year is below this threshold, the company will seek improvement by visiting other mines.

d) significant-threshold

The point at which a relative performance gap with other mines in the observation network is significant.

e) max-payback

This parameter measures the maximum payback period that mining companies are willing to accept when they are evaluating the possibility of updating their equipment or switching to an alternative mining method. This parameter is different for mining companies based on their size.

f) prob-success

The probability that mining companies will succeed in their internal research.

g) max-visits

The maximum number of times a mining company can visit other mines annually.

h) max-cost-reduction

The maximum cost reduction that mining companies can get when they successfully perform internal research.

i) adoption-threshold-reduction

The reduction of adoption threshold when mining companies decide to use a progressive strategy toward innovation.

j) time-mutation-incremental-research

The time required by equipment manufacturers to perform one incremental research project.

k) time-mutation-stepchange-research

The time required by equipment manufacturers to perform one step-change research project.

l) expertise-increase

The incremental increases of level of expertise after equipment manufacturers perform research.

The default parameters are presented in Table 4.2. The simulation initialization is presented in Table 4.3.

Table 4.2 Default Parameters in the Simulation

Parameters	Value	Units
comp-threshold	0.5	unitless
depth-increase	10	feet
max-payback for small mines when evaluating alternative method	8	years
max-payback for medium mines when evaluating alternative method	12	years
max-payback for large mines when evaluating alternative method	20	years
max-payback for small mines when evaluating new equipment	5	years
max-payback for medium mines when evaluating new equipment	10	years
max-payback for large mines when evaluating new equipment	15	years
max-cost-reduction	10%	unitless
adoption-threshold-reduction	0.25	years
time-mutation-incremental-research	6	months
time-mutation-stepchange-research	12	months
expertise-increase after a successful research	0.2	unitless
expertise-increase after a failed research	0.1	unitless

Table 4.3 Simulation Initialization

Parameters	Values	Units
Number of mining companies	1000	company
Number of mining operations	1000	operation
Number of longwall mines	20	operation
Number of equipment manufacturers	50	company
Manufacturers of longwall equipment	50%	unitless
Manufacturers of room and pillar equipment	50%	unitless
Number of longwall mines	20	operation
Proportion of small scale mines	70%	unitless
Proportion of medium scale mines	20%	unitless
Proportion of large scale mines	10%	unitless
Coal mines with deposit type 1 (deeper and thicker)	20%	unitless
Coal mines with deposit type 2 (shallower and thinner)	80%	unitless
Thickness of deposit type 1 (inches)	60 - 180	inches
Thickness of deposit type 2 (inches)	10 - 100	inches
Initial adoption threshold for each mining company	5	success operation
Initial mining depth	200 - 1100	ft
Initial mining cost	.6 - 1.2	(\$/ton)
Initial number of mines in observation network	5	mining operations

4.6. The Rules in Adopting an Innovation

Mining companies in the agent-based model evaluate the possibility of updating their equipment and switching to an alternative mining method only if the age of the current equipment or mining method has already exceeded the payback period. Mining companies will also not consider an alternative mining method or new equipment if the minimum payback period in adopting them exceeds their maximum payback period (*max-payback* parameter).

After evaluating the payback period of switching to an alternative mining method, mining companies evaluate the compatibility and relative advantage of the alternative method. The rules in evaluating the alternative mining method are as follows:

- a) If the adoption threshold > 0 , mining companies estimate compatibility by searching for the minimum and maximum of mining depth and seam thickness at other mines where the alternative method has been successfully applied. If their mining depth and seam thickness are within the range of successful applications, they will decide the alternative mining method is compatible for their mine.

- b) If the adoption threshold = 0, mining companies are willing to try an alternative method without the need to see proven results. They seek information from manufacturers to evaluate the relative advantage of the alternative mining method in terms of productivity, safety, and coal recovery.
- c) If the mining cost with the alternative mining method is significantly lower than the current mining method OR if the performance (productivity, safety, and coal recovery) of the alternative mining method is significantly better, then switching to the alternative mining method is perceived to bring relative advantage to mining companies. The alternative mining method is evaluated by following the steps in Figure 4.15.

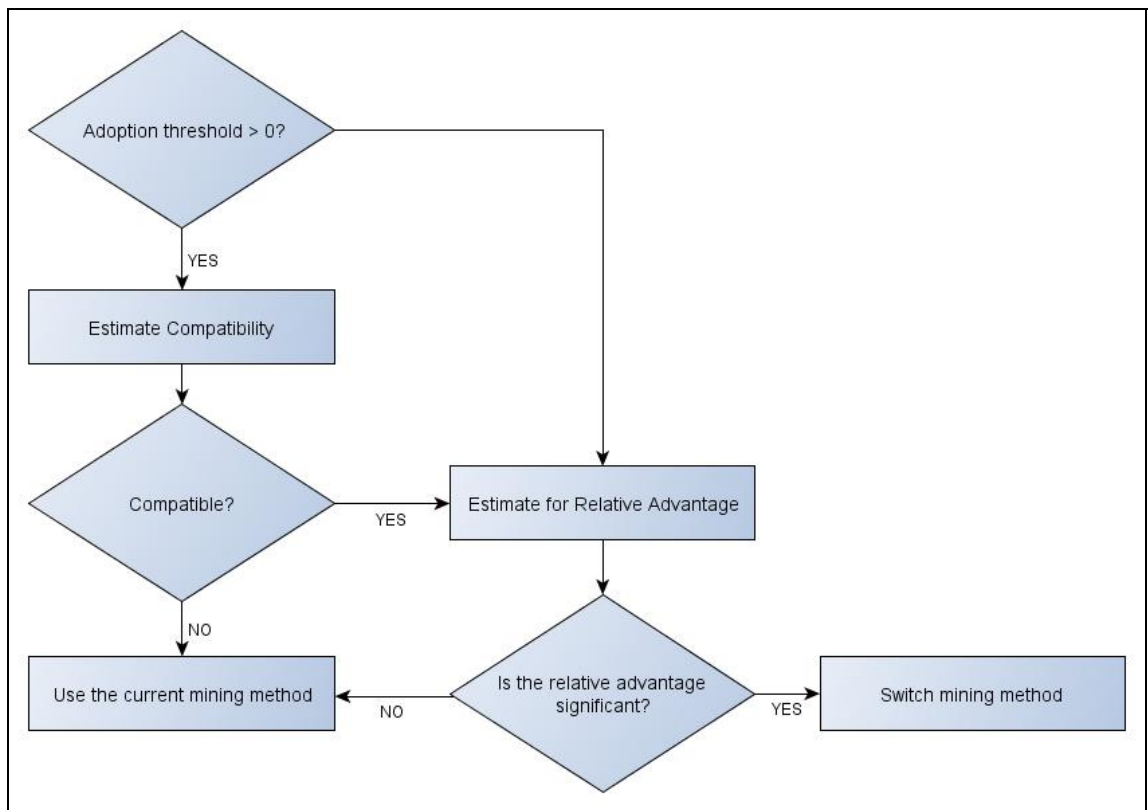


Figure 4.15 Flowchart for evaluating an alternative mining method.

Because mining performance is measured with multiple criteria (productivity, safety, and coal recovery), mining companies in the proposed model utilize a multi-criteria decision making method to evaluate if an alternative mining method offers a

significant relative advantage compared to the current mining method. The steps in evaluating the relative advantage are presented in Figure 4.16.

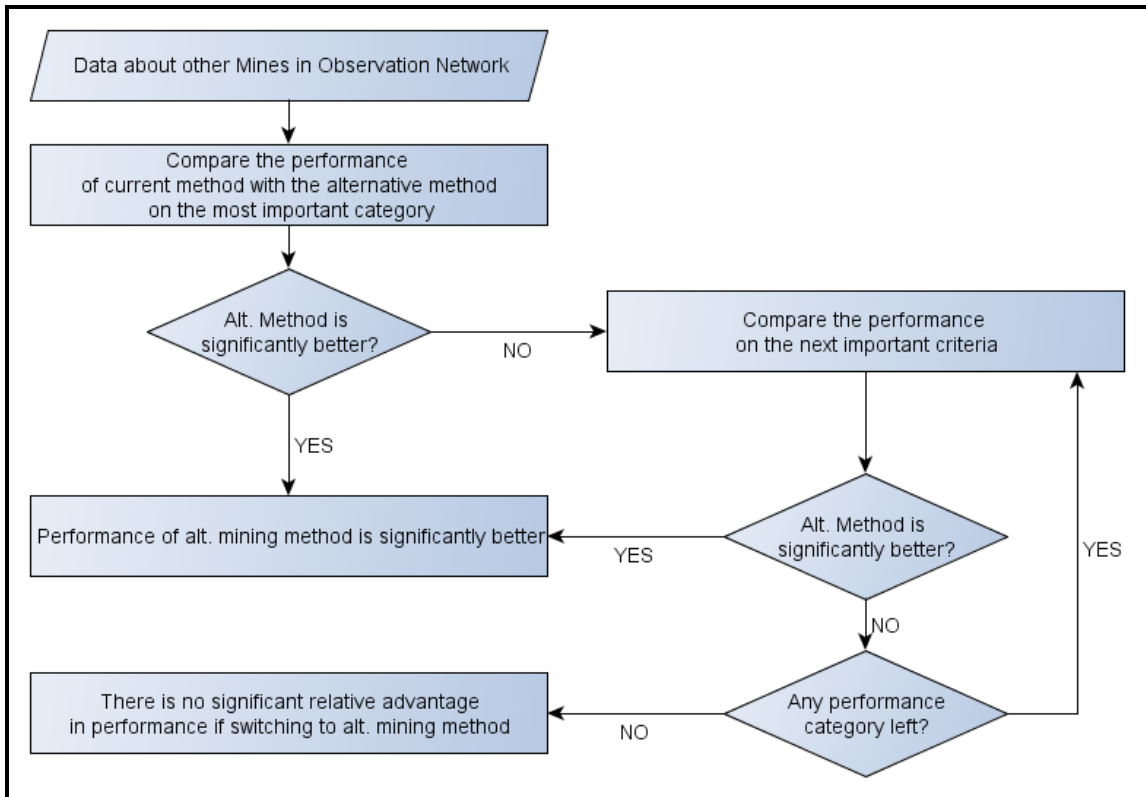


Figure 4.16 Flowchart for evaluating the relative advantage of an alternative mining method.

The steps in evaluating the relative advantage of a particular mining method are as follows:

- a) Rank the evaluation criteria based on their importance to the mining company. Assume that the rank for performance criteria starts with productivity, followed by safety and coal recovery.
- b) Compare the alternative mining method and the current mining method on the most important criterion (in this example the most important criterion is productivity).
- c) If the productivity of the alternative mining method is significantly higher, it is perceived to have relative advantage compared to the current mining method. On the other hand, if the productivity of the current mining method is significantly

higher, the alternative method is perceived as not having relative advantage compared to the current mining method.

- d) If no mining method is significantly better than the other on the first criteria, the comparison continues to the next criterion (in this case, safety).
- e) The comparison stops when one mining method performs significantly better in a specific criterion or if there are no criteria left to be compared.
- f) If there are no more performance categories left to be compared, the alternative method is perceived as not having relative advantage compared to the current mining method.

In the multi-criteria decision making method, these six steps are called the *lexicographic semiorder* decision making method.

4.7. The Rules in Performing Research

Equipment manufacturers decide their research strategy after evaluating the performance of their product and their number of clients. After a research strategy is determined, manufacturers implement their strategy by using the following rules:

- a) Manufacturers have to include n number of technological ability (kene) if they want to innovate or imitate n digits of equipment technology.
- b) Manufacturers can only mutate one element at a time during a research project. Mutation is defined as increasing or decreasing the value in the equipment serial number by one. For example, if the current equipment technology has serial number [2 2], the possible outcome from a research project can be equipment technology with serial number [1 2] or [2 1] or [3 2] or [2 3].
- c) Manufacturers randomly choose which digit from the equipment serial number to mutate.
- d) Manufacturers have to develop their kene if they want to imitate equipment technology of other manufacturers. They also have to achieve expertise until it reaches the average level of expertise of other manufacturers that have already produced the imitated equipment.
- e) After the innovation or imitation process, manufacturers increase the level of expertise in all kene that they included in the research.

- f) Manufacturers will bring successful innovation into production if it meets the minimum fitness value (*relative-fitness-for-production* parameter).

4.8. Mining Performance Evaluation

Mining companies measure the productivity, safety, and coal recovery of their mine based on the potential performance of the equipment technology and its compatibility with their mine. The performance of mine i that is using equipment a in category k is determined by the following equation:

$$\alpha_{iak} = c_{ia} * fitness_a / fitness_{max} * \alpha_{nk} \quad (4.5)$$

where

$k = 1 =$ productivity, $k = 2 =$ safety, $k = 3 =$ coal recovery.

α_{iak} = the performance of mine i in category k when using equipment a .

c_{ia} = the compatibility between equipment a and the coal deposit in mine i .

$fitness_a$ = fitness value of equipment a .

$fitness_{max}$ = the maximum fitness value in the technological landscape equipment a belongs to.

n = the number of digits in equipment a serial number.

α_{nk} = the maximum potential performance of equipment with n digits equipment serial number in category k .

For longwall mines, the performance of each piece of mining equipment (roof support, haulage, and coal mining equipment) is computed. The overall performance of longwall mine i in criteria k is then calculated with equation 4.6.

$$\alpha_{iak} = \min (\alpha_{iak\text{-roof support}}, \alpha_{iak\text{-haulage}}, \alpha_{iak\text{-coal mining}}) \quad (4.6)$$

where

$\alpha_{iak\text{-roof support}}$ = the performance of roof support equipment with n digits serial number in category k .

$\alpha_{iak\text{-haulage}}$ = the performance of haulage equipment with n digits serial number in category k .

$\alpha_{iak\text{-coal mining}}$ = the performance of coal mining equipment with n digits serial number in category k.

The compatibility between equipment and a specific coal deposit is defined as a number between 0 and 1. Simplified fuzzy reasoning is used to determine the compatibility between specific equipment and a coal deposit. The implementation of fuzzy reasoning in this model requires two inputs: information about mining depth and seam thickness. Every generation of underground mining equipment has four fuzzy sets: good depth, poor depth, good thickness, and poor thickness. These sets indicate the best working condition for the equipment based on the mining depth and seam thickness to reach the optimum performance potential of that equipment. The fuzzy sets for each generation of underground mining equipment in the model are presented in Appendix A. Illustrations of the fuzzy sets for specific equipment are presented in Figure 4.17 and Figure 4.18.

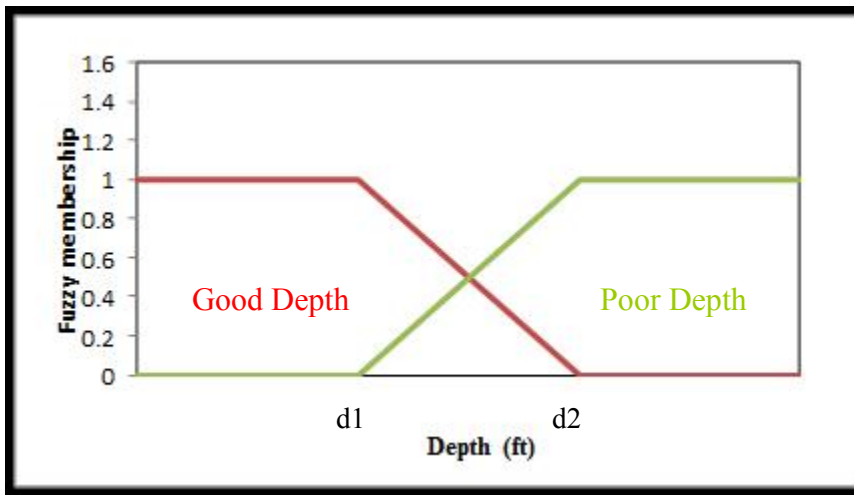


Figure 4.17 Illustration of good and poor depth fuzzy sets.

