SANDIA REPORT

SAND2015-7915
Unlimited Release
Printed September 2015

Natural Gas Value-Chain and Network Assessments

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SAND Report Title

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Earth Systems Analysis

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Resilience and Regulatory Effects

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Policy and Decision Support Analytics

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Earth Systems Analysis

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Abstract

The current expansion of natural gas (NG) development in the United States requires an understanding of how this change will affect the natural gas industry, downstream consumers, and economic growth in order to promote effective planning and policy development. The impact of this expansion may propagate through the NG system and US economy via changes in manufacturing, electric power generation, transportation, commerce, and increased exports of liquefied natural gas. We conceptualize this problem as supply shock propagation that pushes the NG system and the economy away from its current state of infrastructure development and level of natural gas use. To illustrate this, the project developed two core modeling approaches. The first is an Agent-Based Modeling (ABM) approach which addresses shock propagation throughout the existing natural gas distribution system. The second approach uses a System Dynamics-based model to illustrate the feedback mechanisms related to finding new supplies of natural gas – notably shale gas – and how those mechanisms affect exploration investments in the natural gas market with respect to proven reserves. The ABM illustrates several stylized scenarios of large liquefied natural gas (LNG) exports from the U.S. The ABM preliminary results demonstrate that such scenario is likely to have substantial effects on NG prices and on pipeline capacity utilization. Our preliminary results indicate that the price of natural gas in the U.S. may rise by about 50% when the LNG exports represent 15% of the system-wide demand. The main findings of the System Dynamics model indicate that proven reserves for coalbed methane, conventional gas and now shale gas can be adequately modeled based on a combination of geologic, economic and technology-based variables. A base case scenario matches historical proven reserves data for these three types of natural gas. An environmental scenario, based on implementing a \$50/tonne CO_2 tax results in less proven reserves being developed in the coming years while demand may decrease in the absence of acceptable substitutes, incentives or changes in consumer behavior. An increase in demand of 25% increases proven reserves being developed by a very small amount by the end of the forecast period of 2025.

ACKNOWLEDGMENTS

The authors would like to thank Garrett Barter and Todd West for their earlier technical and management contributions to this project, as well as Tom Lowry, Thomas Dewers, Jason Heath, Hongkyu Yoon, Shannon Jones and many others for their guidance and insights throughout the duration of the project. The team is grateful to Sasha Outkin for leading the Agent-Based Modeling aspects of this project, as well as La Tonya Walker and Len Malczynski for developing the core of the system dynamics modeling. This work was funded under the Laboratory Directed Research and Development (LDRD) program at Sandia National Laboratories.

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NOMENCLATURE

ABM	Agent Based Model
ACE	Agent Based Computational Modeling
AEO	Annual Energy Outlook
bcf	billion cubic feet
BtU	British Thermal Unit
CLD	Causal Loop Diagram
CO_2	Carbon Dioxide
DOE	Department of Energy
EIA	Energy Information Administration
EMF	Energy Modeling Forum
EP	Electric Power
FERC	Federal Regulatory Energy Commission
GAM	Gas Allocation Model
GPCM	Gas Pipeline Competition Model
GTL	Gas to Liquids
LDC	Local Distribution Company
LNG	Liquefied Natural Gas
MARKAL	MARKet Allocation
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact
MMcf	million cubic feet
NEMS	National Energy Modeling System
NG	Natural Gas
NGPM	Natural Gas Production Model
NGSM	Natural Gas Systems Model
PR	Proven Reserves
R&D	Research and Development
SD	System Dynamics
SNL	Sandia National Laboratories
tcf	trillion cubic feet
UPR	Unproven Reserves
U.S.	United States
yr	year

1. INTRODUCTION

This project developed two modeling approaches to illustrate shock propagation and physical-to-market feedback in the U.S. natural gas (NG) system, given recent and large-scale production of shale gas. They include an Agent-Based Model (ABM) and a System Dynamics (SD) model. The ABM and SD models have been used to capture the non-equilibrium and endogenous feedback aspects that are representative of the NG system. This approach offers an advantage over general and partial equilibrium models which typically do not account for path dependence, infrastructure constraints and effects of agent behavior or technological feasibility of scenarios.

Two models were developed to capture the semi-autonomous and endogenous feedback aspects of agent based modeling and system dynamics, respectively. General equilibrium or optimization approaches typically require a true 'equilibrium' solution or optimum (global or local) set to be found in order to complete the model run. This is not the case with ABM modeling (that can solve the model equations in a semi-autonomous and semi-stable state based on the varying agent's behavior across a given set of behavior domains). Additionally, system dynamics can determine a steady-state solution similar to that seen in mathematical biological modeling systems that may change over time and with varying inputs (as opposed to a true equilibrium where solutions may or may not be found given the model's current set of constraints) that incorporates feedback from the results throughout the model run that happen to be several decades in this instance.

Figure 1 illustrates the overarching frameworks of the ABM and the SD-based models developed for this project. The ABM approach was developed to build the Natural Gas Systems Model (NGSM) that focuses primarily on the U.S. natural gas infrastructure to illustrate new supply and varying demand 'shocks' to the flows of natural gas, prices, and related bottlenecks in this particular infrastructure arrangement based on data from the GPCM model's underlying infrastructure topology and flow data. The SD approach was used to develop the Natural Gas Production Model (NGPM) that seeks to model the relationships between exploration investment, proven natural gas reserves, and the underlying cost-based (e.g., does not include unforeseen speculative market pricing premiums) prices seen throughout the conventional, coalbed methane and shale gas supply market in the U.S.

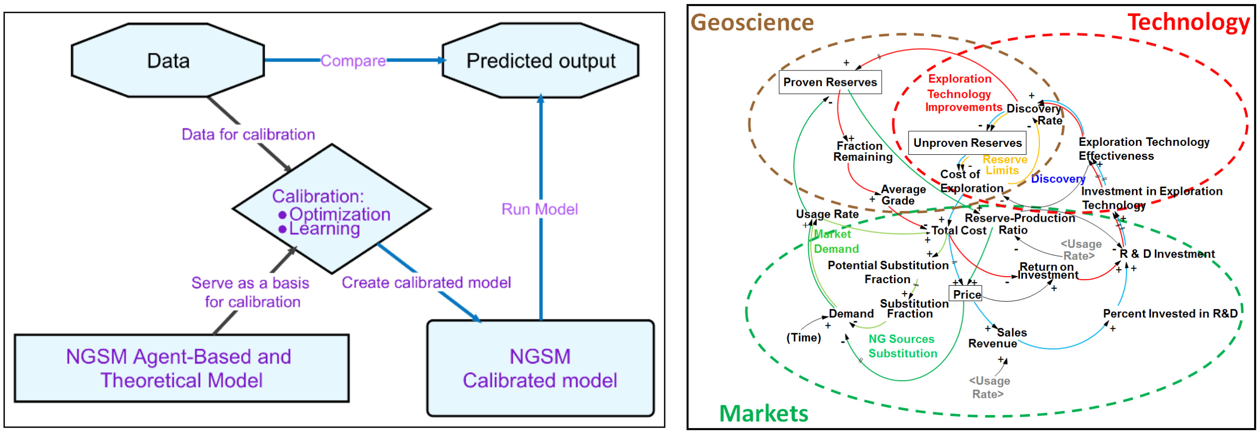

Figure 1. Agent-Based Modeling Framework (left) and the System Dynamics-based Framework (right) that form the bases of the natural gas modeling efforts developed for this project.

The ABM and SD modeling are described in the following chapters. Utilizing these two approaches offers a sensible comparison between the types of input parameters and data required to develop each modeling approach in order to address questions regarding natural gas infrastructure development in the U.S.

2. AN AGENT-BASED APPROACH TO NON-EQUILIBRIUM DYNAMICS OF NATURAL GAS SUPPLY SHOCK PROPAGATION.[1]

2.1 Introduction: Factors in Understanding & Modeling the Natural Gas System Evolution

This chapter outlines an effort at the Sandia National Laboratories to create a framework for representing the shock propagation through the natural gas system including normal NG system normal dynamics, and evaluating effects of different policies. It builds on Outkin et al. (2014).

It is intuitively clear that the NG abundance means substantial changes to the U.S. economy. For this abundance to be used intelligently, an understanding of how this change will propagate and affect the economy and the society at large is required in order to inform appropriate policies and regulations, and enable better decisions by system participants.

The vectors through which the impact of developing abundant NG supplies may propagate include changes to manufacturing, electric power (EP) generation, wider use of gas-powered vehicles, and increased NG exports by means of liquefied natural gas (LNG). Propagation of these changes will likely include an interplay of factors outside the NG production and distribution system. For example, whether a factory will be built in a particular location depends not only on the cost of natural gas, but also on the availability of labor, capital, tax environment, and other factors. Similarly, whether consumers will switch to cars using NG depends on cost, infrastructure, and safety. Economic changes will propagate through many interacting agents who have different objectives, circumstances, and strategies. The behaviors of these diverse agents combined with the rich and complex interactions and feedbacks in the NG system itself and in the overall economic system have the potential to produce a broad range of outcomes, and novel, emergent, previously unobserved behaviors.

Figure 2.1 represents some of the richness of the NG system dynamics and evolution on an example of the LNG exports. Here, we start with an exogenous decision on whether the LNG exports are allowed. Whether the answer is 'yes' or 'no', our model then aims to calculate the implications of this exogenously imposed decision on the NG price, evaluate the supply necessary to support the exports, and evaluate the capacity utilization of the NG network and the network's ability to support the corresponding NG flows. The NG system effects are reflected on the right hand side of Figure 2.1. Outside the exports' immediate effects on the NG network, they will also have less direct and potentially less immediate effects on competing uses of NG, for example on transportation, chemical manufacturing, electric power generation, and the broader economy in general, partially represented on the left hand side of the Figure 2.1.

[1] We would like to thank David Borns, Robert Brooks, Steve Conrad, Tom Corbet, David Daniels, and Len Malczynski for valuable suggestions and comments. All remaining errors are ours.

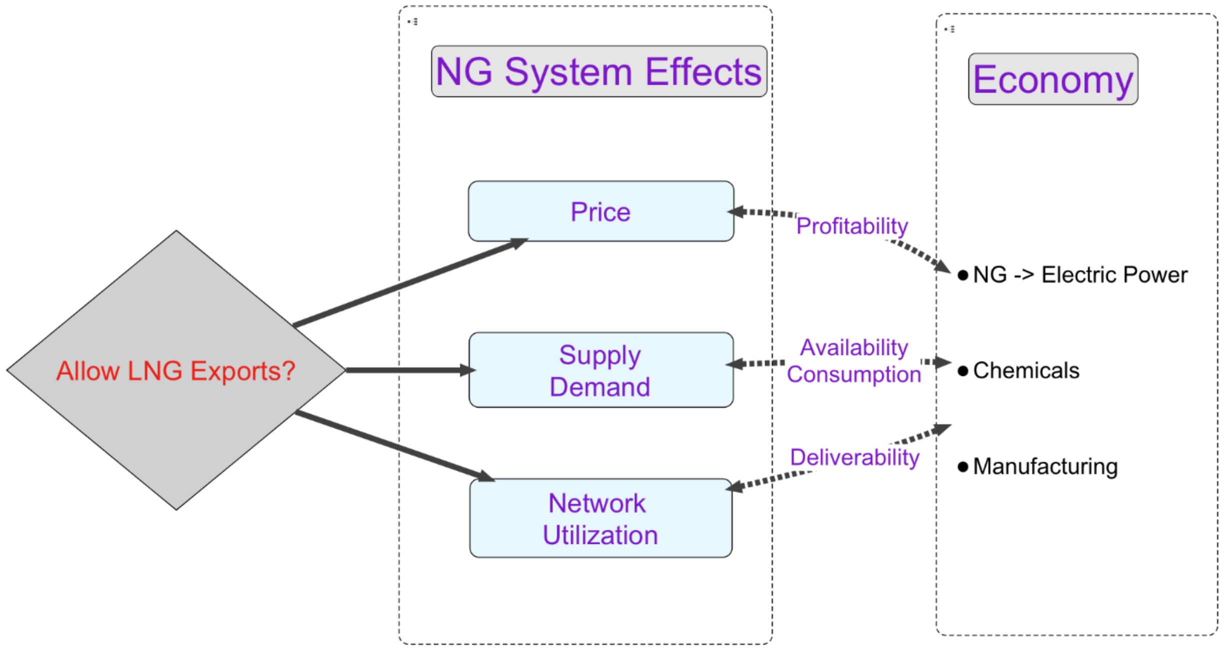

Figure 2.1. Possible effects and flow of causes and consequences as a result of adding an LNG exports terminal.

LNG exports will affect the price, availability, and the network utilization on the natural gas pipeline system. These factors will in turn affect the desirability and the feasibility of different competing natural gas uses, such as electric power generation, uses of NG in chemical industry, and other industrial uses of NG.

Existing tools, primarily general and partial equilibrium models, do not adequately address the shock propagation and system evolution phenomena. Specifically, they do not take into account path-dependence and effects of agent behaviors or the technological feasibility of specific scenarios. While results of such changes may not be completely predictable, our goal is to explore the range of possible scenarios and some of the possible novel system behaviors and their impacts on variables of interest, such as infrastructure development and NG use patterns.