Based on Figure 4.17, mining depth between 0 and d_1 ft is considered the best mining depth to operate the equipment. The performance of the equipment starts to decrease if mining depth is greater than d_1 . Mining operation with mining depth more than d_2 is considered not compatible at all for the equipment. A similar conclusion can also be drawn for the compatibility between the equipment and seam thickness as shown

in Figure 4.18. The best thickness for the given equipment is between T_1 and T_2 inches. The performance of the equipment is not optimal if the seam thickness is beyond this range.

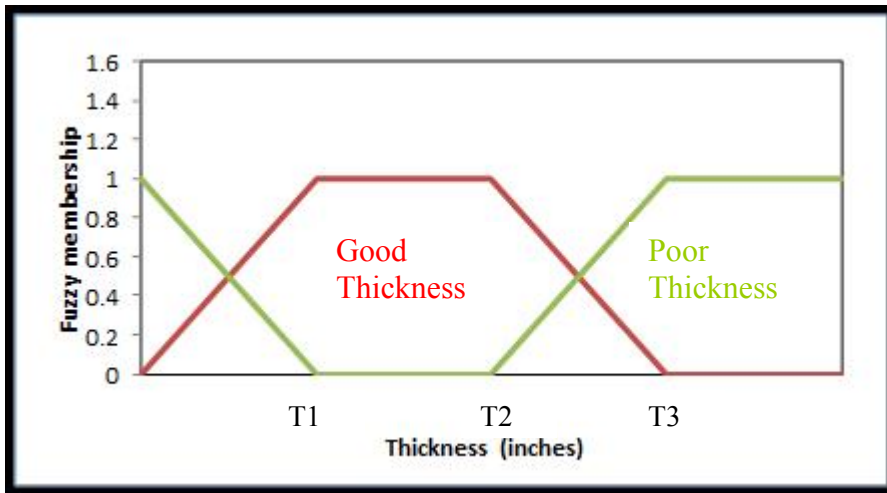


Figure 4.18 Illustration of good and poor thickness fuzzy sets.

In simplified fuzzy reasoning, the conclusion for compatibility is defined based on sets of rules. These rules are determined based on the inference rule *if x is A and y is B , then z is C* , where A and B are fuzzy sets, x and y are mining depth and seam thickness, and C is a constant. By applying this inference rule, we define four rules in evaluating the compatibility of equipment in a specific mine:

1. If the mining depth is good and the thickness is good, compatibility is equal to 1.
2. If the mining depth is good and the thickness is poor, compatibility is equal to .7.
3. If the mining depth is poor and the thickness is good, compatibility is equal to .5.
4. If the mining depth is poor and the thickness is poor, compatibility is equal to .2.

As an example of how the compatibility between mining equipment and a specific mine is determined in the agent-based model, assume that the best working conditions for equipment X are described by the fuzzy sets in Figure 4.19 and Figure 4.20. Let us assess the compatibility between equipment X in a mine with mining depth equal to 500 feet and seam thickness equal to 18 inches.

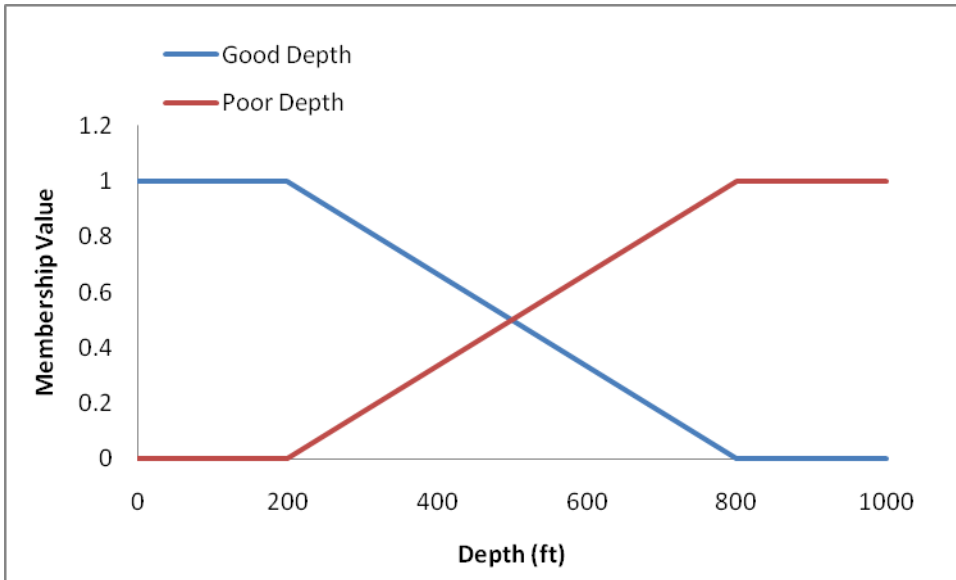


Figure 4.19 Good and poor depth fuzzy sets of equipment *X*.

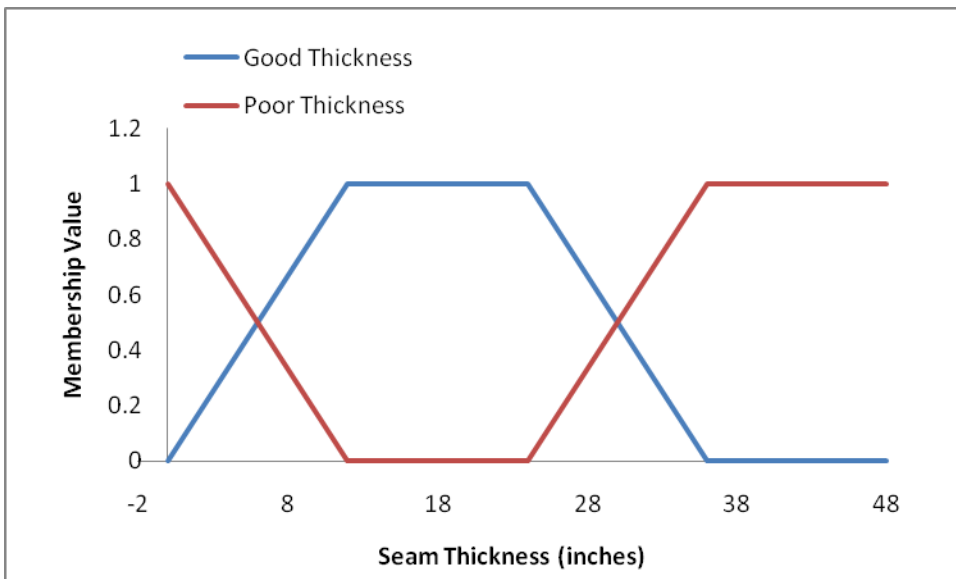


Figure 4.20 Good and poor thickness fuzzy sets of equipment *X*.

The first step in determining compatibility is to measure the membership value of the mining depth and seam thickness in the fuzzy sets of equipment *X*. Based on Figure 4.16, 500 feet of mining depth has a membership value of .5 in both the good depth and poor depth fuzzy sets. Based on Figure 4.17, 18 inches seam thickness has a membership value of 1 in the good thickness fuzzy set and 0 in the poor thickness fuzzy set.

The second step is to determine the adaptability of the premises in rules 1 to 4 based on the membership value. Mathematically, this mechanism is presented in Equation 4.7 and 4.8.

$$w^i = \mu_{A^i}(\text{depth}) \wedge \mu_{B^i}(\text{thickness}) \quad (4.7)$$

$$w^i = \min(\mu_{A^i}(\text{depth}), \mu_{B^i}(\text{thickness})) \quad (4.8)$$

where

w^i = the adaptability of the premise part of Rule i , $i = 1, 2, 3, 4$.

$\mu_{A^i}(\text{depth})$ = the membership value of mining depth in the fuzzy set that is used in rule i . In rule 1, we use Good Depth (A^1) and Good Thickness (B^1) fuzzy sets. In rule 2, we use Good Depth (A^2) and Poor Thickness (B^2) fuzzy sets. In rule 3, we use Poor Depth (A^3) and Good Thickness (B^3) fuzzy sets. In rule 4, we use Poor Depth (A^4) and Poor Thickness (B^4) fuzzy sets.

$\mu_{B^i}(\text{thickness})$ = the membership value of coal thickness in the fuzzy set that is used in rule i .

Based on this mechanism, we can determine the value of w^i for this example as presented in Table 4.4.

Table 4.4 The Value of w^i from the Example

Rule	Fuzzy Sets		w
	A	B	
1	0.5	1	0.5
2	0.5	0	0
3	0.5	1	0.5
4	0.5	0	0

The third step is to infer the conclusion based on the value of w^i by using Equation 4.9.

Rule i : If depth is A^i and thickness is B^i THEN $z = c^i$

$$c_{iX} = \frac{\sum_{i=1}^4 w_i c_i}{\sum_{i=1}^4 w_i} \quad (4.9)$$

where

c_{iX} = compatibility between mine i and equipment X

r = 1, 2, 3, 4.

A^i, B^i = fuzzy sets use in rule i

c^i = constant from rule 1 to 4 ($c^1 = 1, c^2 = .7, c^3 = .5, c^4 = .2$)

w^i = the adaptability of the premise part of Rule i

By using the value of w^i from Table 4.4, we can use Equation 4.9 to determine the compatibility between equipment X and an underground coal mine with 500 feet of mining depth and 18 inches of seam thickness.

$$c_{iX} = \frac{\sum_{i=1}^4 w_i c_i}{\sum_{i=1}^4 w_i}$$

$$c_{iX} = \frac{(.5 \times 1) + (0 \times .7) + (.5 \times .5) + (0 \times .2)}{(.5 + 0 + .5 + 0)} = .75$$

Therefore, the compatibility between equipment X and an underground coal mine with 500 feet of mining depth and 18 inches of seam thickness is equal to .75.

4.9. Justification of the Agent-based Model Design

The design of the agent-based model that we develop is based on data and author interpretation from previous studies. Simplifications were made to reduce the complexity and the scale of the model. The justifications for the design of the proposed agent-based model are as follows:

- a) The simulation considers the diffusion of the longwall mining method since 1914 based on the earliest publication about the longwall mining method in the United States (Easton et al., 1914; Toenges, 1936).

- b) In the agent-based model, mining companies continuously observe several other mines for performance benchmarking. This arrangement in the agent-based model is based on the fact that mining companies regularly monitor their competitors and they generally can gain information about other mines quite easily through informal discussion or mine visits (Ala-Härkönen, 1993b).
- c) Agents consider the payback period of switching to an alternative mining method or updating their equipment to mimic the capital life-cycle barriers in adopting an innovation as described by Batterham (2004) and Souder and Palowitch (1981).
- d) The underground mining equipment evolves during the simulation as actually occurred during the period of interest.
- e) The performance of each generation of underground mining equipment was determined by adopting the performance score developed by Souder and Quaddus (1982).
- f) The Coal Act of 1969 decreased the productivity of underground coal mines. This model accommodates this factor by decreasing the productivity of room and pillar mines during the period corresponding to the years 1969 to 1974.

The agent-based model assumes that there were initially 1000 mines, 20 of which were longwall mines. This is a scaling down from the real data.³⁵ This model assumes that there are two types of coal deposits. This approximation was made to represent the Appalachian (deposit type 1) and Western Coal Region (deposit type 2); most of the mines in the agent-based model are deposit type 1. The initial mining depth of underground coal mines is assumed to be uniformly distributed between 200 and 1100 feet. This range of mining depth was chosen based on the findings of Breslin and Anderson (1976) on underground coal mining in the U.S.

³⁵ According to Risser (1958), there were 2,187 underground bituminous coal mines in 1913.

CHAPTER 5

SIMULATION RESULTS AND ANALYSIS

The agent-based model of the diffusion of the longwall mining method described in chapter 4 was simulated, and data on the number of longwall mines at the end of each year (time step 12, 24, . . . , 900) were generated and then arranged to create a plot of longwall utilization. The documentation of the model is presented in Appendix B. It is noted that the simulation data were collected after the model passed the following verification steps:

1) Procedure testing

In Netlogo software, a specific function or computation in the model is called a procedure. All procedures in the model are tested individually before they are executed as an integrated model. These procedures include procedures that both drive agents' behavior (e.g., evaluating alternative method, computing compatibility of a mining method, mining cost computation, innovation searching) and generate external and internal information for agents during the simulation (e.g., failure event generation, importing actual coal price annually into the simulation).

2) Variables monitoring

The simulation monitors several variables to detect if some functions or computations result in unacceptable values (e.g., negative number for compatibility score, importing wrong value for coal price).

3) Error monitoring

The simulation is designed to halt when a condition that is not consistent or acceptable based on the design criteria described in chapter 4 occurs. For example, the pseudo-code *if the number of mining operation without equipment suppliers > 0 [stop]* is inserted in the Netlogo program to ensure that all mining companies have at least one equipment manufacturer as their supplier during the simulation.

5.1. Model Validation

As the agent-based model of the diffusion of the longwall mining method is based on the historical perspective (history-friendly approach), we follow the model validation steps described by Moss (2008), who suggests that the following steps should be taken to validate an agent-based model:

1. Design agents and their interaction mechanism based on historical studies.
2. Use historical studies to define initial condition and key parameters that can replicate a similar phenomenon; in our case the phenomenon that can be observed is longwall utilization from 1914 to 1989.
3. Use historical data to validate the result from the simulation.

The validation for agents' characteristics, behavior, and interaction mechanisms as well as model initialization is described in the previous chapter. Defining the key parameters and their values in an agent-based model is a rigorous task because of the large parameter space and the influence of interaction between agents. The modeler can understand the behavior of the model only after first having tried different parameters and learned the important parameters in the model, and then the modeler can put more focus on those key parameters. After many trial-and-error attempts, we define the key parameters in the agent-based model of the diffusion of the longwall mining method as follows:

- a) *significant-threshold* = a threshold that determines if the relative performance of one mine is significantly better than the performance of another mine. The value for this parameter is from 0% to 100%. A 50% value for the significant-threshold parameter means that only a performance that is 50% better will be considered significant.
- b) *profit-threshold* = the minimum profit margin agents seek from their mining operation. When the profit margin is below this threshold, agents will actively search for innovation by visiting other mines. The profit margin threshold is a value between 0 and 100%. Every year mining companies in the agent-based model calculate their profit margin by using their mining cost and the coal price in that particular year.

c) *prob-success* = the model parameter that determines the probability of success of mining companies in performing internal research during the simulation.

After defining the key parameters, the next step is to find the combination of these parameters that can capture the basic trend exhibited by the actual data on longwall utilization obtained from Barczak (1992) and the longwall surveys conducted by the magazine *Coal Age* (see Figure 5.1). Barczak's number of actual longwall utilization is measured in number of longwall faces. Although there can be more than one longwall face in a longwall mine, in our agent-based model we assume that one longwall mine has only one longwall face. The comparison between the result from our model and the actual longwall utilization can still be made because most longwall mines only have one longwall face.

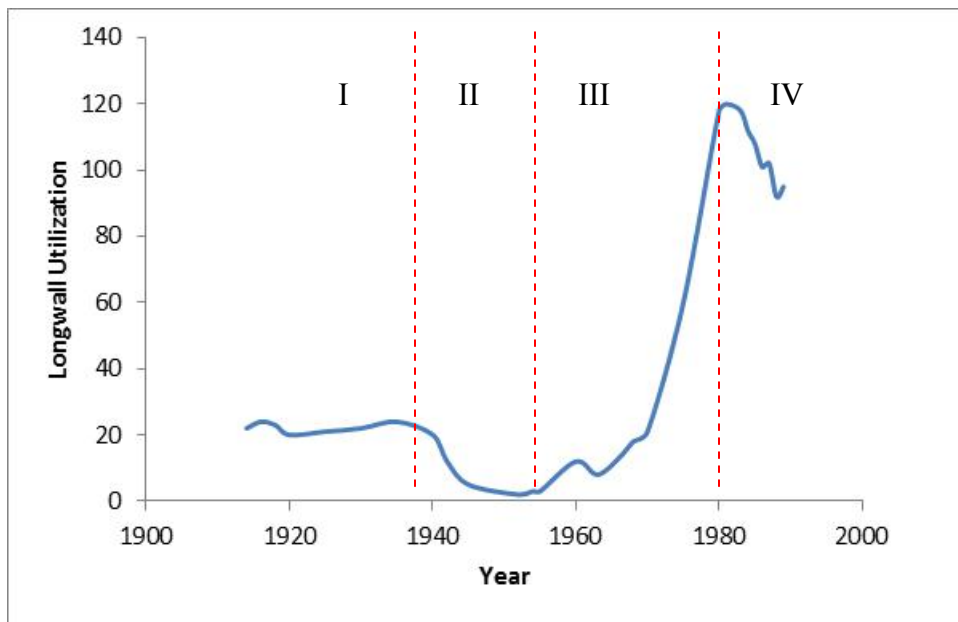


Figure 5.1 Actual longwall utilization from 1914 to 1989.

Figure 5.1 shows four distinct periods (I to IV) with different trends of longwall utilization. In this thesis, the changing trend of longwall utilization is defined as the diffusion pattern. The pattern of longwall utilization started with a slightly increasing longwall utilization until the late 1930s (period I), followed by a declining trend until the early 1950s (period II). The utilization then rapidly increased until the early 1980s

(period III) and decreased after that (period IV). This actual diffusion pattern is used as a reference in comparing the results from the simulation.

5.2. Simulation Results

After many trial-and-error efforts with different values of the key parameters (significant-threshold, profit-threshold, prob-success), the simulation produced a diffusion pattern similar to the one in Figure 5.1. Figure 5.2 is the plot of longwall utilization after 100 simulation replications with the significant-threshold parameter set to 10%, the prob-success parameter set to 10% and the profit-threshold parameter set to 30%. We performed 100 simulation replications to ensure that the results were fairly consistent because the agent-based model has stochastic elements in it. This combined parameter setting was selected as the basic parameter setting in this chapter due to its predictive nature.

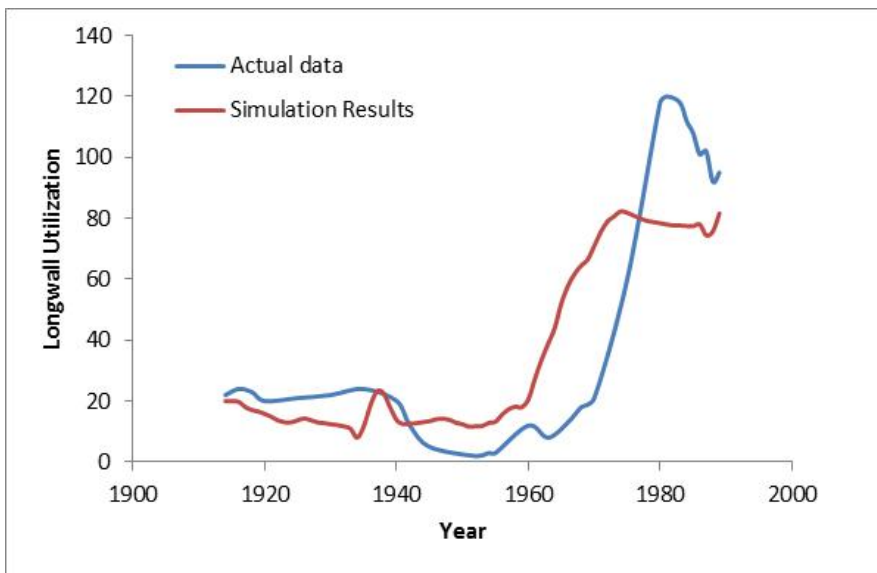


Figure 5.2 Comparison between the actual diffusion pattern and the diffusion pattern from the simulation.

The diffusion pattern in Figure 5.3 is generated by plotting the average number of longwall mines at the end of each year from 100 simulation replications. However, if we take the median and average number of longwall mines at the end of each year from 100 simulation replications (Figure 5.3), we can see that the average and median numbers are relatively equal until year 1940. After year 1940, the difference between the median and

average numbers increases significantly. This indicates a large variation between simulation replications.

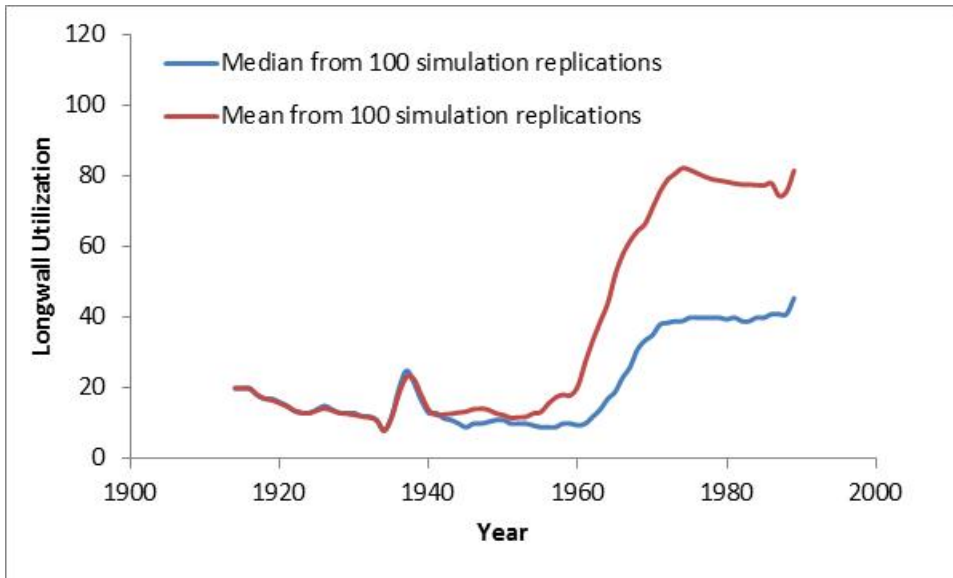


Figure 5.3 Average and median number of longwall mines from 100 simulation replications.

The large variation occurs because few simulation replications from the 100 replications generate a diffusion pattern (see Figure 5.4). Figure 5.4 shows that more than 50% (more than 500 mines) of the initial number of mining companies in the simulation chose to utilize the longwall mining method. The author refers to the diffusion pattern in Figure 5.4 as an “extreme diffusion pattern.” The extreme diffusion pattern shows that rapid adoption occurred in the 1960s and that most of the longwall adopters during that period are small size mines. We then examined the extreme diffusion pattern based on the goals set for mining companies in our agent-based model to have a higher productivity and lower mining cost compared to other mines and to avoid failures at their mine. Figure 5.5 shows the average mining cost of longwall and room and pillar mines during the simulation that resulted in the extreme pattern; longwall mines have shown a lower mining cost since the 1930s.

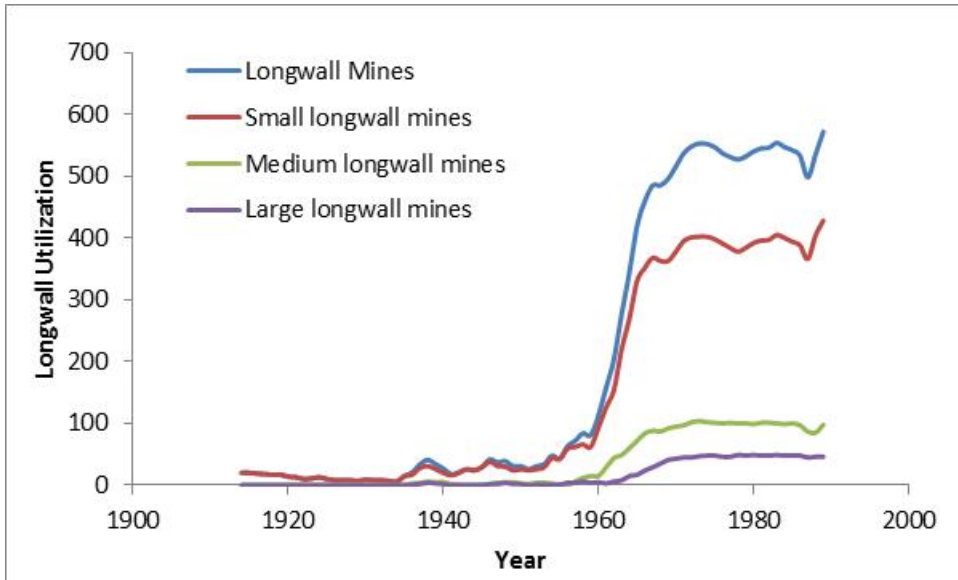


Figure 5.4 The extreme diffusion pattern.

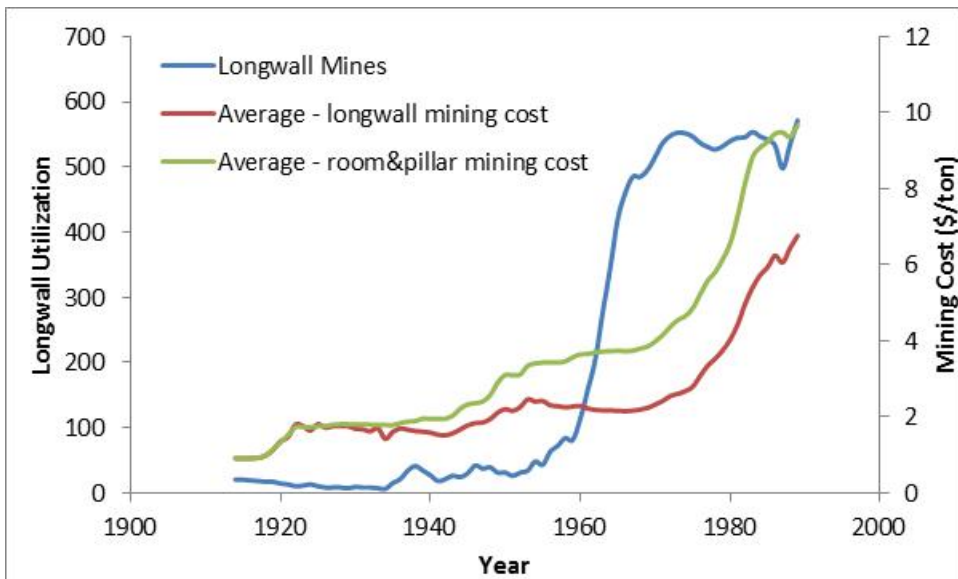


Figure 5.5 Average mining cost of longwall mines and room and pillar mines in a simulation replication that resulted in the extreme diffusion pattern.

The similar leverage does not exist in terms of productivity. Figure 5.6 shows that during the simulation, longwall mines did not reach a higher productivity score than room and pillar mines. What is more interesting is that the number of longwall mines remains constant after the period of rapid diffusion during the simulation, even though most of them experienced failures (Figure 5.7). The failure rate in a particular period is defined as the number of longwall mines that experience failure divided by the total number of

longwall mines in that period. This means that the mining companies that decided to adopt the longwall mining method in the early 1960s decided to utilize the same method despite the failures at their mines.

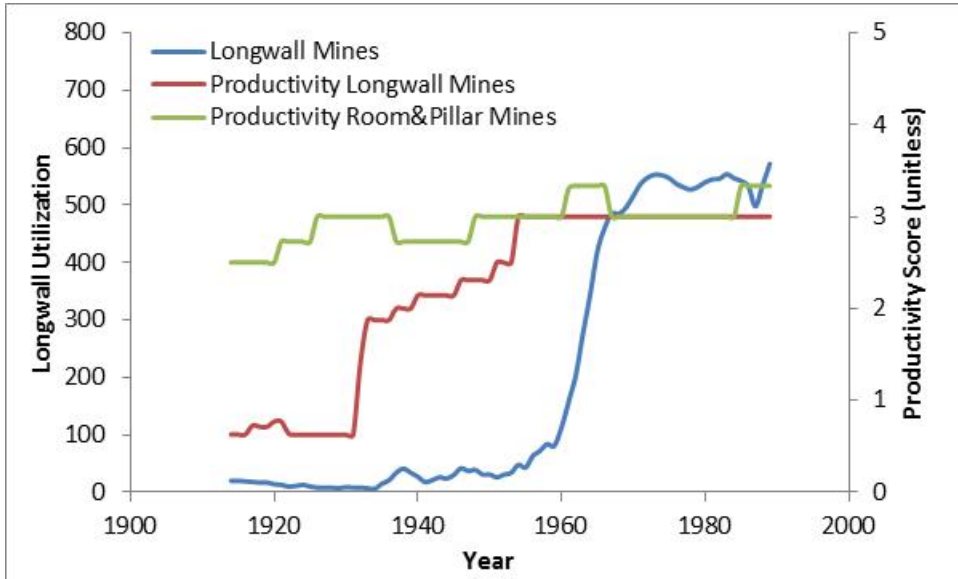


Figure 5.6 Productivity of longwall and room and pillar mines in a simulation replication that resulted in the extreme diffusion pattern.

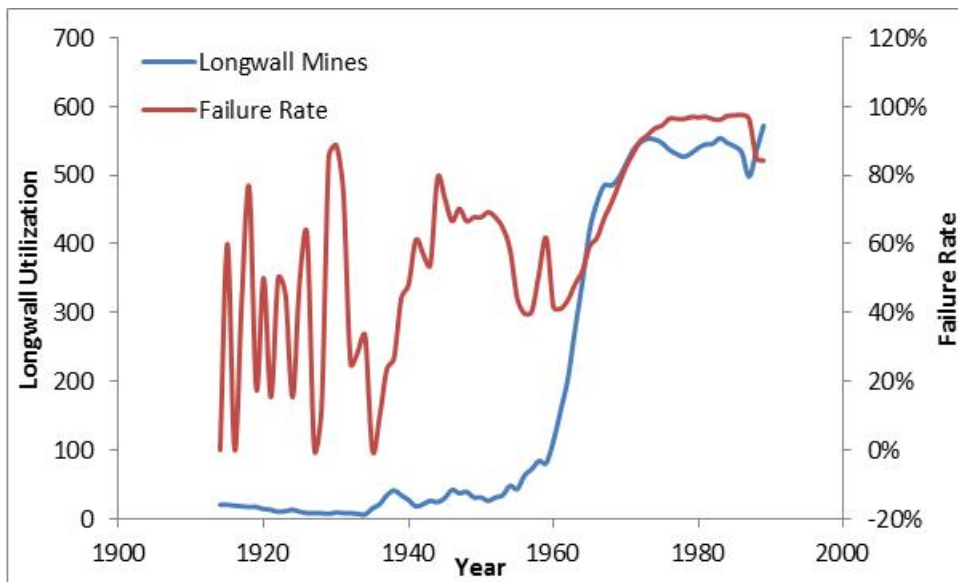


Figure 5.7 Failure rate of longwall mines in a simulation replication that resulted in the extreme diffusion pattern.

Our agent-based model of the diffusion of the longwall mining method shows a situation where potential adopters have to make the adoption decision between two competing technologies. The situation when initial advantage from one of the technologies leads to its adoption by most of the potential adopters and these adopters tend to stick with their technology despite its limitations is called the “locked-in” phenomenon (Arthur, 1989).

David (1985) illustrates the locked-in phenomenon with the example of the dominance of the QWERTY keyboard design. This design became popular during the boom of typewriter sales that started in the 1880s because of the low training cost, keyboard design standardization, and the high switching cost associated with it. The dominance of the QWERTY design continued even after the introduction of the Dvorak Simplified Keyboard (DSK) design, which was perceived as better because it provided greater efficiency in typing and was used to set the world record in speed typing. In fact, a study by the U.S. Navy in the 1940s showed that the efficiency of the DSK design would justify the investment in retraining typists to use it. In the context of the diffusion of innovation, the locked-in phenomenon starts with a leverage of one innovation that leads to dominant share. This domination is hard to break once a sufficient proportion of potential adopters have already made the choice to use it.