This approach employs ABM as a modeling technique for understanding the effects of the natural gas (NG) shock propagation through a system of interconnected semi-autonomous agents and entities. The approach begins with an overview of existing models and modelling approaches, presented in the two following sections. Section 2.2, 'Existing Approaches' outlines the current state of the art in modeling the natural gas systems. Section 2.3, 'Agent-Based Modeling to Represent NG Agents and Interaction Structures' explains the features of the problem space that make agent-based modeling advantageous and outlines our fundamental approach. The section 2.4 'The Agent Based Model' describes the theoretical model mathematically and presents analysis of its properties, such as existence of price equilibria. The section 2.5 'Simulation Model Implementation' outlines the model implementation, and Section 2.6 'Simulation Model Calibration' outlines the data and the process of calibrating the simulation. Section 2.7 presents the results of the case studies.

2.2 Existing Approaches

Modeling the general dynamics of energy-economic-engineering systems has a long history of general and partial equilibrium models using optimization-oriented codes. One of the most recognized least-cost optimization models is the National Energy Modeling System (NEMS) model, used for decades at the U.S. Energy Information Administration (EIA) (Gabriel et al., 2005; Zhuang and Gabriel, 2008). A challenge with models using classic or mixed-integer types of programming approaches is their somewhat sensitive nature to the initialization assumptions chosen for variables affecting, for example, supply, demand, fuel substitution elasticities and prices. A substantial strength to these types of models that are built on the MARKet Allocation (MARKAL), Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE), and related frameworks is their widely known behaviors and ease of programming and acceptance amongst the research community (SEI, 2015). One generic feature of these models is assumptions of perfect knowledge that is used to make optimizing decisions over time.

Similarly, the Gas Pipeline Competition Model (GPCM) is a well-known and respected optimization-based model that is extremely data rich, yet constrained by often assuming perfect foresight and information, assuming that a fully balanced solution (supply, demand) may exist, and having a limited ability to account for path dependency in infrastructure build out scenarios.

In recent years, many efforts have been underway to supplement or challenge this paradigm in an effort to allow for more nonlinear feedback, learning, and emerging behavior-based modeling. Those efforts attempt to combine the strengths of top-down and bottom-up modeling approaches, and extend beyond the limitations of both. These approaches include Agent-Based Modeling (ABM), System Dynamics, and derivations of extended bottom-up modeling approaches (Abada et al., 2013; Chi et al., 2009; Chappin et al., 2010; Hughes et al., 2013; Lee et al., 2014).

An analysis by Beck et al. (2008) explores attempts to combine the strengths of traditional engineering-optimization models with ABM. They do so by including within an optimization framework the feedback effects on technology adoption arising from endogenous decisions by demand agents. Their analysis shows that non-rational economic behavior could lead to non-equilibrium in energy systems networks within the overlying optimization model framework. This is due to the autonomous decision making capability of individual agents. Similarly, Lee and Yao (2013) illustrate the strengths of ABMs over traditional top-down models by demonstrating that ABMs can better represent technology adoption due to their ability to endogenize buying behavior. By incorporating these behaviors, more accurate demand forecasting may be possible when modeling policy options in the coming decades.

2.3 Agent-Based Modeling to Represent NG Agents and Interaction Structures

The NG system is a spatially distributed network with multiple agents making and executing decisions locally and (semi) independently at timescales ranging from days to decades. Understanding the time evolution of such systems necessitates an approach, such as Agent-Based

Modeling, that can reflect the decentralized decision-making, spatial dependencies, and feedbacks present in such a system. Systems with the above attributes can be simulated to a degree by representing the agents and the interaction structures, but they are hard to understand analytically[2]. The approach employed in this analysis is conceptually based on our earlier work in agent-based modeling (Darley and Outkin, 2007), energy modelling work (Barter et al., 2012; Kobos et al., 2011), and economic disruption modelling work (Vargas and Ehlen, 2013). As a departure from normative approaches in economics, our agents are boundedly rational and can be data driven. Here the agents' bounded rationality implies that their decisions may not be optimal in the long-run, but instead are based on the context and the information they have when making a decision. The concept of bounded rationality was introduced to economics by Herbert A. Simon (Simon, 1972). A different take on bounded rationality was given by Albin (1998), who showed that bounded agent rationality is not an assumption, but all that can be achieved in systems of sufficient complexity.

The key features of the NG system that are reflected by ABMs and that are difficult or impossible to reflect by the existing approaches are as follows:

- *Non-equilibrium*: The NG system is arguably out of a long-term equilibrium. Under the new, domestic supplies of NG, it is unclear how this will change the NG system and affect the US or the world economy.
- *Independence and asynchronicity*: The system participants make their decisions asynchronously and semi-independently. For example, there are plans and construction projects to develop the LNG terminals by the investors. The regulatory approvals are done concurrently and will affect the investments already made. There is an ongoing construction of NG electric power plants and abandonment of existing coal plants. The EPA decisions may affect the feasibility of different extraction techniques, such as fracking, of the pipelines construction, and other NG supply of consumption uses. State and other local regulations differ greatly over larger shale gas plays such as the Marcellus Shale which further complicates the ability to model the potential supplies extracted from this region (Blohm et al., 2012).
- *Path-dependence*: The eventual system shape will depend on the outcomes and timing of different decisions and actions by various entities. The system evolution is likely to exhibit path-dependence.
- *Heterogeneous time scales*: Different parts of the system operate on different time-scales. For instance, LNG investments take years to complete, on the other hand the Henry Hub spot prices change very quickly.
- *Heterogeneous decision rules*: Different agents (e.g., say industrial use or gas electric power (EP) power plants) respond differently to NG price changes or volatility. They might also require different infrastructures (EP network, NG supply chains), thus adding a spatial component.

[2] Agent heterogeneity, spatial interactions, and non-linearity of interactions are sufficient in general to make the model analytically intractable. See Holland (1996) for more details.

- *Local interactions and local information*: The NG system participants are generally associated with a specific geographic area and act on the information available in order to achieve their objectives and interact with the entities that are 'near' to them, but not necessarily with the system as a whole.

The objective of our approach is to represent the propagation and interaction of causal factors that affect the natural gas system by representing the market and regulatory interactions affecting the network operation and dynamics, and how the decisions of the operators, investor and regulators in the network combine together to determine the short and long-term evolution of the natural gas system. The model framework includes two basic elements: agents that represent individuals or institutions that make decisions affecting the system, and interaction structures that determine the way agents communicate and influence one another. While agents are considered to be autonomous, their specification has to reflect the rest of the model and its interaction structure. For example, treating the agent as a price taker works when the relevant market price (either local or global) is determined by an external process, which presents the agent with the resultant market price and thus determines the agent consumption. If, on the other hand, price and quantity determination involves negotiation and contractual arrangements with specific other counterparties, then the agent behavior has to be augmented with the ability to search for counter parties, and to enter into such contracts.

The analysis develops and calibrates the model to be representative of the available data, underlying interactions, and causal factors. This approach may provide a degree of short-term predictability of the network dynamics. However, long-term predictability is not our goal. The goal is to understand and differentiate on the qualitative level different scenarios (for example LNG exports versus no LNG exports).

Price forecasting is not the goal of this project, which is to highlight the interactive effects of shock propagation (e.g., a new LNG export demand node) on the existing NG supply-infrastructure-demand system. We use the price for the aforementioned purposes, but treat it as one of the variables describing a particular scenario and enabling qualitative comparisons across different scenarios, such as using NG for exports versus using it mainly for domestic consumption and production.

The agent-based approach has a large positive (as contrasted to normative) component (see Axtell and Epstein (1995) of Darley and Outkin (2007) for example). In this example, the demand functional form, or changes to it, can be inferred from the data, from expert knowledge, from rules of thumb, or from general economic principles, such as utility maximization. When the agent has an objective, it can also be augmented with necessary algorithmic capabilities to achieve it. For example, if the agent's goal is to minimize the average price they pay for the natural gas and they happen to have storage or ability to shift consumption over time, then the agent can engage in predicting the future prices and optimizing their consumption patterns based on such predictions.

The key feature of our modeling approach is to separate the processes operating at different time scales and analyze them semi-independently. The *Fast* component includes supply, consumption, and transmission decisions, and takes into account constraints imposed by network transmission or geographic availability. The *Slow* component includes regulatory decisions (e.g. LNG exports approval), the LNG and gas-to-liquids (GTL) investment decisions and their implementation, or new construction on the NG network.

The approach also represents explicitly the agents' decisions and the interaction structures. Figure 2.2 illustrates the relationships among the basic framework elements of agents and interaction structures, and identifies some of the specific agent types and structures essential for describing the NG system. The methodology begins by populating the framework, beginning with agents and their interaction structures involved in short-term processes. These agents and structures include, where appropriate, consideration of the longer-term processes in which they also participate.

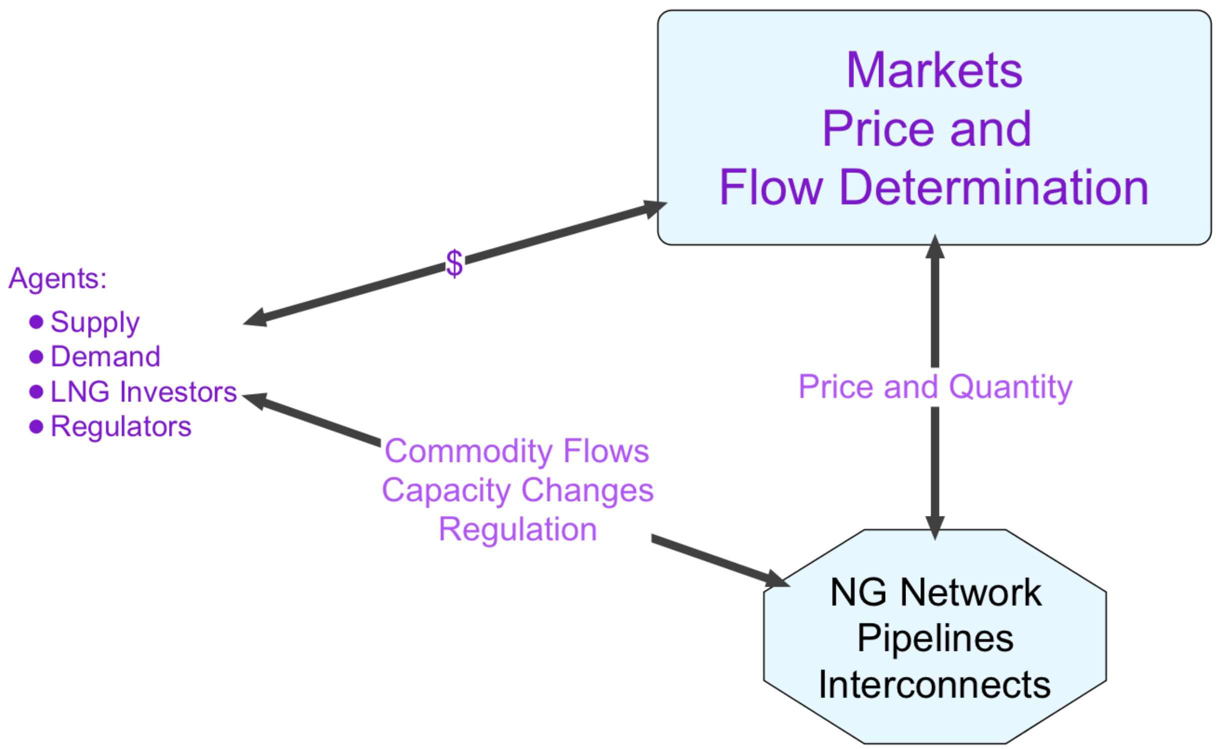

Figure 2.2. Abbreviated model structure: agents, markets, and NG network.

This model structure is briefly outlined in Figure 2.2 that represents the agents and interaction structures. There are two basic kind of interaction structure: markets in which agents communicate information and money, and the NG pipeline network on which agents supply and withdraw NG. Here the agents' interaction in the markets allows for price discovery, and the agents' interaction with the NG network enables the network flows based on the price and quantities determined by the market mechanisms, and subject to the capacity and regulatory constraints.

When creating a model of the natural gas system, some of its inputs can be represented as external data sources. Those include future supply and demand projections, future pipeline construction, and regulatory decisions.

This approach can help policy- and decision-makers explore possible future scenarios and the gauge the effects of policy decisions, investments, and other actions. The goal is pragmatic: create a model that is sufficiently simple and understandable and yet helps developing insights into propagation of changes in the natural gas system and has degree of predictability.

We believe this approach can help policy and decision-makers explore possible future scenarios and the gauge the effects of policy decisions, investments, and other actions.

2.4 THE AGENT BASED MODEL

This is a finite-horizon discrete time model with time $t \in \{1,...,T\}$.

2.4.1 Entities

On the top level, the model contains the following components:

- A set of all agents: $A = \{a_1,...,a_N\}$. This set can include heterogeneous the agents who are associated with specific network nodes and the agents who are not. The latter may include regulators, LNG investors, traders. The set of agents who are nodes on the network consists of supply, demand, storage and interconnect agents. The method denotes the sets of those agents by S, D, T, and I respectively. The method denotes the set of all network agents as V . The sets of agents satisfy the following intuitive relationship: $S,D,T,I \subseteq V \subseteq A$
- The pipeline network E . Each pipeline has a single network node associated with each end of the pipeline and is formally represented as $(u,v) \in E$, where $u,v \in V$. The pipeline capacity can change depending on the direction and is represented as $c(u,v)$ where the flow is from node u to node v . The pipelines are considered bi-directional in general, where the capacity limits associated with flow in each direction do not need to equal each other. One of the capacity limits can be zero if the pipeline can be run in one direction only. If there is no pipeline running from node u to node v, the corresponding directional capacity between them is set to 0. More formally, in this case $(u,v) \notin E$, and $c(u,v) = 0$
- A directed graph $G = (V,E)$ represents the combination of network agents and pipelines as illustrated in Figure 2.3.