The locked-in phenomenon is a path-dependent process. A path-dependent process is a process in which past actions set a specific path or limitation in selecting the current action. The agent-based model in this thesis actually incorporates a path-dependent process because it includes a process in which mining companies have to consider the payback period factor in making adoption decisions, including the payback period of both the innovation (alternative mining method) and the current mining method. When a mining company decides to switch to an alternative mining method, they have to wait for several years before they can consider switching back to the previous method in order to justify the switching cost. Despite this arrangement, the locked-in phenomenon observed in the extreme diffusion pattern is still unexpected.

The main focus in the extreme diffusion pattern is the behavior of small mining companies after the year 1960. The maximum payback period for small mining companies in deciding to switch to an alternative mining method is set at eight years in

the agent-based model. Therefore, eight years is the maximum time that a small mining company has to wait after switching to an alternative mining method before they can consider switching back to the old mining method. So, if rapid longwall adoption by small mines occurred in the early 1960s, they could have changed back to the room and pillar method in the early 1970s. Nevertheless, despite the high failure rate and the absence of productivity leverage in using the longwall mining method after its adoption in the 1960s, the small mines in the agent-based model were locked-in with the longwall mining method until the end of the simulation. This collective behavior was not expected because individual mining companies are set to always seek for improvement when failure occurs at their mine.

The author assumes that this locked-in phenomenon occurred in the small longwall mines because of the interactions between mines that made them more connected as the simulation progressed. The agent-based model set that every mining company initially added five of its closest neighbors with similar deposit types into its observation network. All the mines observe other mines in their observation network for performance benchmarking. As the simulation progresses, the number of mines in a mining company observation network can increase if the company visits mines that perform significantly better than its mine (higher productivity or lower mining cost and without any failure). It is possible that after that rapid diffusion in the 1960s, most of the mines in the small mines' observation networks were utilizing the longwall mining method so that less information about the benefits of using the room and pillar method could be obtained by the small mines.

In order to test this assumption that interaction between mines led to the locked-in phenomenon, the author ran more simulations with the basic parameter setting and with more restrictions on the interaction between mining companies. The simulation then ran using the same basic parameter setting, but with the following scenarios for interaction:

- a) The possibility that mining companies can expand their observation network as the simulation progresses was removed. In this scenario, mining companies can still interact with any other mines randomly during the simulation but cannot add mines to their observation network.
- b) Mining companies can only interact with the mines in their observation network.

After running the simulation scenario without the possibility of mining companies expanding their observation network, the locked-in phenomenon was still found in one of the simulation replications (Figure 5.8). It was also still found when we tried to limit mining companies' interaction within their observation network (Figure 5.9).

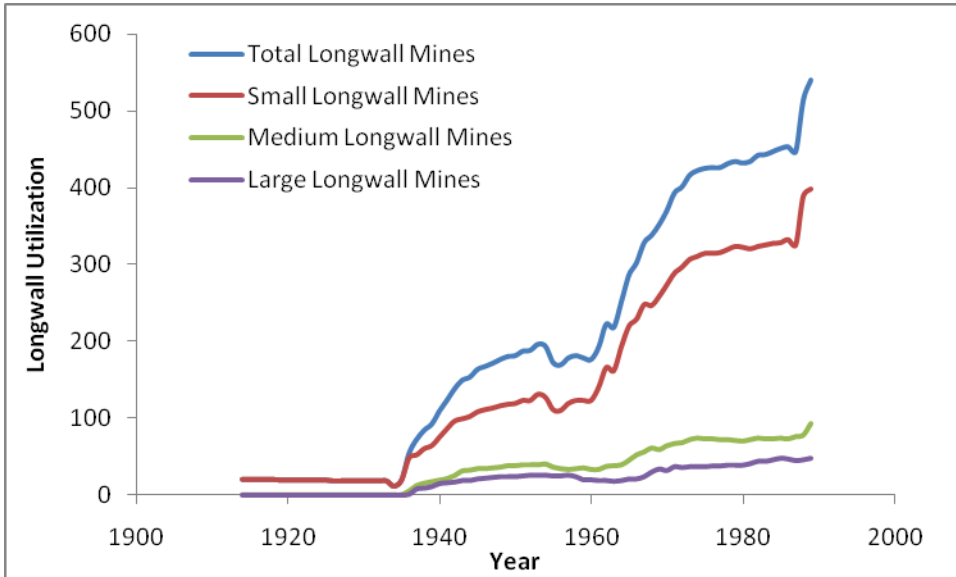


Figure 5.8 The locked-in phenomenon observed when holding the number of mines in the observation network constant.

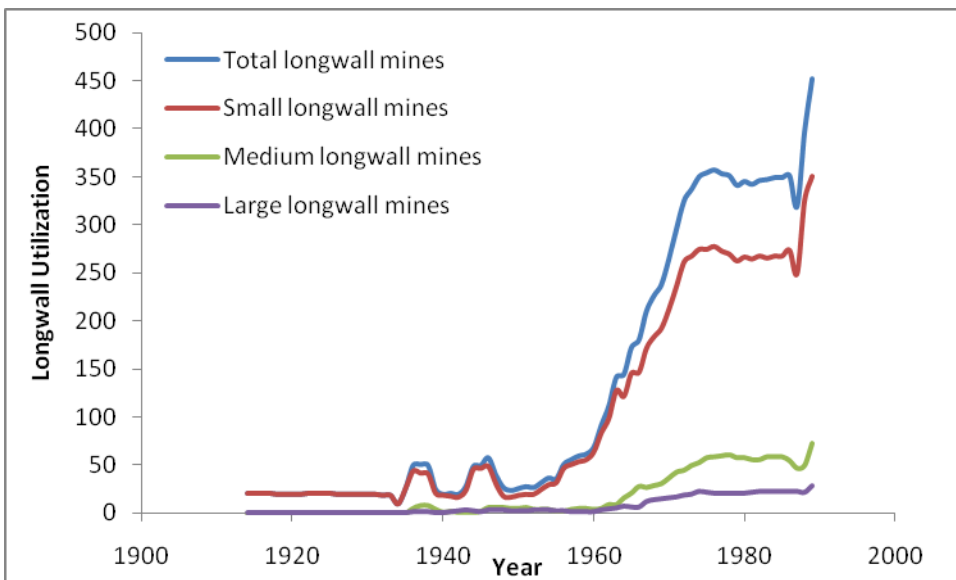


Figure 5.9 The locked-in phenomenon observed when limiting mining companies' interaction within their observation network.

The locked-in phenomenon disappears only after the simulation dictates that mining companies can only interact with one mine during the simulation and they do not have to consider the payback period in making their adoption decision (Figure 5.10). In Figure 5.10, the average value and median value of longwall mines from 50 simulation replications are almost equal. This indicates that there is no extreme diffusion pattern because the variation between each simulation replication is small. Therefore, the author assumes that the requirements to consider the payback period for switching to an alternative mining method and interaction between mining companies in the proposed agent-based model led to a locked-in phenomenon.

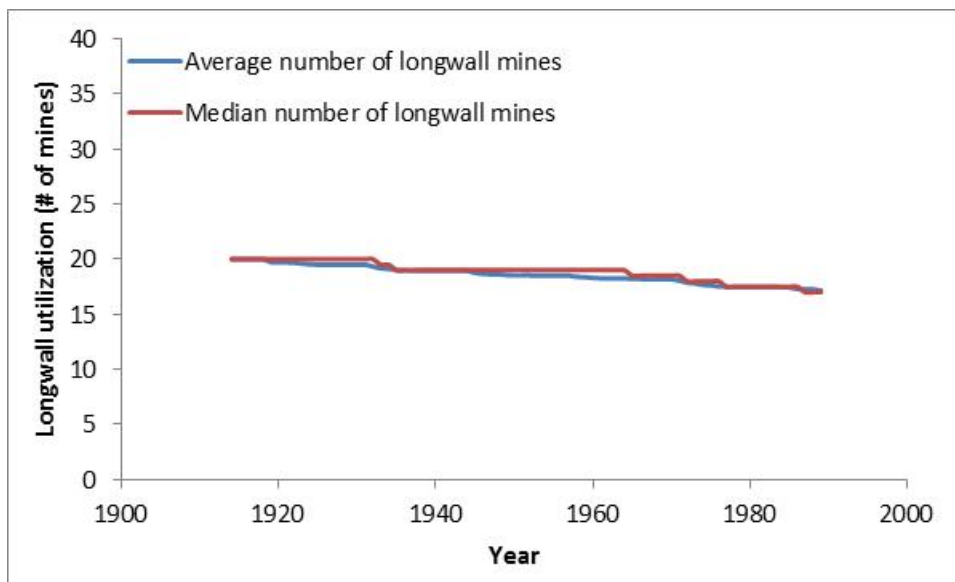


Figure 5.10 The diffusion pattern when mining companies can only interact with one mine during the simulation and do not have to consider the payback period in switching to an alternative mining method.

5.3. Analysis of the Diffusion Pattern with the Basic Parameter Setting

We use the median value of longwall mines at the end of each year from 100 simulation replications to show the diffusion pattern with the basic parameter setting and compare it with the actual diffusion pattern in four distinct periods as shown in Figure 5.11. The average value is not the appropriate estimator to represent the result from the basic parameter setting because some of the simulation replications produce the extreme diffusion pattern. Figure 5.11 shows the diffusion pattern with the basic parameter

setting. All the results presented in this section were obtained after running the agent-based model with the basic parameter setting.

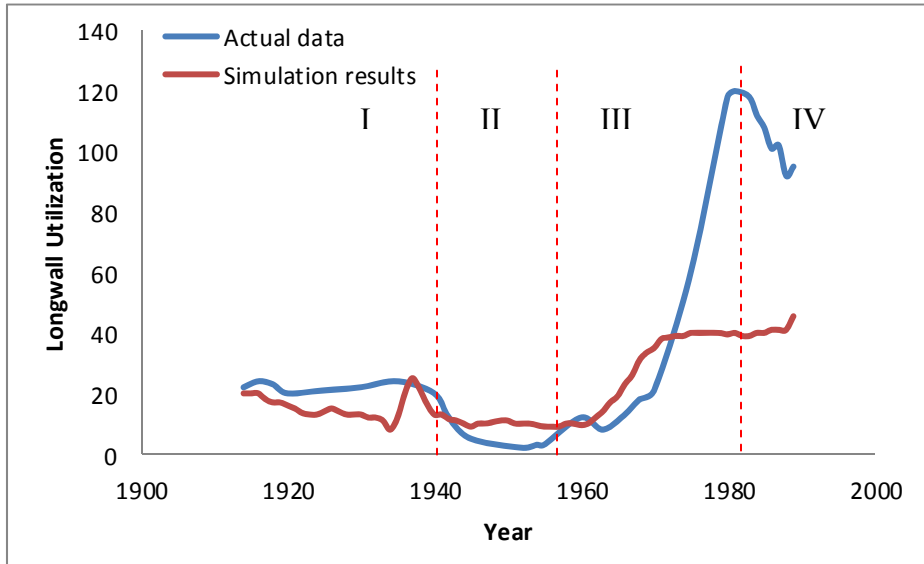


Figure 5.11 Simulation results with basic parameter setting by using the median number of longwall mines from 100 simulation replications.

The diffusion pattern in period I shows a declining trend of longwall utilization that is followed by an increasing trend of longwall utilization, while the actual longwall utilization shows only a slightly increasing trend. This difference occurs due to the random condition of longwall mines in the initial condition. Some longwall mines may have mining depth and seam thickness that are not compatible with the initial longwall equipment technology, which may have led to poor mining performance at these mines. These mines then decided to switch to the room and pillar mining method. Toward the end of period I in the simulation result, longwall utilization increases again because some room and pillar mines reach a point at which they are willing to try the longwall mining method without the need to see successful longwall applications in their observation network (adoption threshold = 0).

In period II, the result from the simulation also shows a declining trend of longwall utilization similar to that of the actual one. In the simulation the declining trend occurs because many small mines in period II decided to stop using the longwall method. Figure 5.11 also shows that in period III the simulation produced an increasing trend of

longwall utilization which is similar to the actual trend of longwall utilization, but with a lower rate of adoption (the slope of the longwall utilization trend from the simulation results is less steep than the actual trend of longwall utilization). This is because the current agent-based model does not allow the possibility of the opening of new mines when the coal price is rapidly increasing as actually happened. In the real world, many of the longwall mines during the rapid rate of adoption in the 1970s were new mines. This can be validated from the fact that many longwall mines that were closed in the 1980s were eight years old on average (Sprouls, 1986). This means that they started their operation during the period of increasing coal prices in the 1970s. Some of these mines were also inefficient mines that closed in the early 1980s due to the declining price of coal. The closing of the inefficient mines contributed to the declining trend of longwall utilization in the early 1980s (Sprouls, 1986). In addition, the increasing productivity and capacity of longwall mines enabled them to meet the demand with fewer mining operations (Barczak, 1992). The current agent-based model does not include in its design the mine closures that occurred due to excessive production capacity or inefficiency. As a result, the declining trend in longwall utilization since the early 1980s (period IV) in the actual diffusion pattern also does not appear in the simulation results.

In addition to examining the diffusion patterns of the longwall mining method, we also compare the utilization of longwall mines in the model based on mine size, seam thickness, and mining depth. The EIA (1995) explained that longwall mines became larger and deeper and started to mine thicker seams. In terms of mine size, the longwall mining method was actually applied in small mines when it was first introduced in the early 1900s. The progression of longwall equipment technology created barriers for small and medium-sized mines to utilize longwall methods at their mines because operating a longwall mine became more expensive. Figure 5.12 shows longwall utilization based on mine size from the simulation result and shows the declining trend of longwall utilization by small and medium mines.

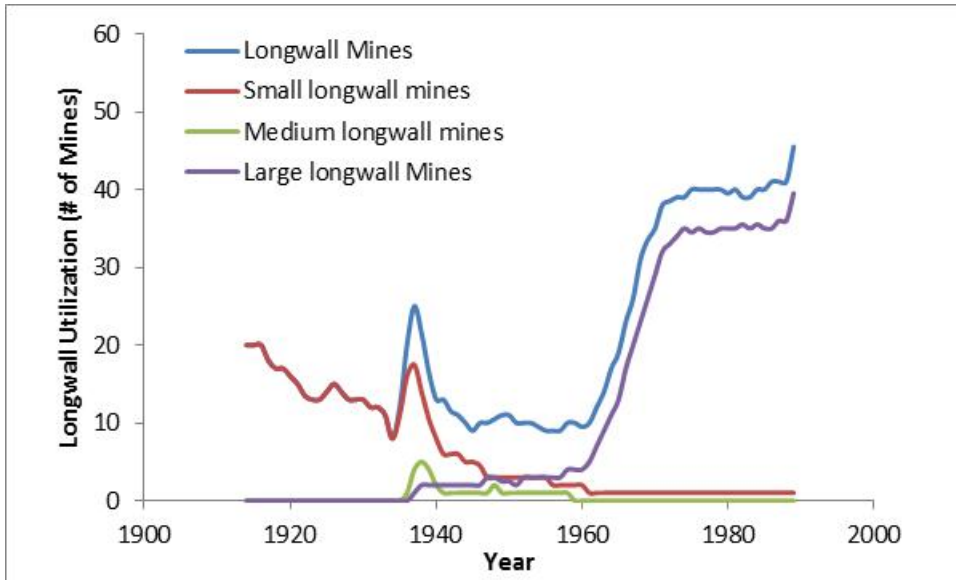


Figure 5.12 Longwall utilization by mine size from the simulation results.

In terms of the seam thickness, the longwall mining method was applied initially in mines with thin-seam coal. This application was the reason for the introduction of coal plow technology in the mid 1950s from Germany, where the longwall mining method was generally used in mines with thin seams (Barczak, 1992). The increasing size and capacity of longwall mining equipment provided opportunities to utilize this method in thicker coal seams.

In the current agent-based model, the seam thickness for all mines is assumed to be constant during the simulation. Figure 5.13 shows the average seam thickness of longwall mines during the simulation. The increasing trend of average seam thickness of longwall mines during the simulation shows that the agent-based model can capture an increasing trend in seam thickness similar to that observed in actual longwall mines.