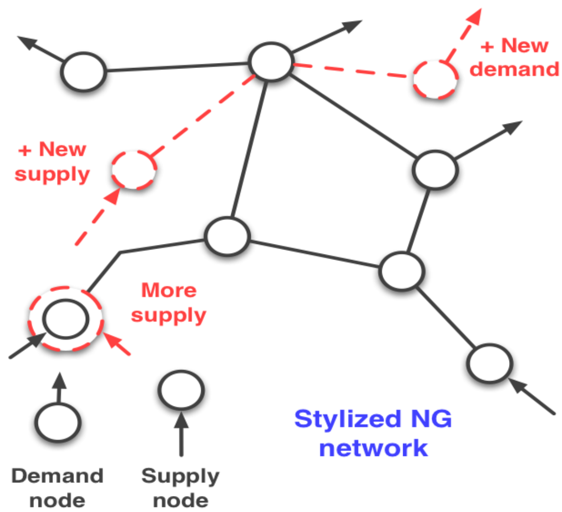

Figure 2.3. A stylized NG network with new demand or supply nodes added.

2.4.2 Model Dynamics

Each agent has a decision making rule, which we call its strategy. At each time step, the agent makes a decision on what to do based on that strategy and the history of past interactions. The approach treats each strategy as a decision making-rule for all eventualities, whose application results in decisions made and actions performed by the agent. The set of actions available to an agent depend on the agent type and may include changes in quantities supplied or demanded, pipeline capacity changes, or regulatory changes. The actions available to an agent are also time and context-dependent: For example an LNG terminal can only be constructed in a location with access to a sufficiently deep port and a decision to start the LNG shipments can only be effective if there are sufficient NG supplies and corresponding pipeline capacity.

The model proceeds at discrete time steps. The time interval covered by the time step can be changed depending on the modelling needs. The current model proceeds at a daily time step. Therefore the agents make daily decisions on how much to supply and consume each day. Those decisions are a part of the algorithm in the model that determines the daily price of the natural gas.

We represent the supply and demand agents as price takers, who provide information on how much they would like to produce or consume to a market clearing algorithm. Taken together with the storage agent decisions, this allows for finding the market clearing price and the corresponding network flows. This part of the model represents the temporal equilibrium that the model attempts to achieve at each time step. It is described in the section titled, 'Short-Term Dynamics. Temporal Equilibrium'.

In addition to that temporal equilibrium the model is capable of representing disruptions, adaptations, and other adjustments that are described in the section titled, 'Long-Term Dynamics and Disruptions'.

2.4.3 Short-Term Dynamics. Temporal Equilibrium

2.4.3.1 Agents and Entities

On a more foundational level, the approach populates the simulation with demand and supply agents, and the pipelines and interconnecting nodes, and algorithms for the transmission network and basic market NG price discovery. The LNG terminals' construction decisions are represented as exogenous shocks to the system. The goal is to make such decisions endogenous in future iterations of the model. Below is a more concrete description of different agents in the model:

Notation

p - NG price
q - quantity

The approach starts with an example of a simple demand agent that acts as a price taker. This example can be treated as a generic template for all agents in the model.

In general, quantity demanded by a given agent i at time t at a given price p can be represented as $q_i(p,t)$, where treating time both as an index and as an explicit independent variable allows incorporating the changing functional form of demand curve (time as index) and treating the seasonality explicitly (time as independent variable). Both for the ease of understanding and due to data limitations, it is beneficial to split this specification into the short-term and the long-term components, where the short-term represents the given and fixed functional form that reflects seasonality and the long-term component reflects the evolution of the demand function over time.

Short-term

Represent quantity demanded by a given agent i at time t at a given price p:

$$q = q_i^0(p,t) \ , \qquad \text{* MERGEFORMAT (1)}$$

where the functional form f_i^0 represents the demand for a particular period of time, say from t_1 to t_2.

Long-term supply and demand changes

Represent the long-term changes in the demand curve:

$$q_i^0 -> q_i^1 \qquad \text{* MERGEFORMAT (2)}$$

where the function q_i^1 represents the demand for a particular period of time.

Here we describe the daily actions of agents and the market clearing algorithm.

Supply Agent. Those agents produce NG and insert it into the NG network for delivery.

This agent decides how much natural gas to supply at a given price: $q_i = q_i(p,t)$. It expresses the quantity the agent is willing to produce at a given price during a particular time period (a day in our current simulation). The supply agent is associated with a specific location on the network. While not implemented in the model at present, this and other agents can be endowed with the ability to take such parameters as profitability and extraction costs into account.

Demand Agent. Those agents receive natural gas from the NG network.
The agent decides how much to receive at a given price: $q_i = q_i(p,t)$. It expresses the quantity the agent is willing to consume at a given price during a particular time period. There are at least three types of consumption agents: Industrial, residential, and generation. Additional types of agents or specific consumption behaviors can be added if specification is available. The approach adapts a convention here that the quantity demanded is expressed as a negative number and the quantity supplied is expressed as a positive one. The agent is associated with a specific location and pipeline.

Storage Agent. Storage withdraws and injects NG from the NG network, depending on the network conditions. The approach defines storage as an agent that can have both supply and demand behavior.

Supply or a demand function for storage agent is expressed as following: $q_i = q_i(p,t,h_i)$. It expresses the quantity an agent is willing to supply to the network or to extract from the network at a given price during a particular time period. This function necessarily depends on the agent parameters, such as the storage capacity and injection and withdrawal rates, and the agent state. The agent-specific parameters are incorporated in the functional form of $q_i(p,t,h_i(t))$. It reflects the capacity of their storage fields (generally geologic formations), the maximum rates of injection and withdrawal that are also limited by installed equipment, as well as the state of the reservoir. The agent state is incorporated in the variable $h_i(t)$ that represents the agent state such as the storage level and other information (history) the agent uses in his decision making. In this prototype implementation, we split the year into storage 'withdrawal' and storage 'replenishment' seasons, with the months of November through March representing the former, and the months of April through October, the latter. The agent is associated with a specific location and pipeline.

Interconnect nodes.

Interconnect nodes have no behaviors and no capacity constraints and are used to represent interconnection points on the network. However, their existence is essential for the network flow calculation

LNG Exporters. LNG exporter nodes are a special kind of agent that both affects the daily dynamics of the network and also represents a long-term disruption.

2.4.3.2. Market Price Dynamics

Many of the factors affecting the NG system dynamics are economic in nature. Therefore, price of NG plays a special role in the simulation. It affects agents' supply and demand decisions as well as the feasibility of specific scenarios such as additions of the LNG export terminals. On a more detailed level, NG price plays the following roles in the model: Provide an underlying concept for finding the network equilibrium; control supply and demand; inform future investment decisions; inform the profitability and feasibility of agents actions; enable market operation and concomitant price discovery mechanisms.

Incorporating the price into the simulation required at a minimum two components: a) a short-term response to prices by the entities on the NG network and b) a mechanism for price determination. We deploy a central Walrasian auctioneer, who sets the price on the entire network, whenever possible, to balance supply and demand on the entire network.

The approach starts with attempting to find the market clearing price for the entire graph G. Specifically, we introduce a function $g(p)$ that represents the imbalance between supply and demand on the network, as the following:

$$g(p) = \sum_{i \in D_G \cup S_G} q_i(p) \tag{3}$$

where by convention the quantity supplied is represented as a positive and the quantity demanded as a negative number.

The algorithm proceeds iteratively. The initial candidate market price is determined by finding such p^* that

$$g(p^*) = 0 \tag{4}$$

if such p^* exists. The next step is to find the flows associated with a particular price on the network. This step is necessary, because the above price determination process only informs how much should be produced or consumed by the individual supply and demand agents, and provides no information on the flows necessary to deliver the required quantities over the network. In general a given market clearing price and the network structure do not uniquely define the network flows.

Determination of the required network flows is accomplished by applying the Edmonds-Karp maximum flow algorithm to the set of supply and demand quantities produced by the equation 4. The algorithm produces a set of directional flows for each pipeline segment $e_j \in E$. It attempts to maximize the total flow over the network for a given price. For a given price p its objective can be represented as following:

$$\max_{s \in S, v:(s,v) \in E} f(s,v) \tag{5}$$

where $f(s,v)$ is the flow from the supply (source) node s to its receiving node v. Therefore the formula 5 represents the total maximum flow out of all supply nodes. This problem can be equivalently represented as maximizing the total flow into all the demand nodes. See Cormen et al. (2001) for more information.

It is possible that the flows implied by solving the equation 5 may not be feasible given the pipeline capacity constraints. If this occurs, we then iterate by splitting the network into a set of subnetworks that are connected only by pipelines that are at their capacity and repeat the above steps for each of the subnetworks until convergence is achieved. The splitting of the network occurs only if there are subgraphs that are connected to other subgraphs only by pipelines that are over capacity. It is described more formally in the Equation 6 and illustrated in Figure 2.4.

$$\bigcup_{i=1}^{N} G_i = G,\ c(u,v) < f(u,v),\ \forall i \neq j, \forall\ u \in G_i,\ \forall v \in G_j : c(u,v) > 0 \tag{6}$$

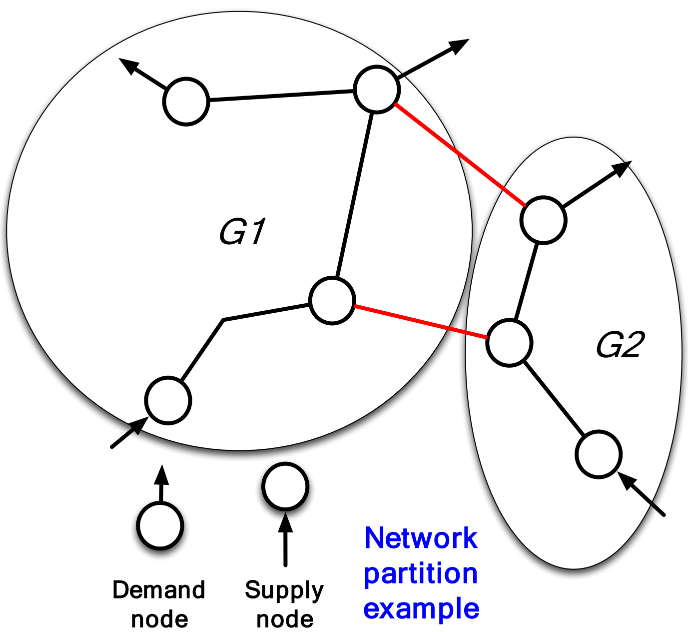

Figure 2.4. An example of the network partitioned into two subgraphs G1 and G2 separated by capacity constrained pipelines indicated in red.

The ABM does not include transportation costs at present; therefore it is possible to have the same price for nodes separated by large distances.

2.4.3.3 Model Analysis: Existence of Price Equilibrium

In this section, the description highlights how an equilibrium price on a network can be achieved under simplifying assumptions. This analysis provides a useful result for testing numerical implementations.

The approach specifically assumes:

1. Nodes on the network represent supply, demand, and interchange or zone nodes only. Specifically, the storage nodes act as supply or demand.
2. The supply and demand node behavior is described by linear monotonically increasing functions.
3. The pipeline capacity is sufficiently large to accommodate any flows.

Let's further assume that supply and demand functions for individual nodes as described above are continuous and respectively monotonically increasing or decreasing with price and have upper and lower bounds. The existence of the upper and lower bounds come from the finite amount of natural gas available.

We calculate the imbalance between supply and demand on the network, as defined in equation (6) above as following:

$$g(p) = \sum_{i=1}^{N} f_i(p) \tag{7}$$

By construction, $g(p)$ has an upper and lower limit and is continuous. If it attains both the positive and negative values (i.e., there exist a price at which supply is larger than demand and there exist a different price at which demand is larger than supply (both in absolute terms), then by the intermediate value theorem there also exists a price p^* at which $g(p^*) = 0$. We call p^* an equilibrium price.

2.4.4. Long-Term Dynamics and Disruptions

Disruptions

Pipeline breaks. A pipeline can be eliminated from the network and the resulting prices and flow determined by the above algorithm.

Supply and Demand Changes

The supply function changes exogenously over time in the base case, based on the data available from GPCM.

Long-Term Supply and Demand Changes

Those are represented as exogenous long-term shocks to the system operating at the level of individual agents.

Supply and demand inferences from other sources can be connected to the ABM here as an alternative source of supply and demand information.

LNG Exports

The LNG export facility is represented as an exogenous shock to the system.

2.5 Simulation Model Implementation

The ABM approach used an existing model of the NG system short-term dynamics, called Gas Allocation Model (GAM) developed at Sandia National Laboratories as our starting point in terms of the software implementation and the GPCM model created by RBAC as fundamental motivation and a source of the data (see Brooks (1981) for more on the GPCM approach). More information about GAM can be found in Mitchell et al. (2010).

As a main immediate departure from GAM, the approach introduces price as the variable that governs the supply and demand decisions, and enables the discovery of a market clearing price that matches the supply and demand on the network subject to the pipeline system capacity constraints. The approach also adds an ability to represent additional agent-based behaviors, including those not associated with specific nodes on the network, such as investment agents. On the software level, the approach uses the strategy pattern (see Gamma et al., 1995 for more information) to represent the agent behaviors. This allows switching between different agent behaviors at run time or at the simulation set-up time.

The current model represents the short-term production and consumption decisions, the resulting market price, and concomitant pipeline flows and allows representation of such scenarios as LNG export terminal additions to the system.