The trend of mining depth for longwall mines have been increasing over the years. The simulation result presented in Figure 5.14 demonstrates that our agent-based model shows a similar trend. During the simulation, the rapid increase in longwall mining depth in the late 1940s that was followed by a slightly declining depth indicates that some deep mines tried to use the longwall mining method during that period. These mines then switched back to the room and pillar mining method because of the poor performance of longwall equipment in deep mines during this period in the simulation.

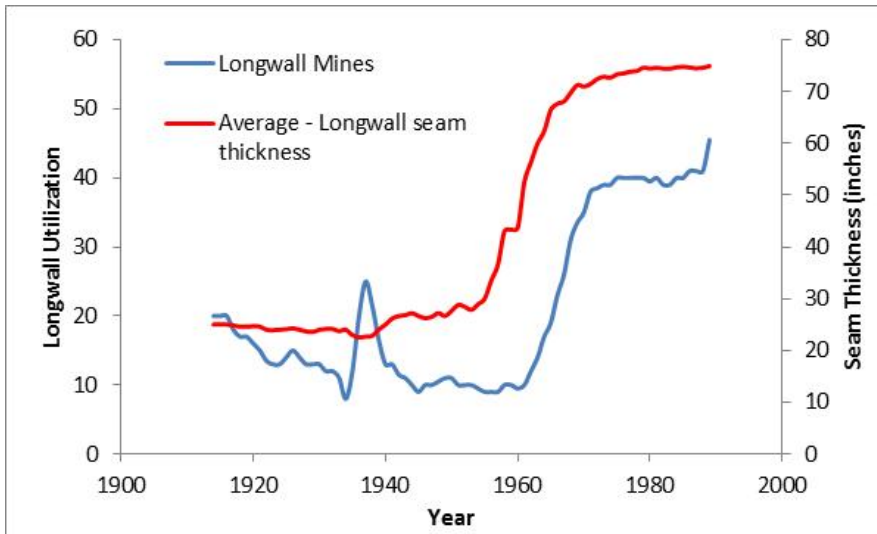


Figure 5.13 Average seam thickness of longwall mines during the simulation.

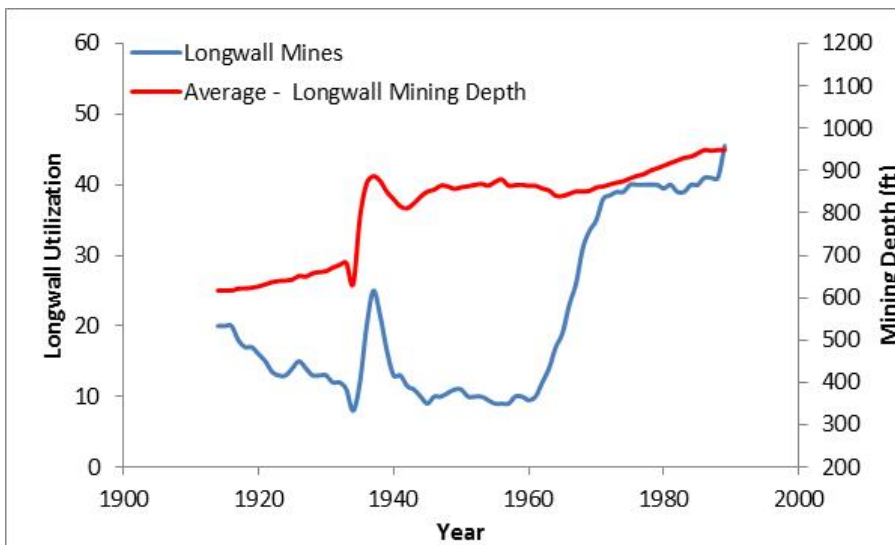


Figure 5.14 Average mining depth of longwall mines during the simulation.

5.4. Sensitivity Analysis

The diffusion pattern that resulted from a simulation with the basic parameter setting (significant-threshold = 10%, the prob-success = 10%, and the profit-threshold = 30%) is used as a reference in performing sensitivity analysis. The most sensitive parameter in the model is the significant-threshold. Increasing the value of the significant threshold from the basic setting (10%) in the model means ordering mining companies in the agent-based model to be less competitive. With a significant-threshold equal to 15%,

mining companies do not feel threatened when their competitors have higher productivity or lower mining cost less than 15%. Therefore, as shown in Figure 5.15, the total longwall utilization toward the end of the simulation when the significant-threshold is set to 15% is less than the longwall utilization with the basic parameter setting. Increasing the significant-threshold up to 50% resulted in very low longwall utilization (only seven longwall mines). On the other hand, reducing the significant-threshold parameter makes mining companies more competitive during the simulation. Figure 5.15 shows that the number of mines utilizing longwall methods toward the end of the simulation is higher than the basic parameter setting when the significant-threshold is set to 5%.

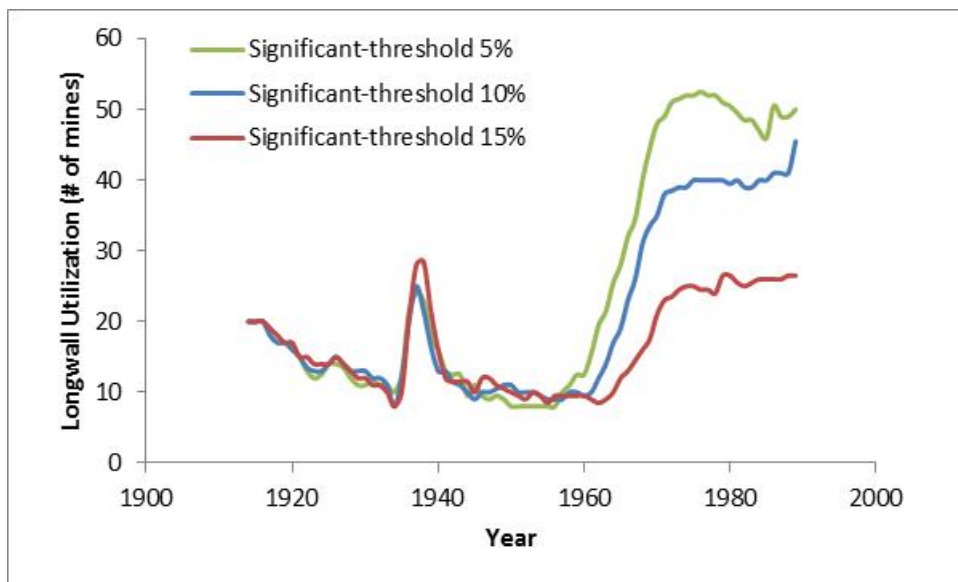


Figure 5.15 Longwall utilization with different significant-threshold settings.

Information about the significant-threshold that reproduces the similar diffusion pattern is beneficial for technology producers in the mining industry. They can set the significant-threshold as a standard when they introduce new technology to mining companies in order to estimate whether it will be considered. If the performance of the new technology is better than that of the old technology but less than the significant threshold, then it is unlikely that mining companies will consider adopting the new technology.

The diffusion pattern in the model is also sensitive to change in the prob-success parameter. Increasing the value of this parameter from the basic setting (10%) means that the rate of success for mining companies in performing internal research is higher. A significant change in the diffusion pattern occurs when the prob-success is set at 50% (Figure 5.16). In the agent-based model, successful internal research reduces mining cost up to 10% without any impact on productivity. Therefore, the sensitivity analysis shows that mining companies in the agent-based model would prefer to perform internal research rather than switch to an alternative mining method when the successful rate of performing internal research is high enough and can bring in a certain portion of cost reduction regardless of the higher productivity level that the longwall mining method can offer.

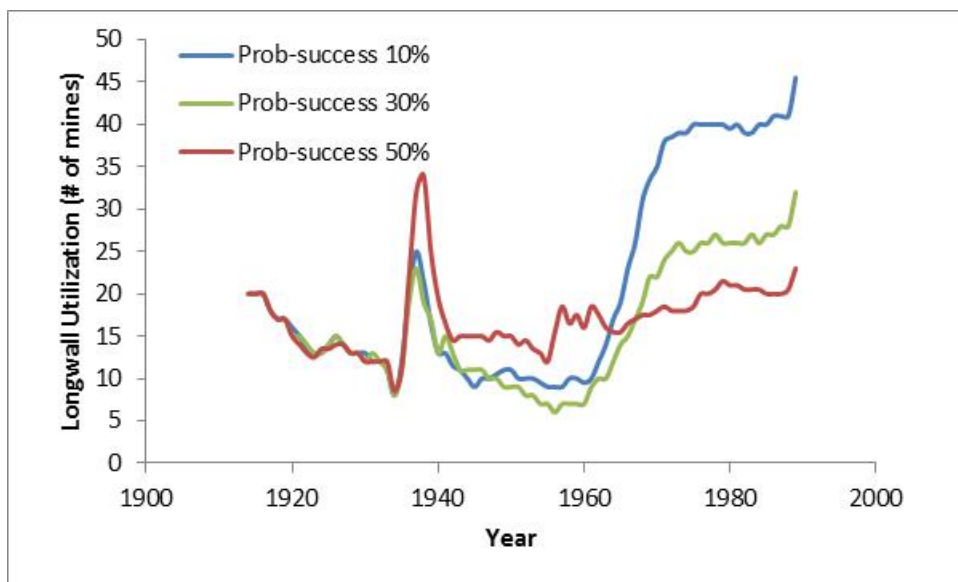


Figure 5.16 Longwall utilization with different prob-success settings.

Changes to the profit-threshold do not significantly alter the diffusion pattern (Figure 5.17). This is interesting because we set the model such that mining companies actively interact with other mines to seek for innovation when their profit margins fall below the profit-threshold. This implies that more interaction did not lead to more longwall adoption as long as the interaction shows that the benefit of switching to the longwall mining method is not significant in terms of increasing profitability, which is a

logically plausible condition. This shows that the simulation runs do not produce counterintuitive results.

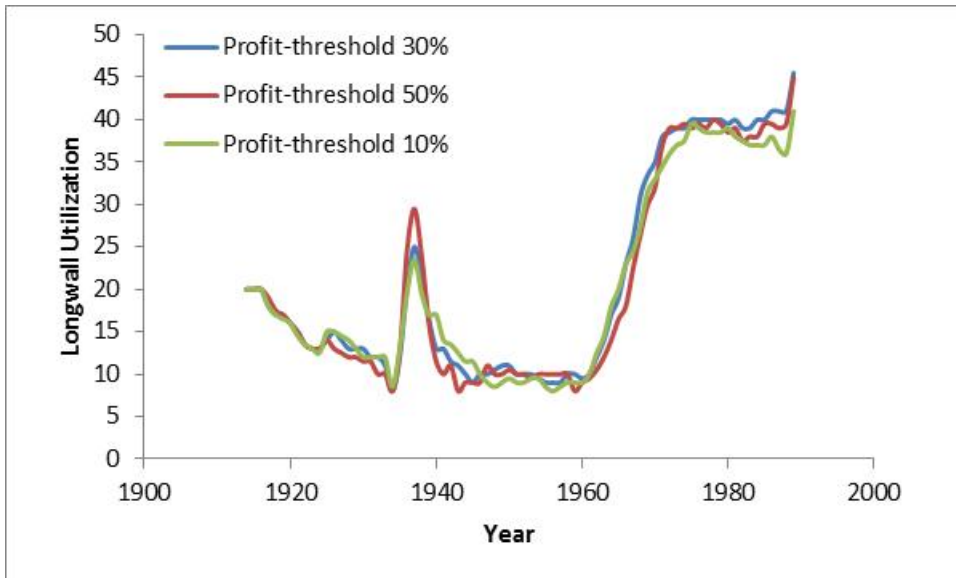


Figure 5.17 Longwall utilization with different profit margin thresholds.

In the agent-based model, the influence of regulation is designed by reducing 20% of the productivity of room and pillar mines starting with the year 1969. Figure 5.18 shows that the diffusion pattern without regulation is similar to the diffusion pattern with regulation scenario. This condition occurs because the influence of regulation is modeled simply by reducing the productivity of mines that use a mining method other than longwall. In the actual history, regulation (the Coal Act of 1969) actually triggered innovative activities from manufacturers and mining companies so that they could comply with the regulation. These innovative activities led to improvement in underground mining equipment. In the model, the improvement of underground mining equipment is modeled to be independent from the regulation influence for purposes of simplification.

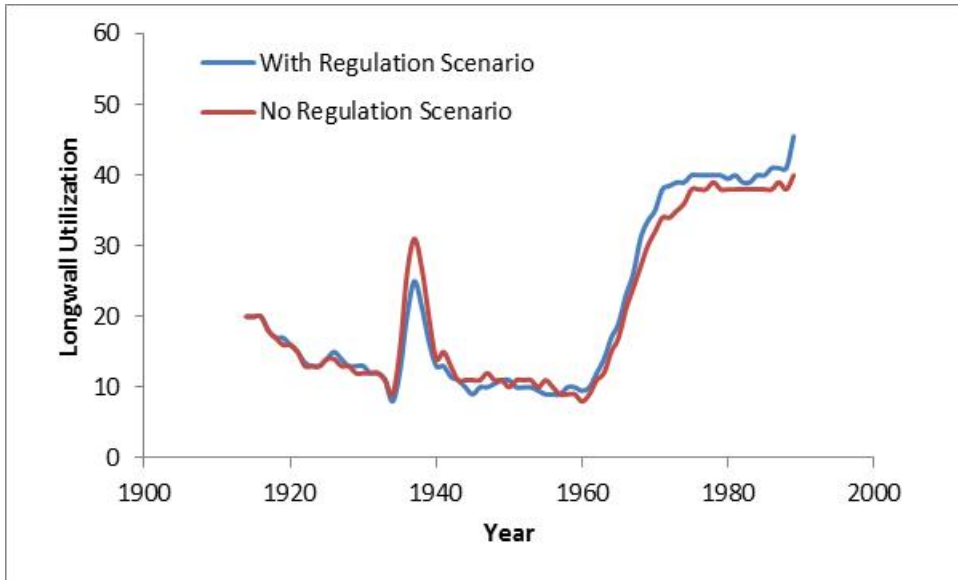


Figure 5.18 Longwall utilization with regulation and no regulation scenarios.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

Agent-based modeling offers the possibility of designing each individual agent with its own adaptive behavior in a complex system. Given this feature, a diverse group of agents involved in the diffusion of innovation process can easily be modeled. Agent-based modeling also offers the possibility to model different types of interactions that occur in the mining industry that may influence the diffusion process.

This thesis provides a framework to be used as a guide in developing agent-based models for studies related to the diffusion of innovation in the mining industry. The framework is sufficiently broad to provide flexibility to the modeler to control the level of complexity of the agent-based model, but also sufficiently specific for application in the mining industry. The proposed agent-based model was constructed based on a historical perspective on the longwall mining method.

The results from the simulation show a diffusion pattern that is similar to the actual history. From this perspective, we showed the predictive nature of the model. The simulation results also show the capability of agent-based modeling to capture emergent phenomena. Despite the same initial conditions and parameter settings, the simulation produces an extreme diffusion pattern in which most of the mines in the agent-based model become longwall mines. The extreme diffusion pattern shows that most of the longwall adopters are small mines. These small mines keep using the longwall mining method until the end of simulation even though they experience failures and do not gain productivity leverage by using the method. This situation is called the locked-in phenomenon. This collective persistence is an emergent phenomenon captured by our model because the author did not impose a preference for a specific mining method into the behavior of each individual mining company in the model. In the design of the agent-based model, each individual mining company is always set to continuously aim for lower mining cost and higher productivity compared to its competitors and to avoid

failures at their mines. When any of these goals is not met, a mining company is set to find information about a better technology to improve its performance.

Continuing to use an inferior technology with lower productivity seems counterintuitive given that mining companies always seek for lower mining cost and higher productivity. However, in a historical study of British coal mines in the 1920s and 1930s, Scott (2006) shows that British coal mines during that period were locked-in with un-mechanized haulage systems even though they were aware that mechanized haulage systems were being used in other coal mines in central Europe. Scott lists technical difficulties in incorporating the mechanized haulage system into the existing mining layout and the fragmented royalties system as the internal factors in the British coal mining system that led to the locked-in phenomenon.

6.1. The Strengths and Limitations of Agent-Based Modeling

The benefit of using agent-based modeling in studying the diffusion of innovation is the capability to explicitly model different agents involved in the process. Agent-based modelers have flexibility in determining the complexity of agents' behavior. The decision making process can be set to be very simple by using an adoption threshold or very sophisticated as in a game theory approach. In addition to this strength, agent-based modeling can capture the collective behavior toward an innovation that is not explicitly imposed on each individual agent in the system.

Despite the possibility to design an agent-based model with complex agent behavior, most papers about the diffusion of innovation that make use of agent-based modeling present a highly abstract model with a very simple construction and description of the agents and the complex system (Kiesling et al., 2011). These papers do not attempt to model the spread of specific innovations in the actual market but instead focus on exploring various theories related to networks and interactions and how they can be implemented in agent-based modeling. Some believe that agent-based models with a very simple description may not really capture the diffusion process. This raises the question of whether agent-based modeling can be used to study actual innovation diffusion (Garcia & Jager, 2011). It should also be noted that making the agent-based model very close to realistic can greatly increase the complexity of the model.

We attempted to use agent-based modeling to simulate the diffusion of an innovation that actually took place in the mining industry. Some of the main challenges that we found in developing the agent-based model are related to the validation of input and output. The core of agent-based modeling lies in the detailed and accurate construction of each individual agent within a complex system, including how agents adapt and react to changes in their internal and external conditions. Constructing a model reflecting the mining industry with the level of detail required by the agent-based modeling approach is very challenging because detailed information about underground coal mines during the early introduction of the longwall method is very limited, particularly about the decision making process companies used in deciding the most appropriate mining method for their mines. Surveys on longwall utilization in the U.S. did not start until the early 1980s, and most of the literature on the development of the longwall mining method in the U.S. is focused on the collective behavior of the coal mining industry. In addition, the interaction and the network structure between mining companies and manufacturers has rarely been the main focus in previous studies about longwall development.

Another challenge to input validation is to decide how to model the changes in mining companies' internal conditions (e.g., mining cost fluctuation and mining depth progression at individual mines) that can lead to and influence their adoption decisions. When the detailed data required for agent-based modeling are not available, unbiased logical assumptions and simplifications were made in order to have a simple model that can be understood and tracked without diminishing the model's capability to mimic the actual diffusion process. The author acknowledges that the simplifications and assumptions made in the model may undermine the complexity in the actual diffusion of the longwall mining method.

In terms of validating the output, the result from the agent-based model in this thesis was compared with the actual data on longwall diffusion and was found to produce a similar diffusion pattern. However, as Epstein (2006) notes, the ability of the agent-based model to reproduce a specific phenomenon is necessary but not sufficient to completely explain the phenomenon. When an agent-based model can produce a similar phenomenon, it means that the modeler has been able to find a combination or

combinations of parameter settings and logical conditions that reproduce the target phenomenon. Therefore, the result in this model can be seen as one interpretation by the author of the diffusion process of the longwall mining method that happens to be reproducing the diffusion pattern that occurred in the real world.

6.2. The Key Finding

The key finding from this thesis is that interaction between mining companies in the agent-based model can lead to emergent phenomena, in this case the locked-in phenomenon. This finding strengthens the main feature of agent-based modeling as the modeling approach that can capture the collective behavior in a complex system which is not explicitly imposed on each agent in the system.

The proposed agent-based model may not capture all the complexities that exist in the real mining world, but it showed that the complexity of collective behavior in the mining industry could be explained by local interactions driven by simple rules between entities within the industry. This is the key finding of this study. As Axelrod and Cohen (1999) note, complexity research is “a framework that suggests new kinds of questions and possible actions” (p. 19). This finding suggests that interaction between diverse entities should receive more attention in the study of the collective behavior of the mining industry toward an innovation without ignoring the technological, economical, and environmental aspects of the innovation.

6.3. Future Work

In order to further study the diffusion of technological innovation in the mining industry as a complex phenomenon, the author suggests that future work related to the diffusion of innovation be focused on unique characteristics of different agents in the mining industry. This information will benefit the construction of agent-based models.

The author also suggests further study of the decision making process that takes place in the industry because the adoption decision making process critically influences the diffusion of innovation. Study of the decision making process should not be limited to mining companies as the potential adopters, but also to manufacturers and government agencies. For example, a researcher could investigate how equipment manufacturers

make decisions about when to launch their newer and better products and how this decision influences the rate of adoption. The new product may be better, but manufacturers may also cannibalize their older product by launching new products. The author also suggests further study on the interaction among mining companies and between mining companies and other entities in the industry to gain insight into how interaction influences the decision making process related to the adoption and generation of an innovation.

Some believe that one of the main reasons mining companies adopt innovation is to comply with regulation. This thesis models the influence of regulation in a simplified way. Therefore, it would be interesting to see future studies that attempt to analyze the influence of government regulation in more detail, including modeling how regulation is established from the interaction between the regulator and different agents in the mining industry.

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APPENDIX A
THE FUZZY SETS USED TO DETERMINE COMPATIBILITY

A.1. Fuzzy Sets for Longwall Mining Equipment

This model assumes that the compatibility of a longwall mining method is determined by the type of roof support and coal cutting equipment. The roof support equipment determine the best mining depth condition while the coal cutting equipment determine the best seam thickness for longwall. Every generation of roof support and coal cutting equipment has fuzzy sets that determine the best mining condition for the equipment. The following graphs illustrate the fuzzy sets for each generation of longwall equipment.

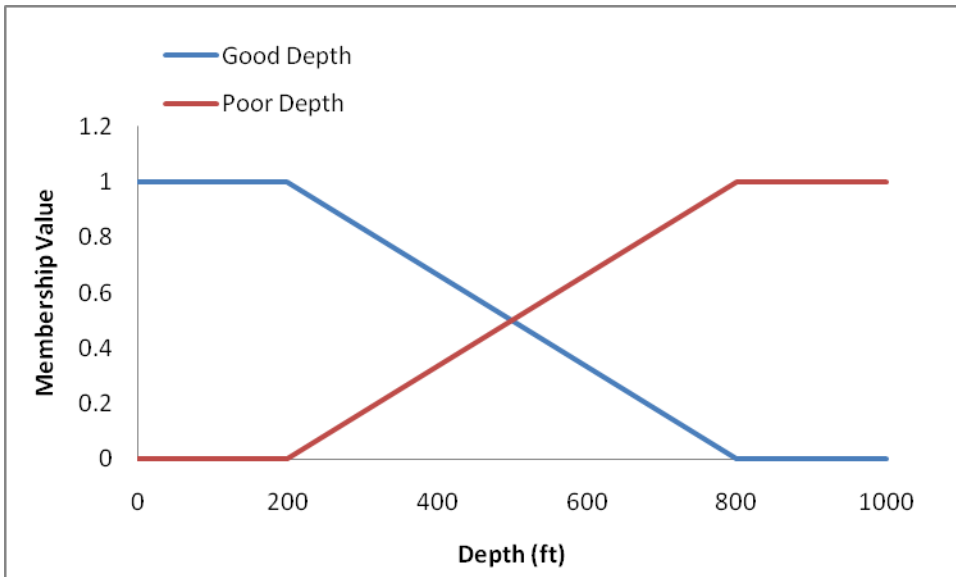


Figure A.1 Fuzzy sets for the first generation of roof support equipment.

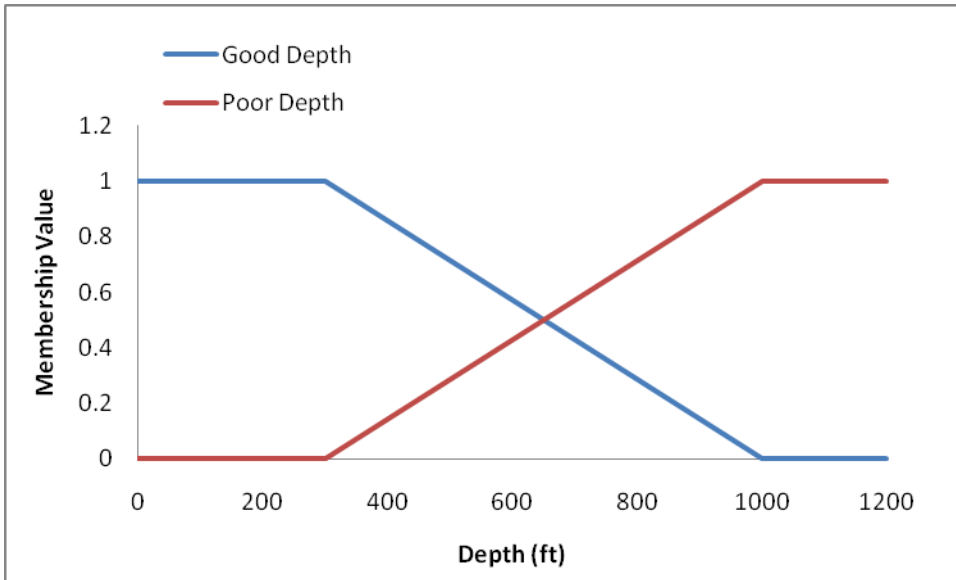


Figure A.2 Fuzzy sets for the second generation of roof support equipment.

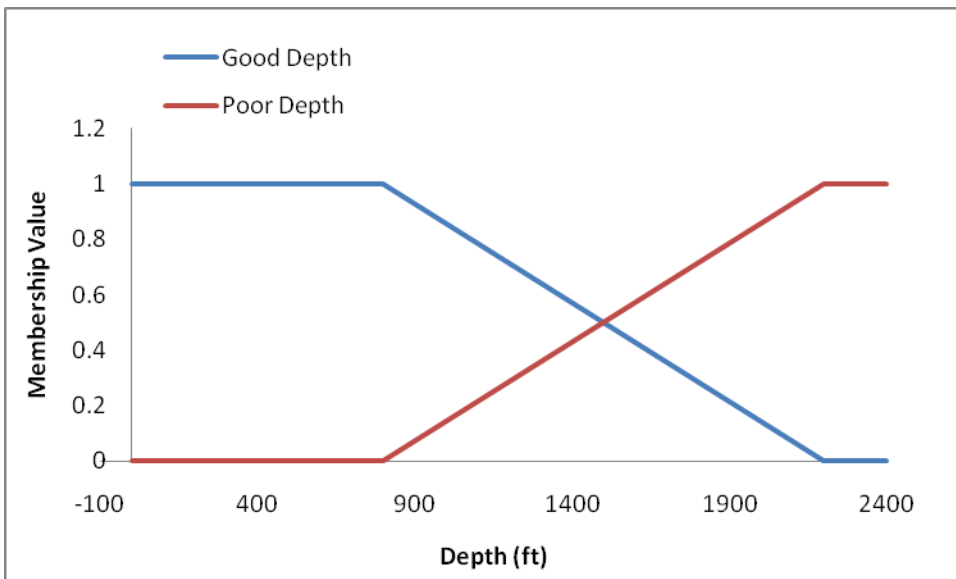


Figure A.3 Fuzzy sets for the third generation of roof support equipment.

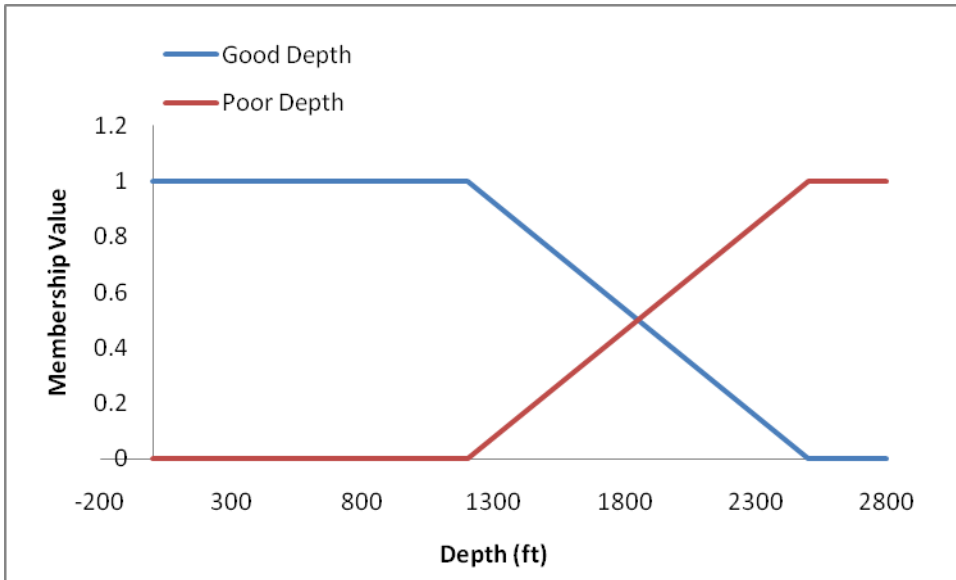


Figure A.4 Fuzzy sets for the fourth generation of roof support equipment.

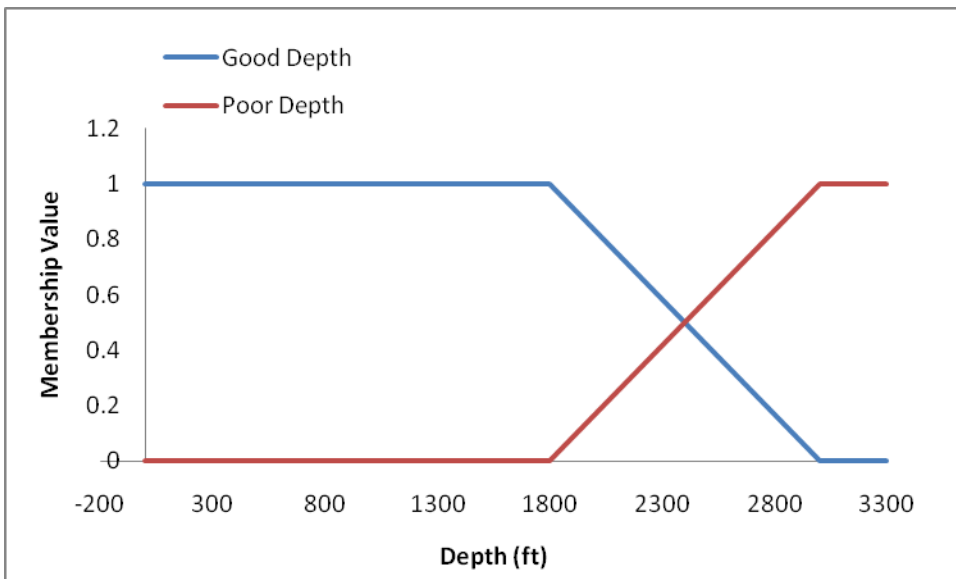


Figure A.5 Fuzzy sets for the fifth generation of roof support equipment.

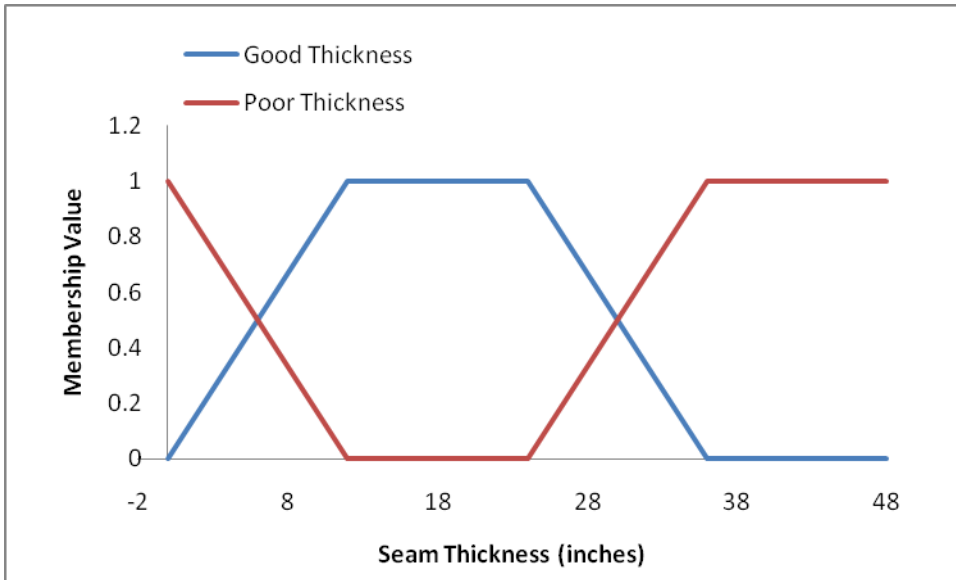


Figure A.6 Fuzzy sets for the first generation of coal cutting equipment.