The core of the simulation model has been implemented in Java. It interacts with an Oracle database to allow retrieval of the information and storage of the simulation results. Some of the analysis has been done in JUNG (a java library for networks analysis, visualization, and modelling) and R (an open-source statistics software package).

2.6 Simulation Model Calibration

The approach to calibrating the model against the data is outlined in the Figure 2.5 below.

The approach enables partial NG network calibration to GPCM[3] and other available data. In particular, it enables the specification of the demand and supply for the nodes on the network by piecewise linear functions per GPCM specification. For example, the equation 8 represents a piecewise linear demand function.

$$q = \left\{ \begin{array}{ll} q_1, & p \le p_1 \\ q_1 + \beta_1(p - p_1), & p_1 < p \le p_2 \\ q_1 + \beta_2(p - p_2), & p_2 < p \le p_3 \\ q_3, & p > p_3 \end{array} \right\} \tag{8}$$

This example supply curve is illustrated in Figure 2.5 below.

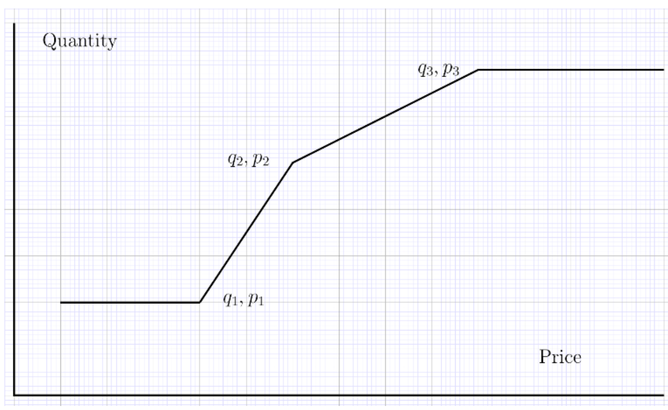

Figure 2.5. A stylized representation of the supply function for a particular geographic location or a network node.

In the GPCM specification, the supply is represented by three coordinates representing four linear segments as illustrated above and demand by two coordinates representing three linear segments. For general piecewise demand or supply representation, the approach assumes the quantity supplied or demanded is constant when the price is outside the interval (q_1, q_3) as illustrated in Figure 2.5.

The prototype model allows investigating the effects on the NG network of both excess supply and increasing demand. In general, it can represent the network modifications and supply and demand node additions, as represented in Figure 2.4, a stylized NG network with new demand or supply nodes added.

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[3] GPCM is a tool for the natural gas market analysis and forecasting, created by RBAC, Inc. See www.rbac.com and Brooks (1975, 1981) for more information.

2.7 Case Studies

Several case studies were developed to illustrate the sensitivities and abilities of the NGSM. In addition to a base case, a liquefied natural gas (LNG) export scenario, high NG supply and low natural gas supply scenario were developed. The base case study builds from the core components of the ABM based on the GPCM dataset of the U.S. natural gas pipeline network's demand, transportation and supply nodes. The base case illustrates the steady-state solution reached by integrating these two components to offer a set of price, supply, demand and seasonality results for which to compare the other scenarios. Next, the LNG scenario illustrates the results of this change to the base case if a representative increase of 15% demand would change in terms of the natural gas pipeline throughput, working market price and the dynamics between the sub and larger infrastructure network represented in the ABM. The 15% assumption was adapted from previous work developed by Montgomery et al. (2012) that looked at the macroeconomic impacts of LNG exports in the U.S. using general equilibrium modeling approach. Additionally, a high U.S. shale Resource and low U.S. shale resource supply set of scenarios were developed to assess these effects on the natural gas infrastructure. They also build from the list of potential scenarios explored by the NGSM for the Stanford Energy Modeling Forum (EMF) (EMF, 2015; Outkin et al., 2015).

The core results from the analysis suggest we put another figure or more illustrating the, 'prevailing price on the network is $2.21/mmbtu' with a few more scenarios or at least some type of parameter or model structure sensitivity illustration on it such as (1) a base case scenario, (2) this LNG export scenario in one location, and if possible, (3) another LNG scenario (to keep things simple) but in a different location in the U.S. This type of figure could help readers understand the ABM's sensitivities from the base case for an LNG terminal, and then its sensitivity based on geography (if this is possible) by allowing them to compare the two LNG sites.

The approach investigates four different case studies:

- Base case: no changes to the system
- LNG export terminal addition at Sabina Pass at 15% of total system demand
- High NG supply case. Based on the Stanford Energy Modeling Forum 31 (EMF, 2015) specification.
- Low NG supply case. Based on the EMF 31 specification.

The ABM analysis of the effects of hypothetical scenarios is based on comparing the model results with and without the hypothetical change to the system. The current focus is on the effects on prices and the network capacity utilization.

To understand the effects of changes on prices, the approach compares the prices in 'before' and 'after' scenarios. In general, the effects of adding a LNG export terminal are conditional on the availability of pipeline capacity to deliver gas to the terminal, for obvious reasons. The approach evaluates and compares four configurations to understand the effects of network change on prices and the network capacity utilization:

1. Network with no change.
2. Network with an additional node, but with no pipeline capacity change.
3. Network with an additional node, and increased capacity that is immediately connected to the additional node.[4]
4. Network with an additional node and no pipeline capacity constraints at all.[5]

A node representing LNG exports integrates with this illustrates adding to the existing NG network. Here the addition of a large exporting terminal serves as a shock to the system that changes the NG network utilization, congestion, and price levels.

2.7.1. Base Case

Figures 2.6 and 2.7 illustrate the base case NG withdrawals and prices of the ABM, respectively.

[4] At present the approach uses rules of thumb and expert knowledge (when available) to define the ad-hoc pipeline capacity expansion. In general, a network theory based algorithm for a generic network expansion with the goal of alleviating the existing bottlenecks can be used for such purpose. Such an algorithm will not produce a full prediction on the possible future states of the network, but will rather inform the states of the network that could support the anticipated changes to supply and demand.

[5] While hypothetical under the current natural gas distribution system, this configuration allows one to understand what the flows would be in a situation where given the current network topology and no constraints exist on the flows. This would help identify where future pipeline expansion, and may benefit the flows and subsequent price stability in an expanded evolution be informative of the current network's topology required network capacity changes necessary to support the additional export flows.

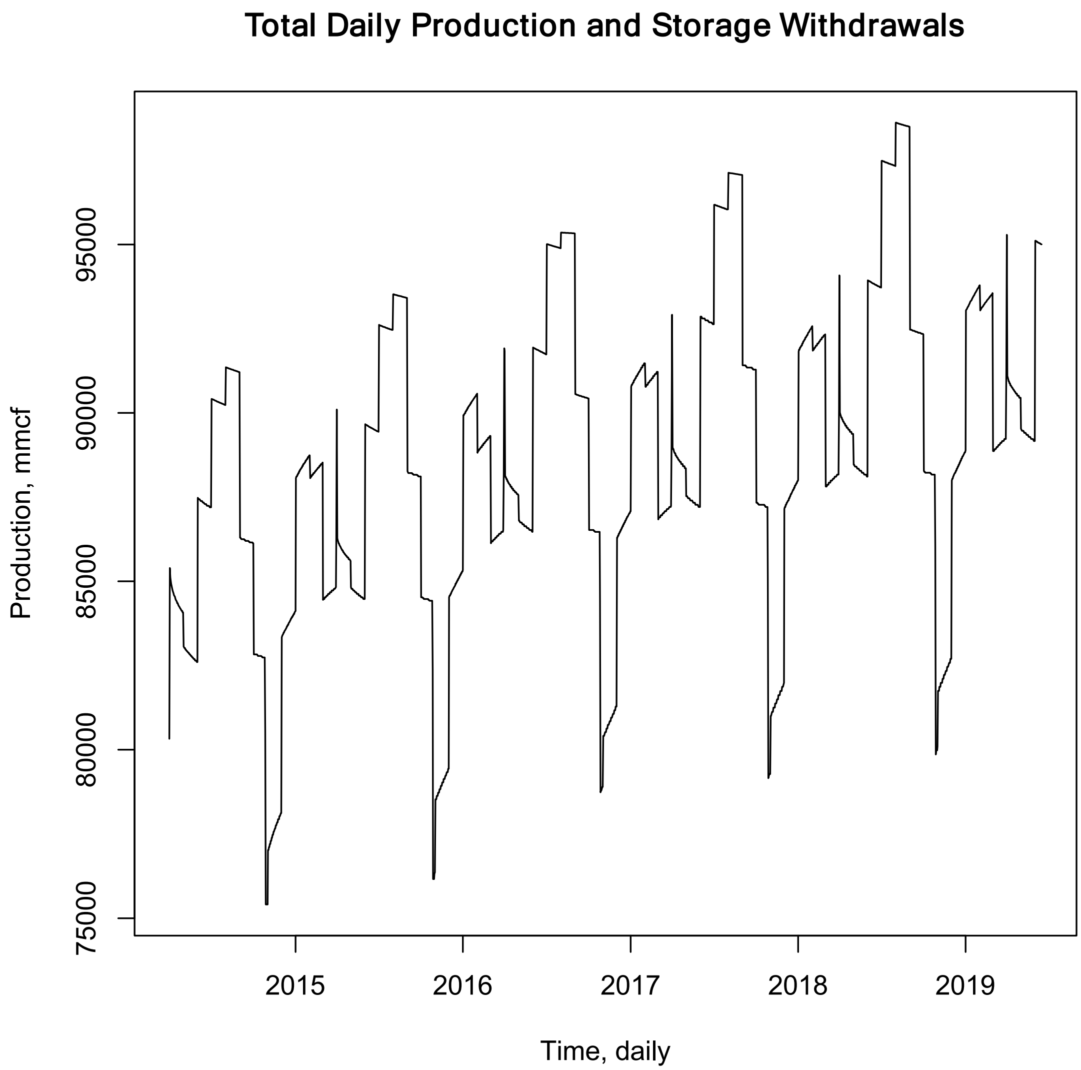

Figure 2.6. Total Daily Production and Storage Withdrawals, Base Case.

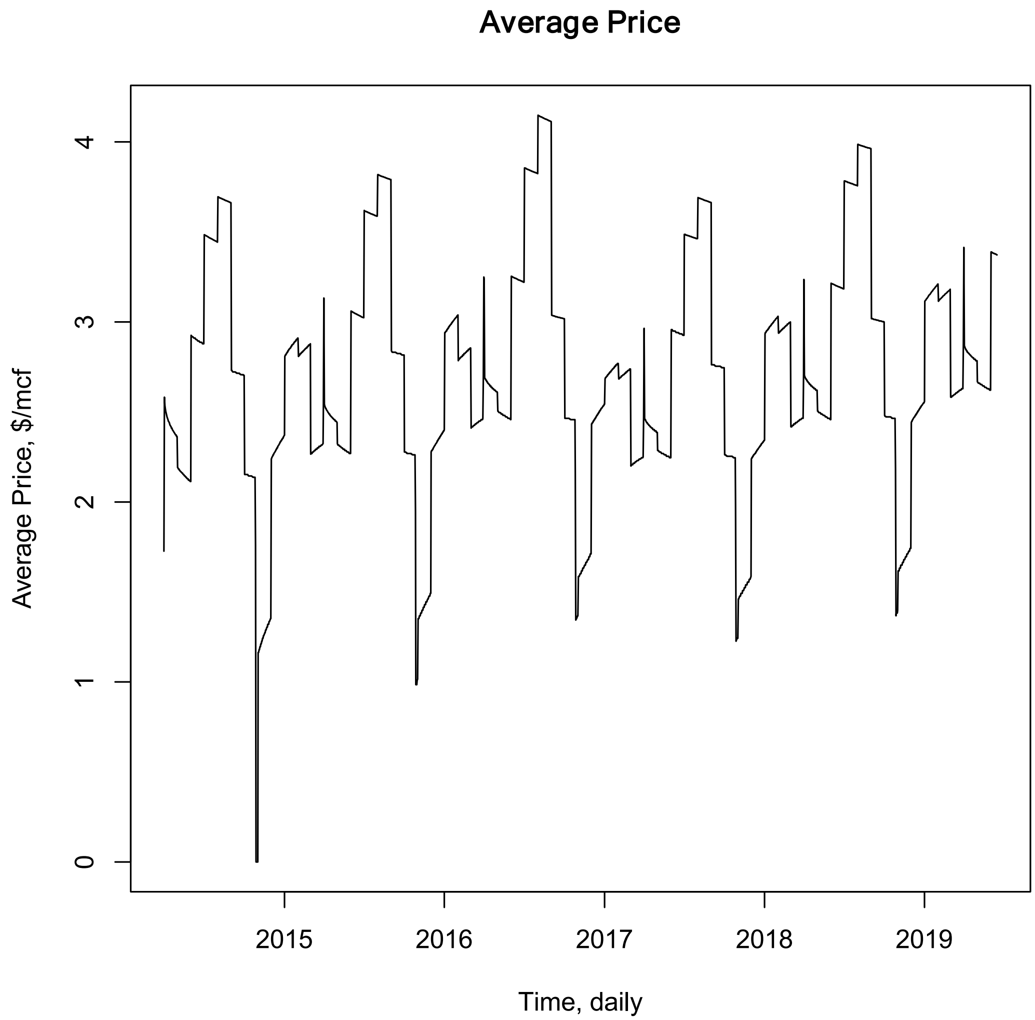

Figure 2.7. Total Daily Production and Storage Withdrawals, Base Case.

2.7.2. LNG Exports Example Analysis

Our prototype example analyses an LNG export terminal addition to the network, evaluates the corresponding natural gas price changes, production and consumption changes, and the effects on the network and individual pipeline's capacity utilization.

We have investigated in a preliminary fashion adding an additional LNG demand to an existing system. We have run a stylized simulation, based in part on the GPCM data on supply, demand, and network pipeline capacity on a stylized network with 762 supply and demand nodes. We have based our LNG addition scenario in part on the potential LNG export scenarios described in Montgomery et al. (2012), and represented the additional demand due to LNG exports scenario equal to 15% of the system-wide demand. This is an aggressive demand increase and may or may not be realized. However, it allows for investigation of the range of possible outcomes. We have observed that prior to addition of the LNG exporting terminals, the prevailing price on the network is $2.21/mmbtu. After adding the LNG exporting capacity, the prevailing network price goes to $3.61/mmbtu[6], thus affecting a substantial increase in the domestic price of natural gas.

While a large amount of additional model development work and analysis needs to be done, our initial results demonstrate the potential for the agent-based approach to modeling and understanding the NG network. The full potential of ABMs will be realized when the LNG and other agents decisions are endogenous. Scenarios including competition between LNG, industrial, and transportation uses can represent both the outcomes and the interplay between the timing of different decisions, and the corresponding path dependence.

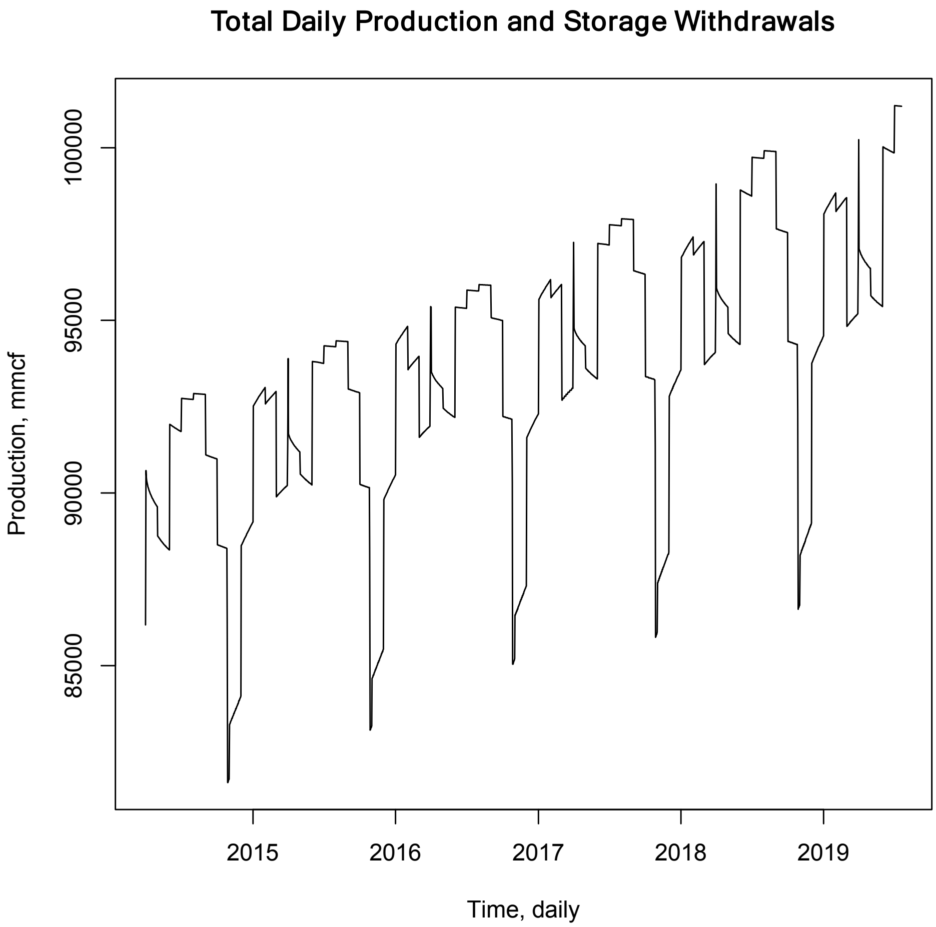

Figure 2.8. Total Daily Production and Storage Withdrawals, Base Case.

[6] Both of the 'before' and 'after' prices are the result of the illustrative, stylized simulation that has been only partially calibrated to the real world data at this stage of the research and is not intended to represent the real-world prices. The magnitude of the price increase after the LNG terminal's addition demonstrates the potential of this approach to incorporate additional agent feedback and the need for additional data calibration to incorporate a more complete set of real world conditions.

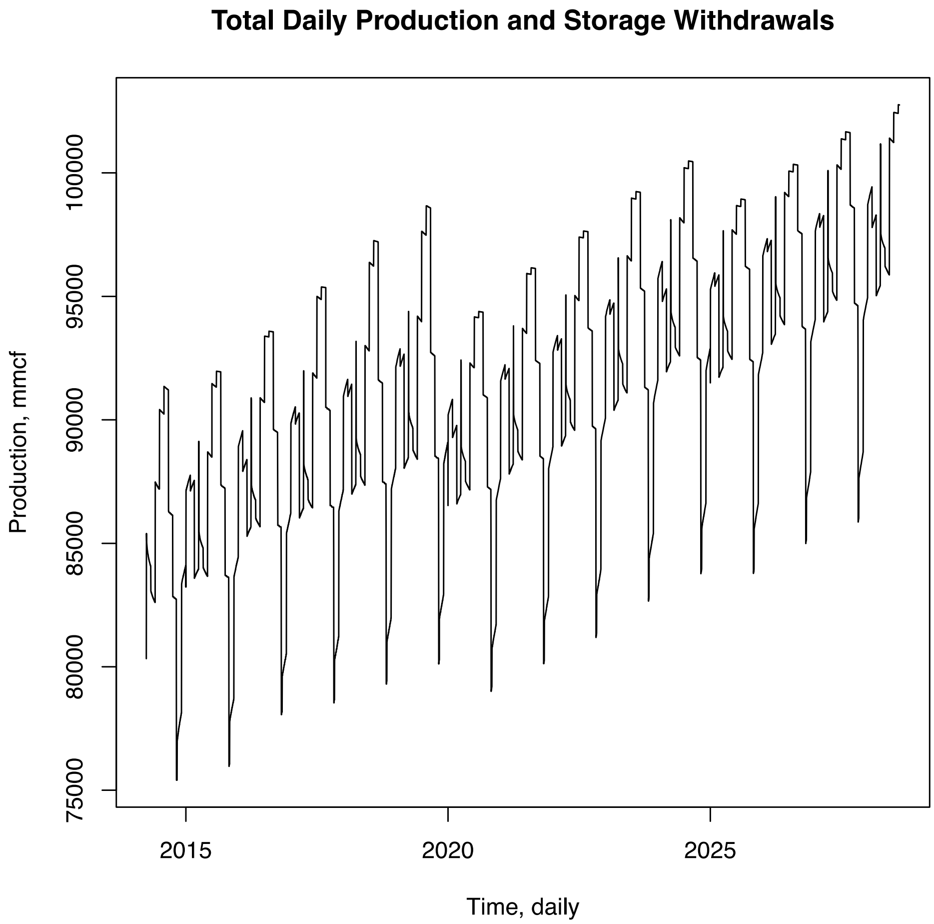

Figure 2.9. Total Daily Production and Storage Withdrawals, Low Supply Case.

2.7.3. Comparisons Across Different Scenarios

The production results for the base case and LNG scenario are given in Figure 2.9. The daily production and storage withdrawals are markedly higher in the LNG scenario over the base case.

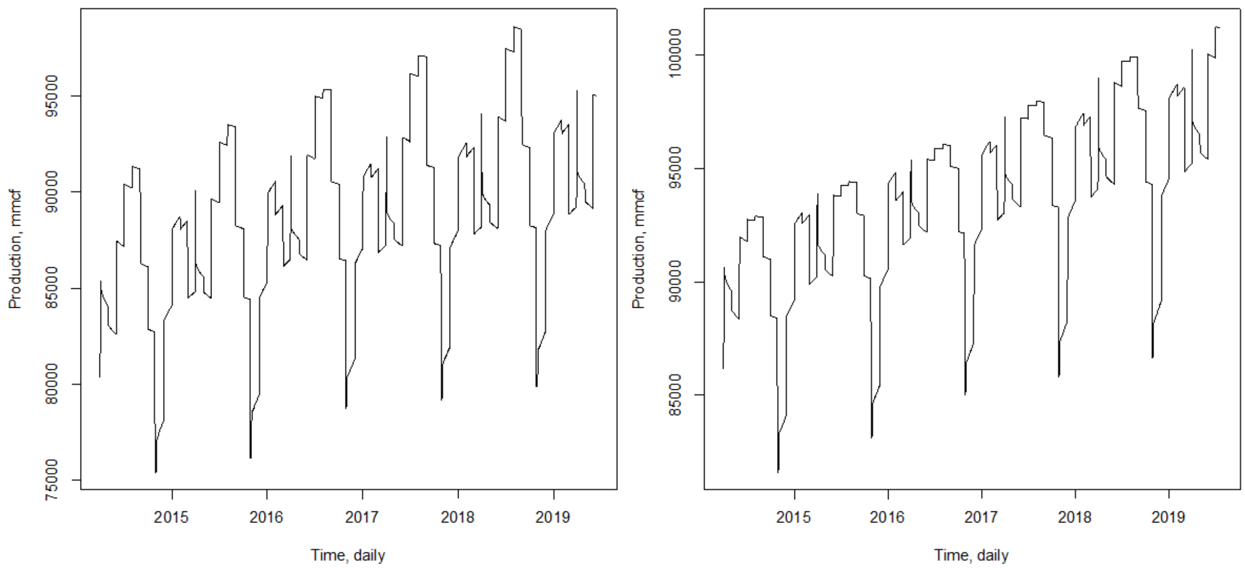

Figure 2.10. Base case total daily production and storage withdrawals for the base case (left) and liquefied natural gas (LNG) scenario (right).

The ABM developed a similar, low natural gas supply scenario. Figure 2.10 illustrates how the low natural gas supply scenario, developed to reflect a declining supply over time from shale gas supplies due to technological or environmental regulatory response divers, reduces daily production and storage withdrawals.

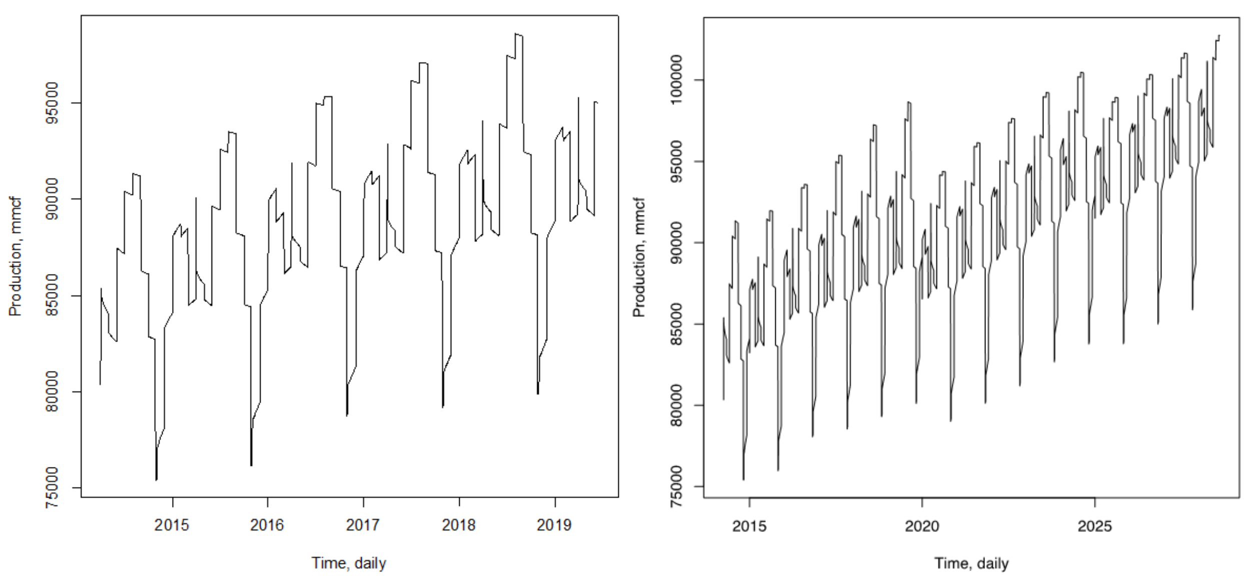

Figure 2.11. Base case total daily production and storage withdrawals for the base case (left) and low natural gas supply scenario (right).

Figure 2.12 illustrates the ABM average natural gas price for the base case, high supply, low supply and LNG export scenarios.