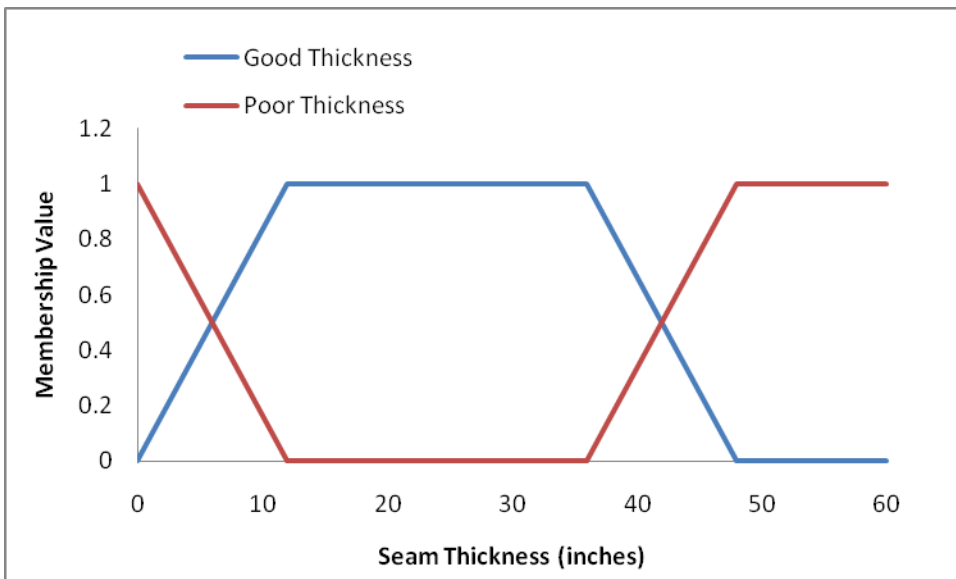


Figure A.7 Fuzzy sets for the second generation of coal cutting equipment.



Figure A.8 Fuzzy sets for the third generation of coal cutting equipment.

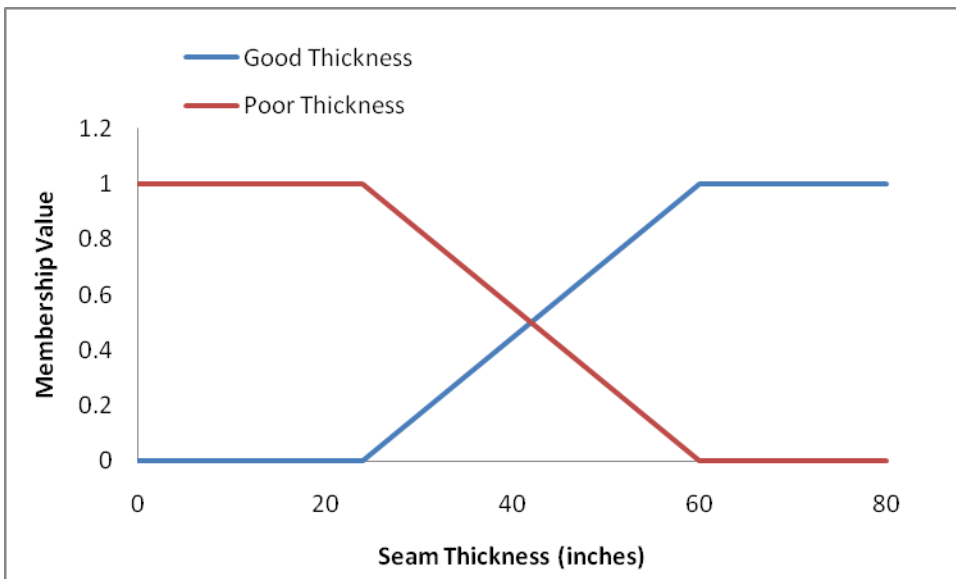


Figure A.9 Fuzzy sets for the fourth generation of coal cutting equipment.

A.2. Fuzzy Sets for the Room and Pillar Mining Equipment

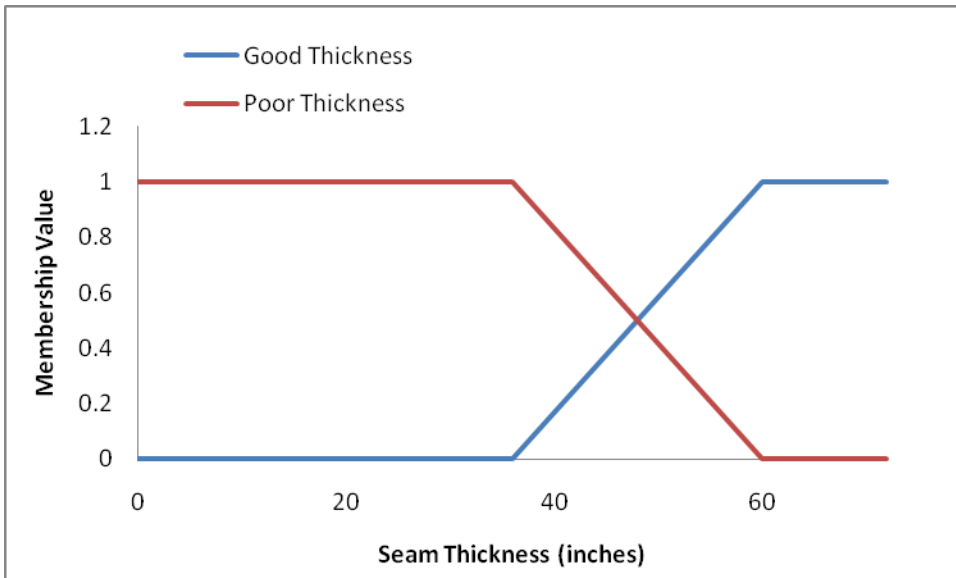
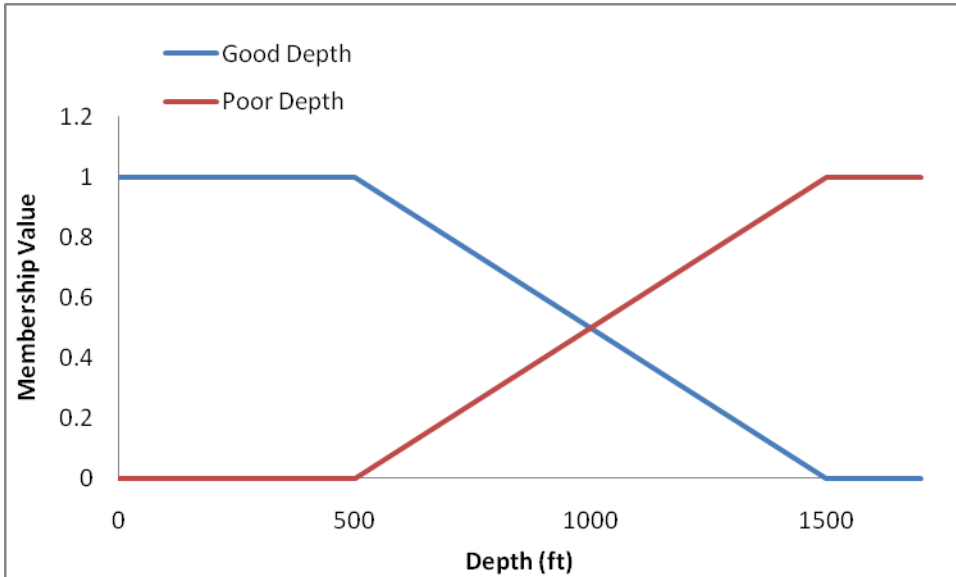


Figure A.10 Fuzzy sets for the first and second generations of room and pillar equipment.

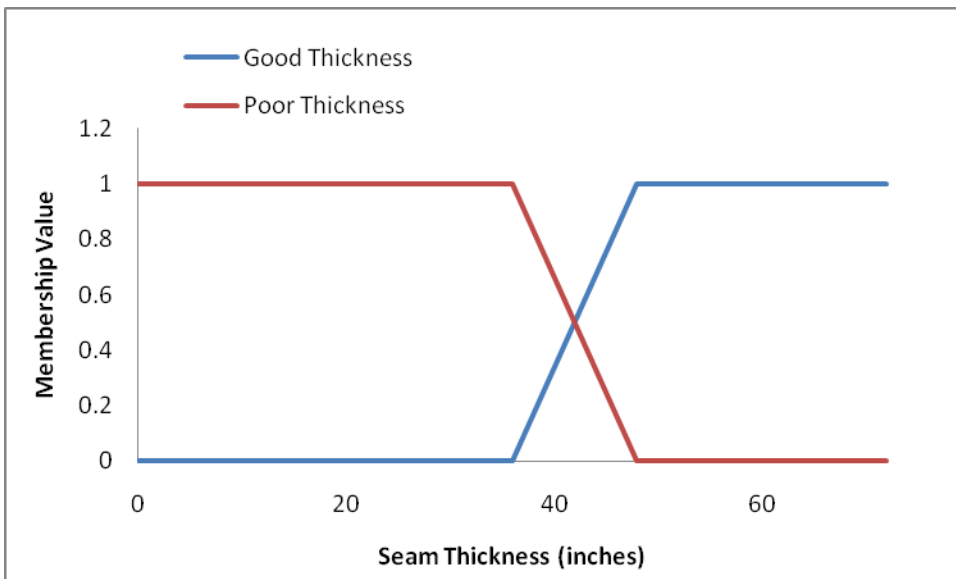
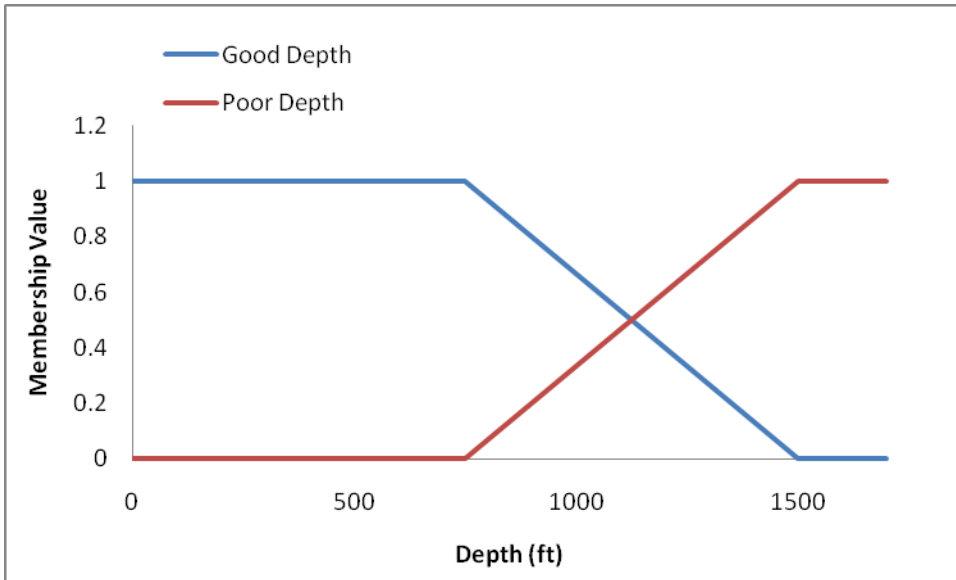


Figure A.11 Fuzzy sets for the third generation of room and pillar equipment.

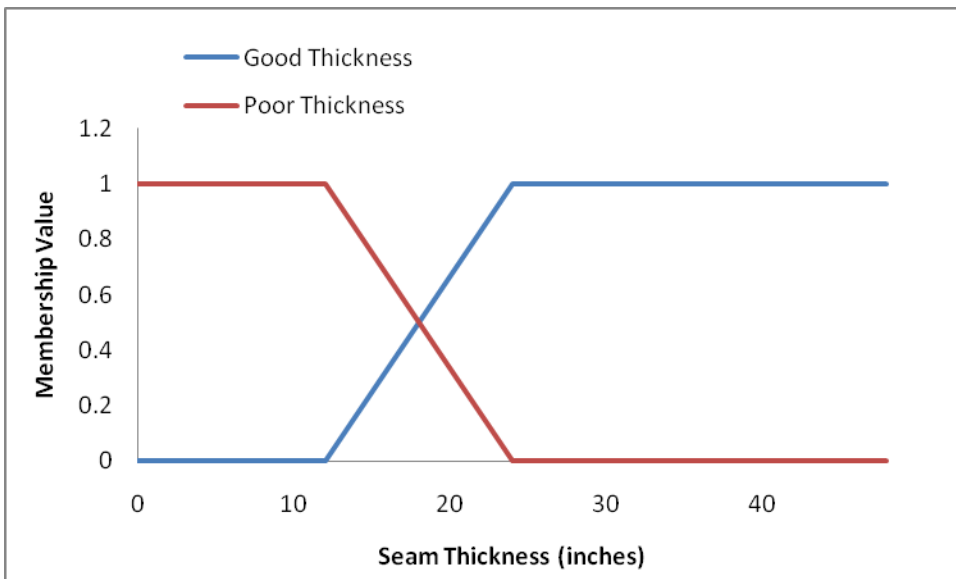
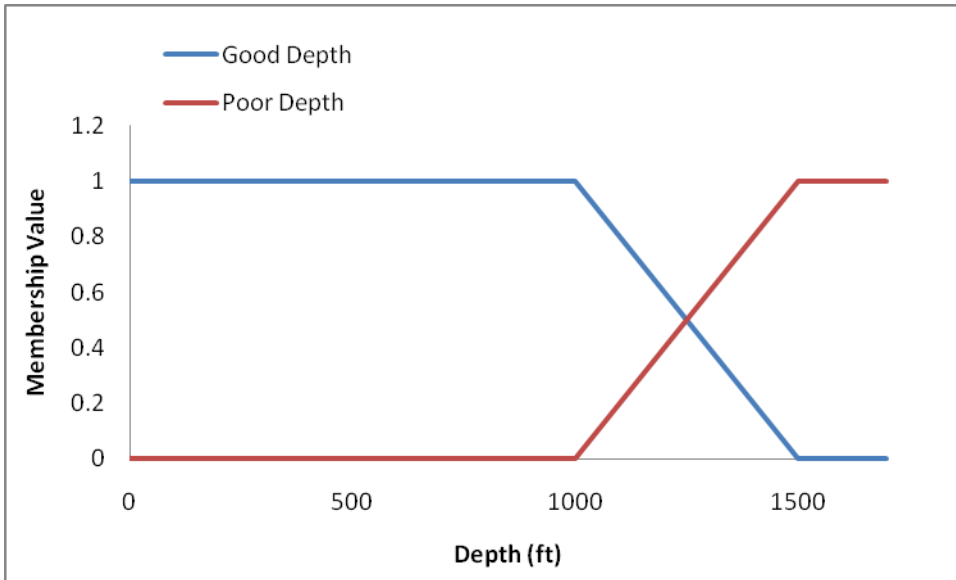


Figure A.12 Fuzzy sets for the fourth and fifth generations of room and pillar equipment.