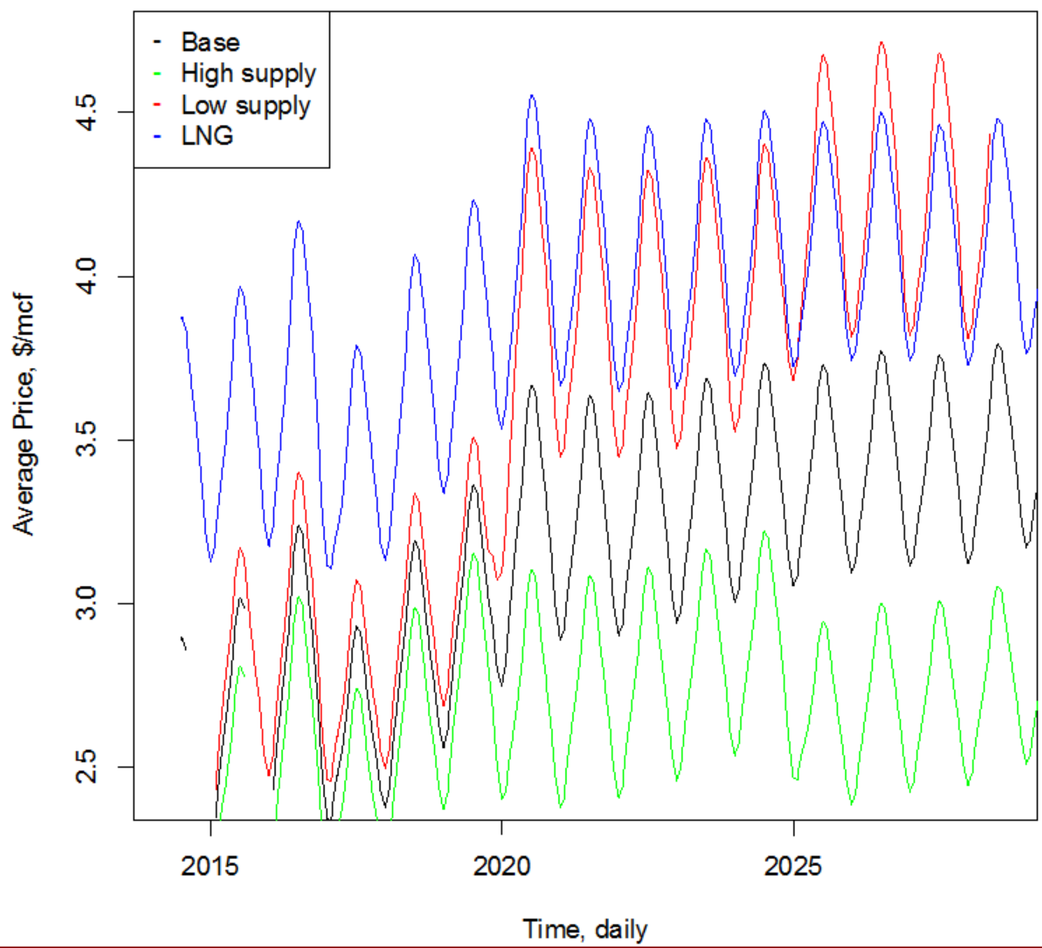

Figure 2.12. Average price for a 90 day moving average for the Base Case, High Supply, Low Supply and liquefied natural gas (LNG) scenario results.

The trends illustrated in Figure 2.12 indicate the high supply case results in relatively lower prices across the NG distribution system in the coming years. Seasonality accounts for the oscillations across all of the scenarios' results. The low supply case results in generally higher prices than the base case and the LNG export scenario generally increases prices in the first half of the simulation period. Near the end of the simulation time period, the price increasing effects of the LNG export scenario, due to infrastructure limitations, become less effective due to infrastructure build out via the supply, demand and storage agent's evolving behavior to reduce costs, and prices generally decrease as compared to the low supply scenario at the end of the simulation period. Figure 2.13 illustrates the percentage change in the 90 day moving average of the price to more clearly illustrate the trends underlying results presented in Figure 2.12.

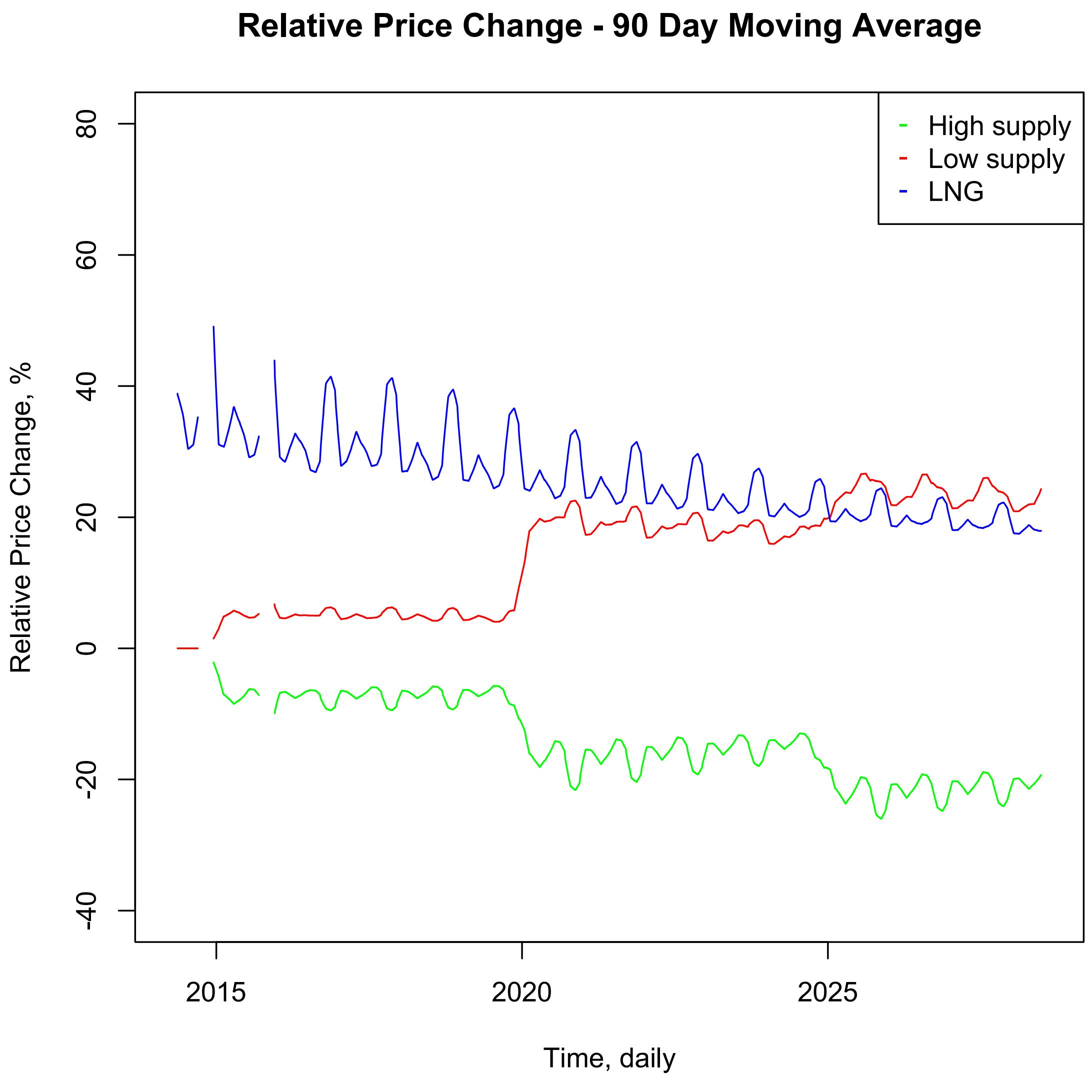

Figure 2.13. Relative Price Change for a 90 Day Moving Average
Note: High, Low and LNG Scenarios.

Table 2.1. Natural Gas Price Range for the Scenarios Analyzed.

	Approximate Averaged Scenario Price Range ($/mcf)			
Time Period	**Base**	**LNG**	**High**	**Low**
2014 - 2020	2.2 – 3.3	3.2 – 4.2	2.2 – 3.1	2.2 – 3.5
2020-2025	2.7 – 3.7	3.5 – 4.5	2.2 – 3.1	3.4 – 4.4
2025-2030	2.9 – 3.7	3.5 – 4.5	2.2 – 3.0	3.5 – 4.7

2.8 ABM Conclusions

Developing and applying an ABM demonstrates the applicability of agent-based modeling to answering various questions in the Natural Gas supply chain. The US NG system has undergone an abrupt change due to increases in supply driven by the ramp up of hydraulic fracturing technology, adding substantial supplies. This has created a system where little historic data exists to represent the possible system evolution. The goal of the proposed modeling effort is to understand in a qualitative and quantitative fashion possible future states of the NG system, effects of possible regulatory actions. This paper outlines a conceptual model as well as a prototype implementation and illustrates it with the studies of four different scenarios, that include an example of a stylized network shock caused by an addition of significant LNG exporting capacity, high and low NG availability, and their comparisons with the base case. We believe the agent-based modeling is a viable tool to understand the future possible evolution of the NG system.

3. QUANTIFYING THE SHALE GAS PHENOMENON: PROJECTING THE IMPACTS OF INVESTMENT AND TECHNOLOGY ON PRODUCTION POTENTIAL

3.1 Introduction

In recent years there has been a rapid expansion of shale gas production in the United States (U.S.) due to the more wide spread application of hydraulic fracturing technology. Additionally, a potentially large shift in demand from coal to natural gas-based electric power or even potentially exporting liquefied natural gas (LNG) may further increase the incentive to manage production appropriately to maximize return on investment. Modeling the changes to the national natural gas supply, evolving energy demands and the cyclical and dynamic investment feedback present several challenges. First, the rapid increase in newly expanded natural gas supplies, led by the application of hydraulic fracturing has been transformative for shale gas extraction and has been proven to be the key to unlocking U.S. domestic reserves of shale gas. Second, there still exists substantial geological uncertainty into the longevity of the shale gas fields using current technology, and short cycle production decline curves are common. Addressing the constantly changing stocks of proven reserves and desired reserve to production ratios in the face of larger supplies and lower prices present a supply to demand modeling challenge. Third, regulatory and demand response changes add more uncertainty to the applicability and longevity of investment seen in the exploration and extraction industry – further complicating the feedbacks to assess the longevity of natural gas supplies and subsequent market prices.

The type of natural gas produced in the U.S. now includes a substantial amount of shale gas in addition to conventionally-produced gas, and coalbed methane. In 1990, for example, conventional and shale gas represented 97% and 1% of the total natural gas produced in the U.S., respectively. By 2011, conventional and shale gas shares changed substantially to 58% and 34% of total U.S. production. The trend to continue producing shale gas is expected to grow to over 50% of the U.S. production by the 2030s (Medlock, 2012; EIA, 2013a; Gracceva and Zeniewski, 2013). Figure 3.1 illustrates the production trends of natural gas in the United States over the last several decades.

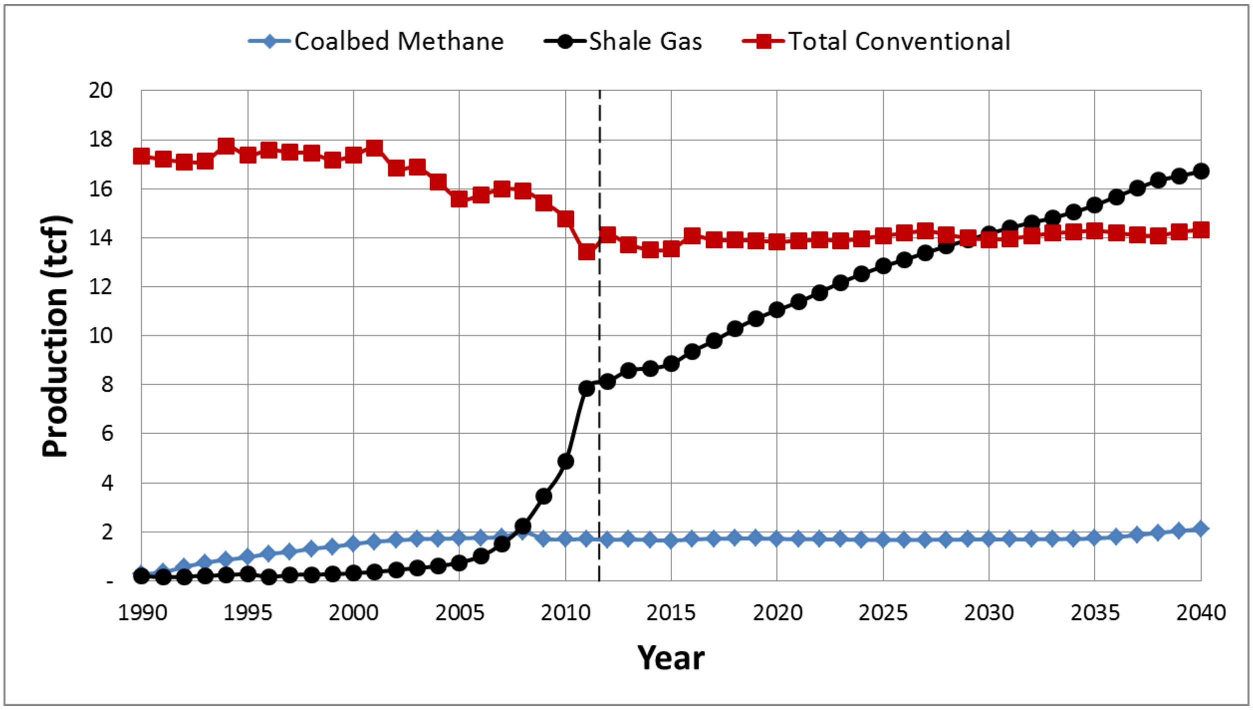

Figure 3.1. The production of shale gas in trillion cubic feet (tcf) has far outpaced production from other sources in the U.S. in recent years EIA, 2013a. (Note: Historical data 1990−2011).

To test the effects of salient technology, market and geologic scenarios, the Natural Gas Production Model (NGPM) was developed by Sandia National Laboratories (SNL). Figure 3.2 illustrates the overarching assessment methodology and causal loop diagram (CLD) framework of NGPM. Each component of the CLD will be described in more detail throughout this paper. Topically, NGPM focuses on the geoscience, technology and market aspects of the system. With this structure, the analysis can develop scenarios that directly address uncertainties in these areas that combine the physical (geoscience, engineered technology) and financial (markets) aspects of the integrated natural gas production market. The analyses include three types of natural gas production such as that extracted using conventional techniques (conventional and tight gas referred to in Figure 3.1), coalbed methane and shale gas.

Using the system dynamics methodology brings the ability to quantify feedbacks across the physical and economic aspects of the natural gas market such that price can be developed endogenously. Other research efforts that address recent increases in shale gas production include a play-specific production set of analyses (Weijermars, 2014; Ikonnikova et al., 2015), optimization modeling (Medlock, 2012), stochastic modeling (Bistline, 2014) and agent based modeling (Outkin et al., 2014). Using system dynamics builds on the strengths of these techniques, but offers the additional benefit of combining aspects from all three approaches (optimization / calibration, Monte Carlo methods, and endogenously-derived systems behavior) into on transparent framework for scenario analysis.

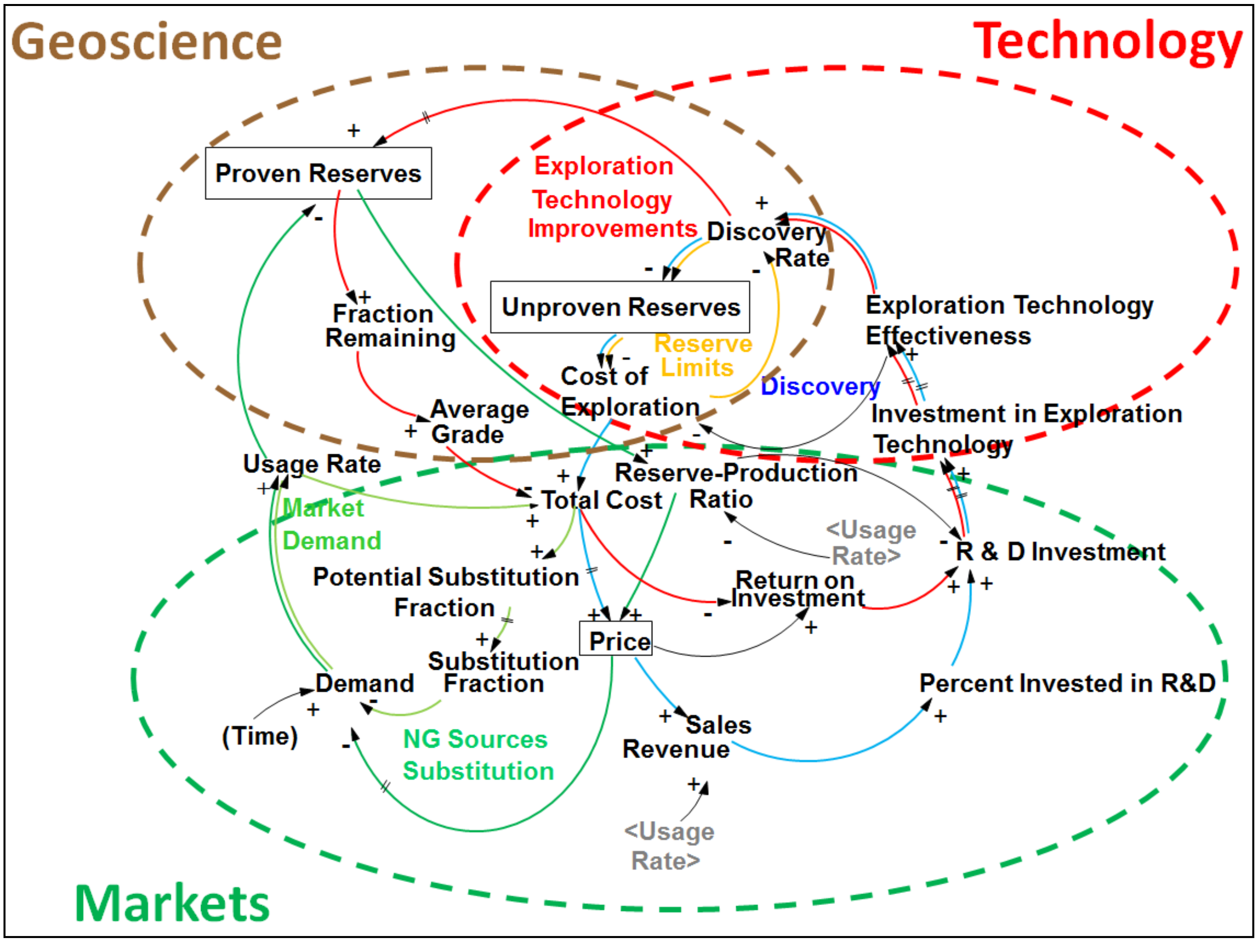

Figure 3.2. The assessment methodology and causal loop diagram. Note: Adapted materials from Naill (1973), Behrens (1973), Sterman and Richardson (1985), Kobos et al. (2015) and Walker et al. (2014; 2015).

3.2 The Natural Gas Production Model

The Natural Gas Production Model (NGPM) is highly interconnected and reliant the reserve limitations, market demands, and currently available technology for exploration and extraction. The NGPM directly addresses each of these components by developing an underlying module for reserve limits, the discovery cycle, exploration technology, market demand, and natural gas source substitution. The flexibility of the input parameters and uncertainty space (Monte Carlo analysis) for each module allows NGPM to successfully calibrate to historical data and develop scenarios to test the effects of new technology and policy developments in the coming decades. The study used parameters collected from literature and other known examples when possible. The NGPM has three overarching core components: the geological data for proved reserves, an exploration technology module that affects discovery and unproven reserves, and a markets module that include market demand and the return on research and development.

The underlying equations of the NGPM were developed and calibrated against historical data and market drivers for natural gas exploration, production and subsequence investment and R&D

feedback for the U.S. The system dynamics-based model allows for the sufficient flexibility to model the quantitative relationships between target supplies of natural gas, supply elasticities, and the market feedback governing the production of conventional natural gas, coalbed methane and shale gas. The model includes the years 1993 to 2025.

Underlying the model's architecture is a foundation of generally-accepted industry nomenclature regarding the convention of natural gas quantities among the suite of data sources employed for the analysis. Notable attempts to standardize the naming convention for terms including technically recoverable reserves, technically unrecoverable reserves, inferred reserves and related terms include those by the Society of Petroleum Engineers and the World Petroleum Council (SPE, 2005), and the U.S. Bureau of Mines and U.S. Geological Survey (1976). All classification systems examine two characteristic axes of a resource, knowledge of the quantity and cost of extraction. Work developed by the Massachusetts Institute of Technology (MIT, 2013) supports the classification of natural gas into Unproven Reserves (UPR) and Proven Reserves (PR), thereby preserving the general ideas expressed in more formal classification work by simplifying the supply space. The modeling approach adopted this naming convention.

3.2.1 Reserve Limits

This relationship represents physical constraints in the Natural Gas production system. The analysis includes three types of NG classification including coalbed methane, conventional gas with tight gas, and shale gas. The NG supply is disaggregated in this analysis into two accumulations, Unproven and Proven Reserves. Figure 3.3 illustrates the dynamics of the Unproven Reserves. The Reserve Limits CLD, as with others, develops such that an arrow indicates the direction influence, and the positive or minus sign indicates the relationship between two variables if the first variable increases (as a standard convention to describe CLDs). For example, as the Discover Rate increases, Unproven Reserves decreases as indicated by the negative sign. Similarly, following this convention, if the Unproven Reserves were to increase, the Cost of Exploration would decrease as indicated by the negative sign.

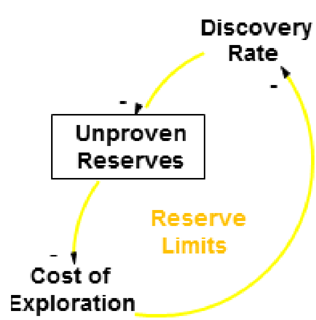

Figure 3.3. Reserve Limits Module. (Note: a negative sign represents the direction of influence from the previous variable, e.g., if the Discovery Rate increases, then the Unproven Reserves decrease).

The underlying equations dictate the direction and size of influence between the variables. The Unproven Reserves decrease when the Discovery Rate increases. Similarly, if the Unproven

Reserves increase, the Cost of Exploration decreases. The discovery rate, in turn, depends on investments from previous discoveries and demand from the economy and demands. The unproven reserves are represented by the relationship,

$$\mu_i = \int_1^t \left(\iota_{i,t-1} - \delta_i\right) dt + \varrho_i \qquad (3.1)$$

where μ_i is the unproven reserves classification type ***i*** where ***i*** = coalbed methane, conventional gas and shale gas, ι_i is the initial unproven reserves at either the beginning of the analysis but then uses the value from the previous time step throughout the period of analysis, δ_i is the discovery rate, and ϱ_i is the representation of an exogenous technological shock to, for example, increase Unproven Reserves. Table 3.1 illustrates the values of several key model variables based on historic data.

Table 3.1. Initial model input values (in 1993) for the main driving variables based on historic data.

Variable	**Value**	**Source / Note**
Initial Unproven Reserves (tcf)[1]	---	
Coalbed Methane	196.5	EIA, 2009 (Technically Recoverable Resource; EIA (AEO), 2013a for total production percentage values of total (1.5, 92.2, 6.3) % for coalbed methane, conventional and shale gas, respectively.
Conventional Gas	2112.9	
Shale Gas	46.6	
Discovery Rate (MMcf/yr)[1]		Initial Discovery Rate at ***t****=0*
Coalbed Methane	1,691,617	
Conventional Gas	24,365,498	
Shale Gas	2,143,871	
Exogenous increase in Unproven Reserves	0	Initial value at ***t*** = *0*; t = 2005, Shale Gas = 702.4 tcf; ***t*** = 2010, Coalbed Methane = 153.9 tcf.
Proven Reserves (tcf)		Adapted from EIA, 2015b (165,015 bcf proven reserves) and applied percentages by NG type from the EIA, AEO (2013a), production dataset of NG production by source.
Coalbed Methane	10.40	
Conventional Gas	152.14	
Shale Gas	2.48	
Usage Rate (tcf/yr)[1]		
Coalbed Methane	0.75	
Conventional Gas	17.14	
Shale Gas	0.22	

1. Calculated.
2. Adapted from the USGS (2013), used the basin-specific, 5% likelihood scenario of undiscovered, unproven reserves.

3.2.2 Discovery Cycle

The discovery cycle CLD includes several key variables that influence the discovery rate for natural gas. The discovery rate ($\delta_{i,t}$) is an equation that accounts for the effective investment in exploration ($EIIE_{i,t}$) divided by the cost of exploration ($COEL_{i,t}$).

$$\delta_{i,t} = \frac{EIIE_{i,t}}{(COEL_{i,t})} \tag{3.2}$$

$$COEL_{i,t} = TI_{i,t} * y_i \tag{3.3}$$

where the effective investment in exploration $(EIX_{i,t})$ depends upon the investment for exploration using an assumed exponential material delay of the input of the third order such that the investment in exploration technology $(EP_{i,t})$, Discovery Delay $(DD_{i,t})$ third order input drive the relationship:

$$EIX_{i,t} = DELAYMTR\,(EP_{i,t}, DD_{i,t}, 3) \tag{3.4}$$

where the discovery delay for the coalbed methane, conventional gas and shale gas use a base case optimized setting of 3.96, 2.42 and 2.12 years, respectively.

$$COEL_{i,t} = TI_{i,t} * y_i \tag{3.5}$$

and

$$y_i = y_a + (y_b - y_a)\,\frac{x_i - x_a}{\Delta x} \tag{3.6}$$

where $TI_{i,t}$is the technology input change by source of natural gas,

$$x_a = n\Delta x \tag{3.7}$$

and n is chosen such that

$$n\Delta x < x_i \leq (n+1)\Delta x \tag{3.8}$$

and

$$y_a = \underset{y}{\rightarrow}(n+1) = \underset{y}{\rightarrow}(n+1) \tag{3.9}$$

$$y_b = \underset{y}{\rightarrow}(n+2) = \underset{y}{\rightarrow}(n+2) \tag{3.10}$$

where the values of n for y_i are chosen based on the bounding values adopted from Naill (1973) in the base case using this linear interpolation. [7] This interpolation factor allows the model to utilize input that adjusts the cost of exploration based on the fraction of unproven reserves remaining (x)[8]. The initial costs of exploration were determined to be \$2.22e-3, \$2.90e-3 and \$5.77e-4 per cubic foot in order to match historic proven reserves.[9] This is one method to

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[7] Base case uses a table function that employs the following trend to represent a cofactor to develop an increasing cost of exploration as the ratio starting value of assumed resources relative to the actual resources available increases to represent an increasing cost of exploration through time until a new source is included.

[8] Where the initial value of the unproven reserves for coalbed methane, conventional gas and shale gas in the base case are: 196.54, 2,112.86 and 46.58 tcf, respectively.

initialize the model which then determines the appropriate price feedback to match historic proven reserves under the base case demand, return on investment, and other key driver levels and trends. The model calculated the optimized initial levels for discovery delay (years), the desired reserve to production ratio and marginal cost multiplier for each of the three natural gas types.

Figure 3.4 illustrates the feedback between the discovery rate and its influence on cost, price, invested R&D and ultimately exploration effectiveness.