APPENDIX B

MODEL DOCUMENTATION

B.1. Files in the CD

The CD that comes with this thesis contains six files and two folders. The files are *Netlogo4.1Installer.exe*, *Netlogo User Manual.pdf*, *hfujiono thesis model.nlogo*, *coal-price.txt*, *inflation-rate.txt*, and *Thesis-Hfujiono.pdf*. *Netlogo4.1Installer.exe* is used to install Netlogo software that the author used to develop the agent-based model for the thesis. This file can also be downloaded from <http://ccl.northwestern.edu/netlogo/download.shtml>. *Netlogo User Manual.pdf* contains a complete user manual to use Netlogo software. The *hfujiono thesis model.nlogo* file is the agent-based model in the thesis. This section describes the manual to run the agent-based model in the thesis, including procedure to install and setup the model.

The inputs for the agent-based model can be found in the *coal-price.txt* and *inflation-rate.txt* files. These files have to be saved in the same folder with the *hfujiono thesis model.nlogo* file. *Thesis-Hfujiono.pdf* file is the pdf file of the written copy of the thesis. The folders in the CD include **rngs** and **matrix** folders. Both folders contain Netlogo extension required to run the agent-based model in this thesis.

B.2. Setting Up the Model

After installing the model, copy both the **rngs** and **matrix** folders into the extension folder under the Netlogo program. The common path to find the extension folder is as follows: <c:\Program Files\Netlogo 4.1.3\extension>. After that, we can open the *hfujiono thesis model.nlogo*. Figure B.1 shows the opening screen, which is the interface screen when we open the file. The code of the model can be found by clicking on the procedures tab as presented in Figure B.2.

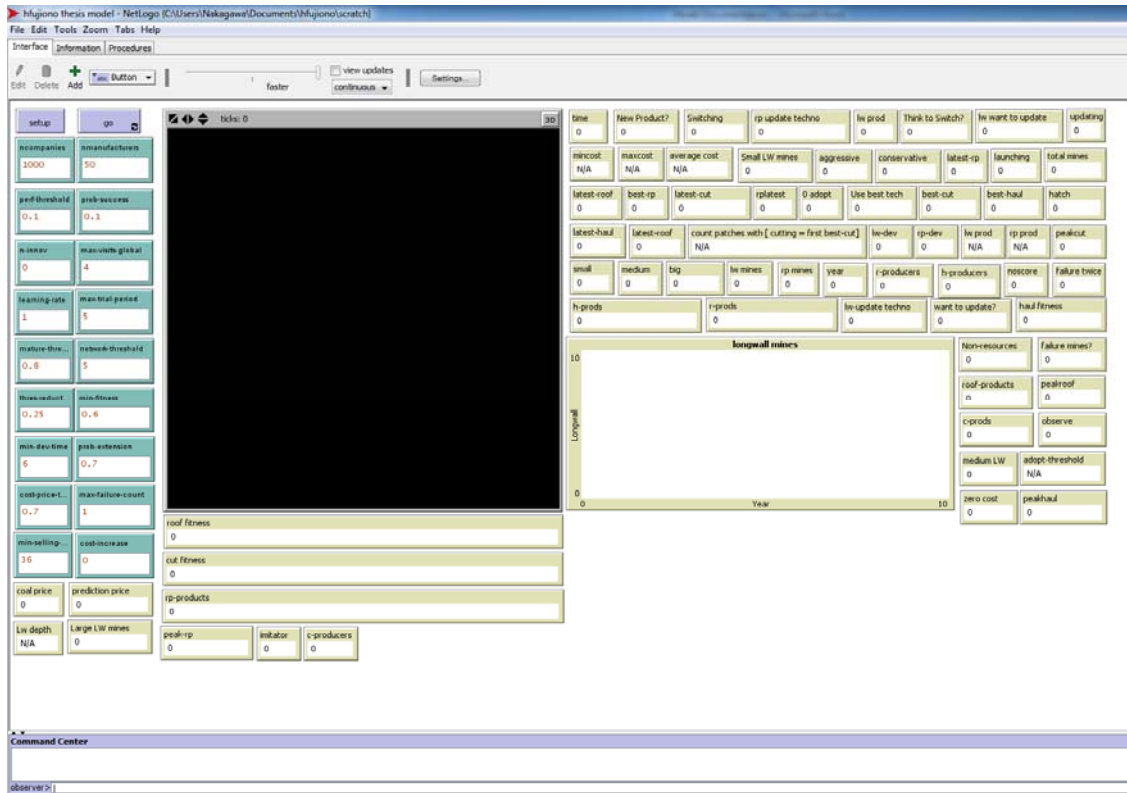


Figure B.1. Netlogo interface.

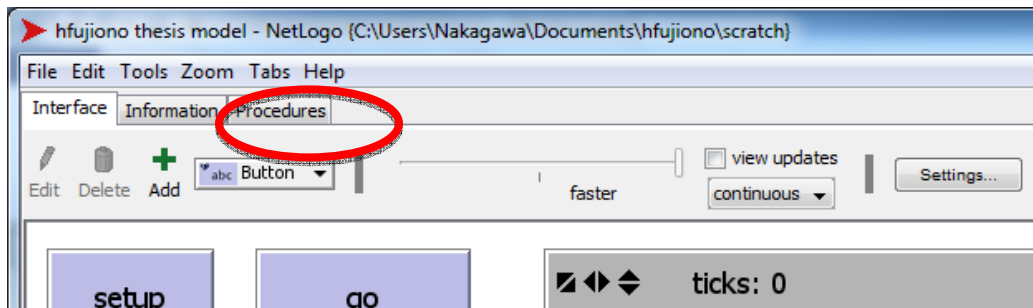


Figure B.2. Netlogo interface

On the interface screen (Figure B.3), the green boxes are the parameter that we can set while the light yellow boxes are the variables that we can monitor during the simulation. The plot area shows the number of longwall mines during the simulation.

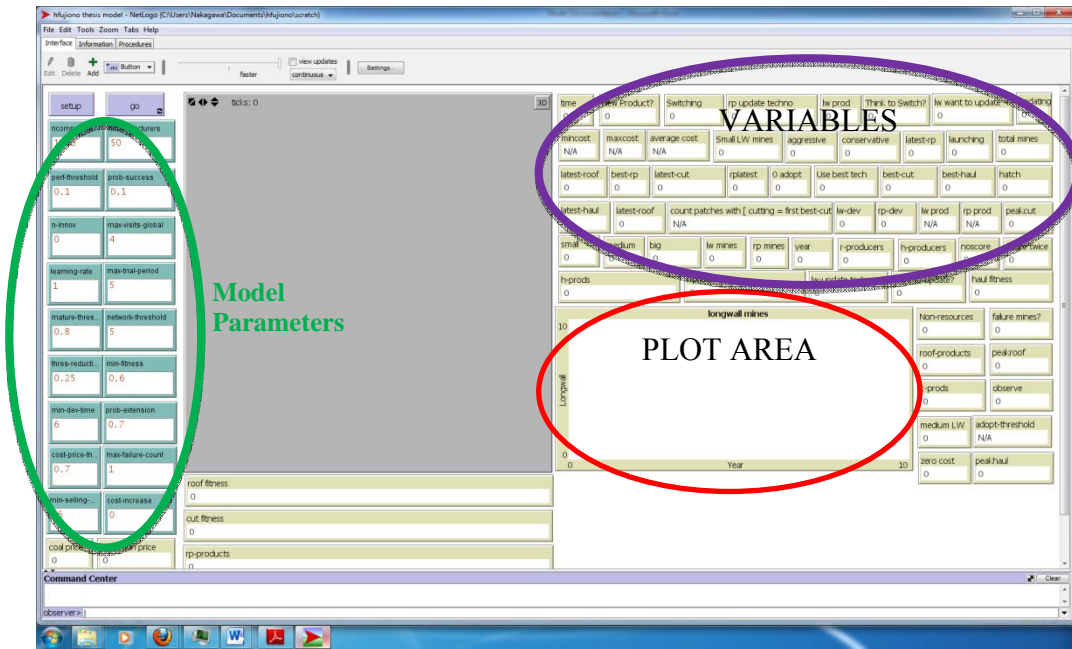


Figure B.3 Parameters, variables, and plot area in Netlogo interface.

Figure B.4 and B.5 illustrates how we can setup the value for the three important parameters in the model: significant-threshold, prob-success, and profit-threshold. When we want to run the model, we put the value for significant-threshold parameter in the perf-threshold box, the prob-success value in the prob-success box. In order to setup the value of profit-threshold parameter, we put the value of $(1 - profit-threshold)$ to the cost-price-threshold box.

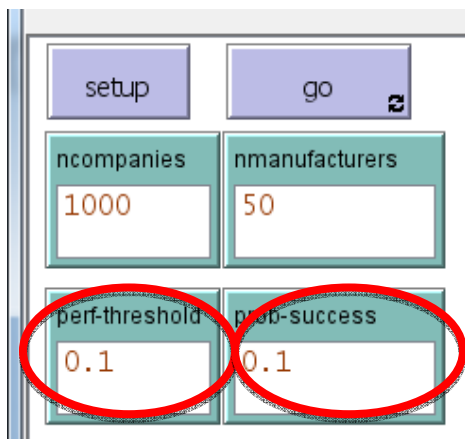


Figure B.4 Setting the significant threshold and prob-success parameters to 10%.

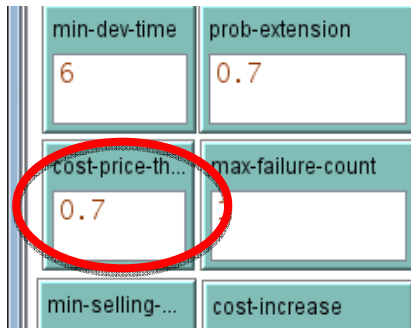


Figure B.5 Setting the profit-threshold parameter to 30% (cost-price-threshold = 1 – profit-threshold).

B.3. Running the Simulation

When we run the agent-based model, we use the *setup* button to set the initial condition and the *go* button to run the simulation (Figure B.6). We can turn off the view updates option to increase the speed of simulation run by *un-checking* the *view updates* option.

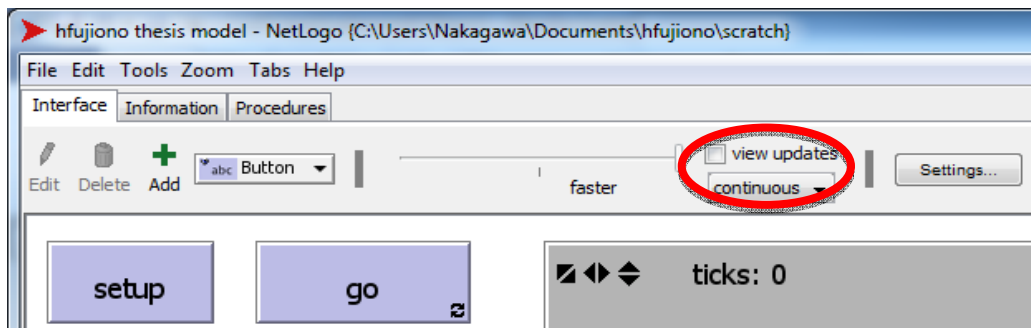


Figure B.6 The setup and go button.

We can also perform multiple simulation runs automatically with Netlogo and record the result from each simulation run into a spreadsheet file or csv file by using the behavior space tool (Figure B.7). Once we open the behavior space tool, we will create new experiment or edit or duplicate existing experiments (Figure B.8). We perform sensitivity analysis, multiple simulation runs, and record many different variables during simulation run by using the behavior space tool (Figure B.9). The first box shows the experiment name, in this case it is Experiment Thesis. The second box shows the parameter of the model. We can try different value for each parameter. For example if we want to perform 100 simulation runs for prob-success = 0.1 and 0.5, then we can type

[*"prob-success" 0.1 0.5*]. The third box shows the number of simulation replications while the fourth box lists variables that we want to record during the simulation. More details on how to use the behavior space tool can be found in the Netlogo user manual document.

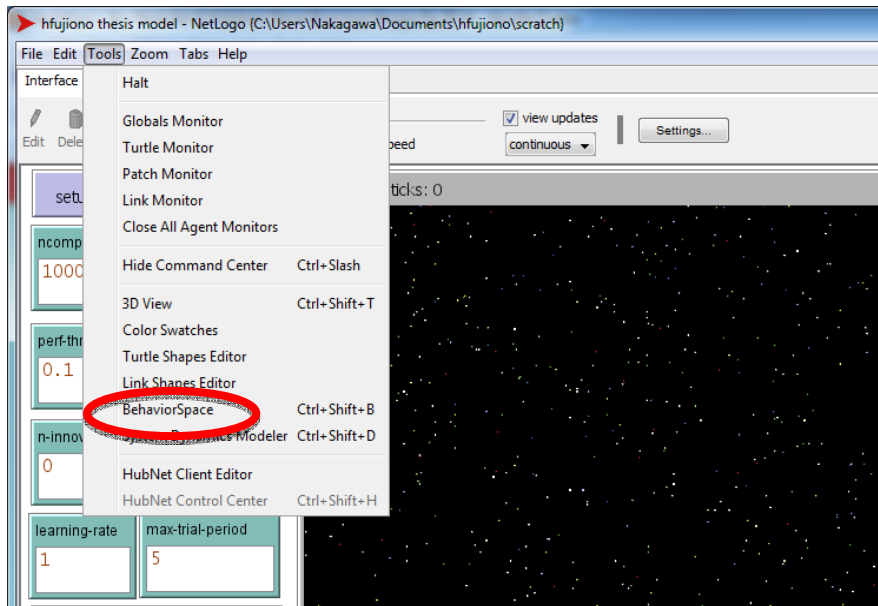


Figure B.7 Behavior space tool for multiple simulation runs.

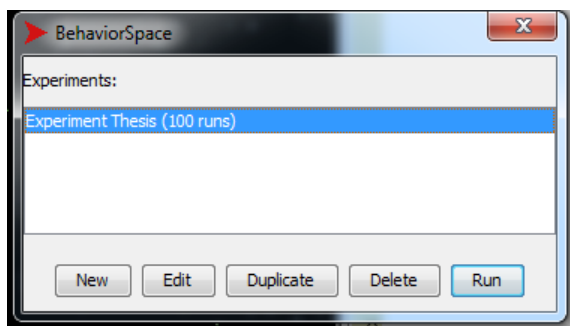


Figure B.8 Options in behavior space tool.

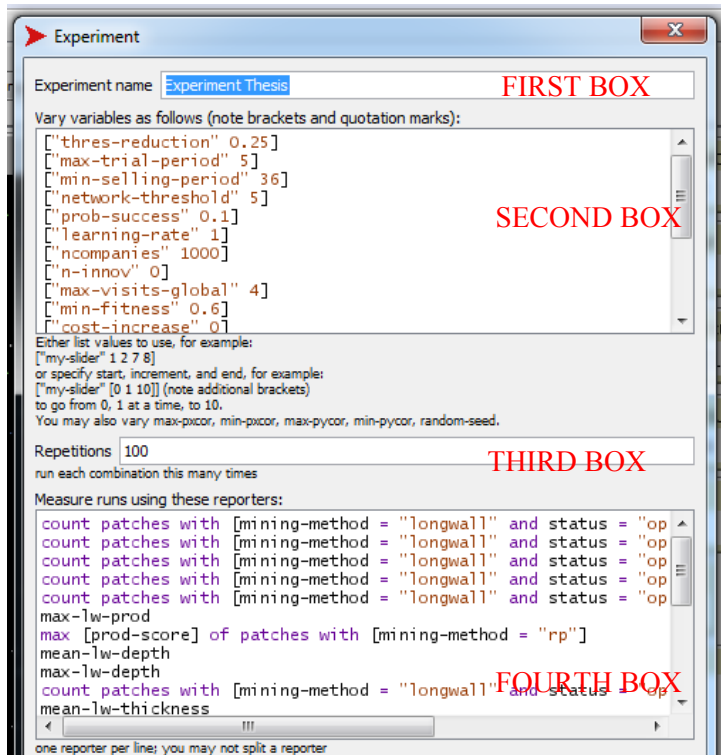


Figure B.9 Setting up the behavior space tool.