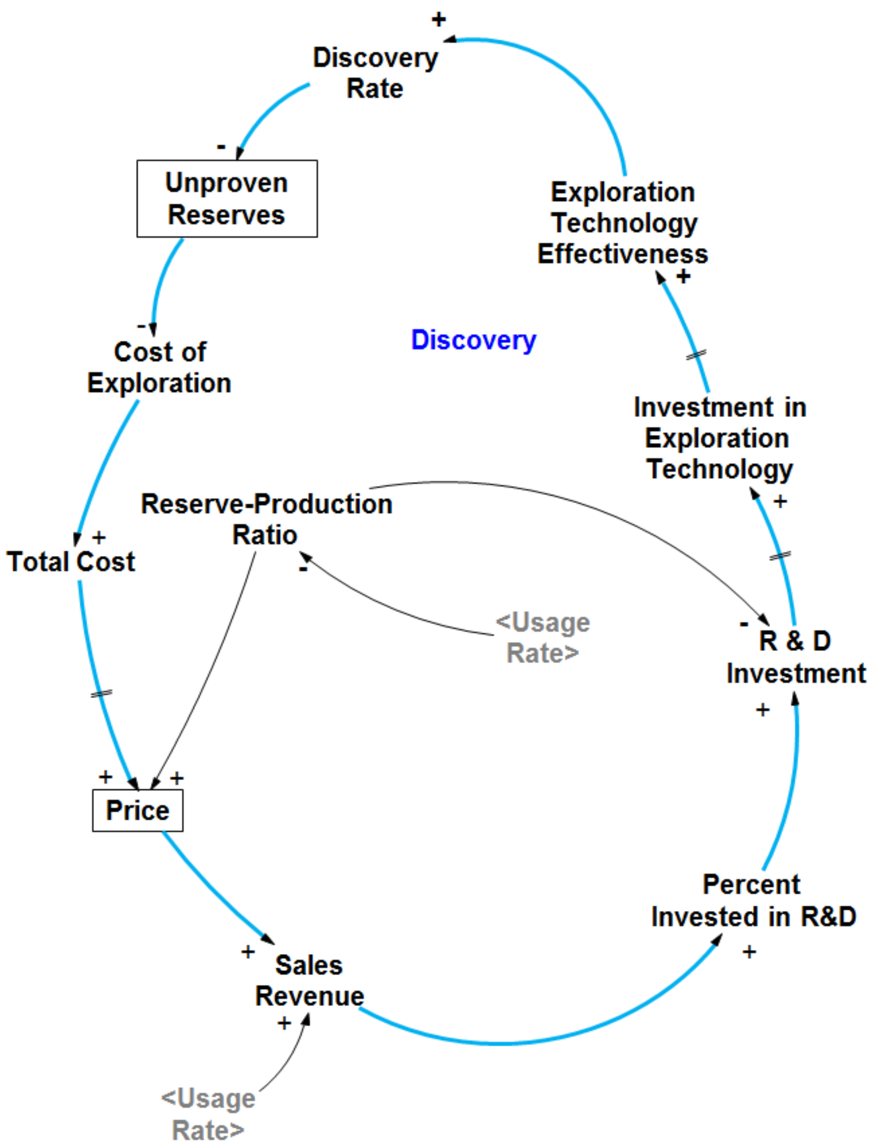

Figure 3.4. Natural Gas Discovery Module.

[9] The values of the initial costs of exploration required to more accurately match proven reserves were determine using the optimization tool within Powersim Studio.

3.2.3 Exploration Technology

The Exploration Technology Improvements module begins with assessing the Proven Reserves across the three NG classifications. This module shows the balancing loop where investments in exploration technology may increase the discovery rate which ultimately will increase Proven Reserves. The module includes several factors that affect this process such as the scarcity of natural gas (fraction remaining, average grade) that affect the total cost including extraction, production and explicit exploration costs. Total costs may come down due to technology's resulting production increase (or cost decrease for similar production levels) thereby increasing the return on investment. Figure 3.5 illustrates the exploration technology improvements module and how an increase in proven reserves increases the fraction remaining in the natural gas resource. A higher fraction of reserves, for example, leads to a lower cost of exploration and total cost, thereby leading to more favorable R&D investments, increasing the amount of R&D going to exploration technology. This feedback system ultimately increases the discovery rate of new natural gas resources.

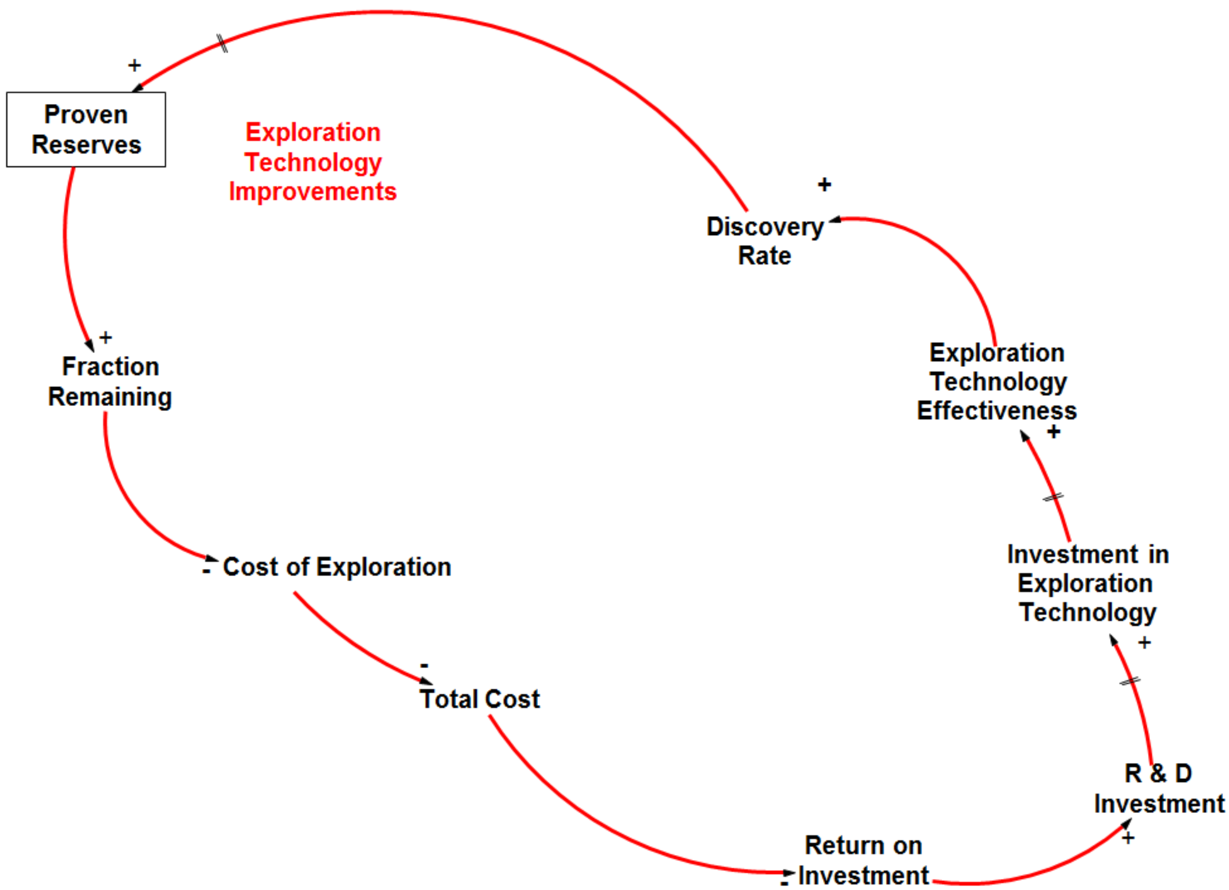

Figure 3.5. Exploration Technology Improvements Module.

The Proven Reserves is represented by the relationship,

$$\rho_{i,t} = \int_1^t \left(\alpha_{i,t-1} + \delta_{i,t} - \beta_{i,t}\right) dt \tag{3.11}$$

where ρ_i is the proven reserves, $\alpha_{i,t-1}$ is the proven reserves classification type $\boldsymbol{i}$ at either the beginning of the analysis but then uses the value from the previous time step throughout the period of analysis, β_i is the usage rate.

$$\alpha_{i,t} = \begin{Bmatrix} \alpha_{i,t} = \{\alpha_1, \alpha_2, \alpha_3\}, \ \ if\ t = 0 \\ \rho_{i,t-1} = \{\rho_{1,t-1}, \rho_{1,t-1}, \rho_{1,t-1}\}, \ \ if\ t > 0 \end{Bmatrix} \tag{3.12}$$

$$\beta_{i,t} = \left(\gamma_i * \left(e^{c*\Delta t}\right)\right) * DM_t \tag{3.13}$$

$$DM_t = f(P) \tag{3.14}$$

$$P = SMT_t * PM \tag{3.15}$$

where γ_i is the initial usage rate, $e^{c*\Delta t}$ is the exponential growth multiplier, c is the growth constant (0.03)[10], Δt is the difference between the initial time and the current time, DM_t is the demand multiplier based on Naill, 1973. The price (P) is then based on the smoothed total cost (SMT_t) weighted by the reserve to production ratio (16 years in the base case), and multiplied by the price multiplier table (PM).

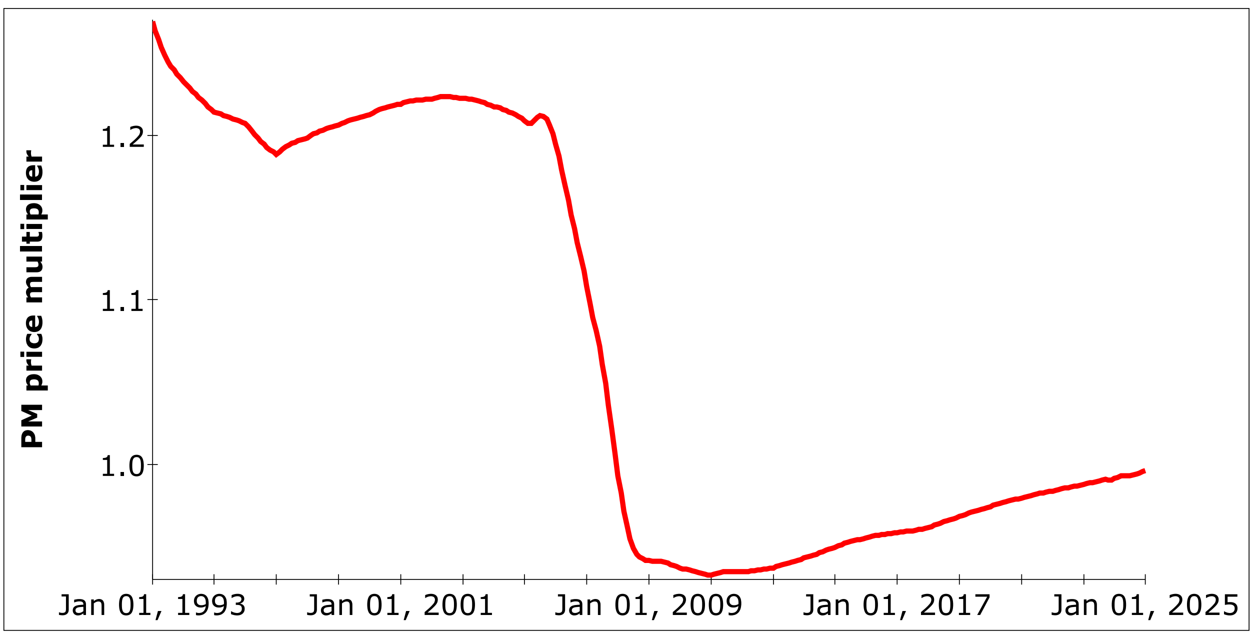

Figure 3.6. The price multiplier table representing an inverse relationship between the amount of proven reserves, and the effect on price (scarcity pricing factor).

$$FURR = \frac{UPR_{i,t}}{UPR_{i,x}} \tag{3.16}$$

[10] Based on EIA Annual Consumption Data of 1993 through 2006, optimized for model calibration (EIA, 2013b).

$$UPR_{i,x} = \begin{cases} UPR_{i,x} = \{UPR_1, UPR_2, UPR_3\}, \ \ if\ t = 0 \\ UPR_{i,x} = \{UPR_1 + y_1, UPR_2 + y_2, UPR_3 + y_3\}, \ \ if\ t \geq 2005 \end{cases} \tag{3.17}$$

where $FURR$ is the fraction of unproven reserves, $UPR_{i,t}$ is the unproven reserves by type at time t, $UPR_{i,x}$ is the unproven reserves by type based on initial estimates, and then corrected estimates after 2005 to account for shale gas production increases.

The cost of exploration ($COEL_{i,t}$) may also change over time. The total cost to produce natural gas ($TC_{i,t}$) is a combination of the total cost of exploration ($COEL_{i,t}$) multiplied by a hypothetical adjustment factor to account for a percent change for the marginal cost of the resource.[11] The marginal cost represents the costs associated with extraction.

$$TC_{i,t} = (COEL_{i,t}) * (MAR_{i,t} * PCMAR_{i,x}) \tag{3.18}$$

where marginal cost ($MAR_{i,t}$=*5.00, 2.94, 3.30)* for coalbed methane gas, conventional gas and shale gas, respectively[12],

$$COEL_{i,t} = TI_{i,t} * y_i \tag{3.19}$$

and

$$y_i = y_a + (y_b - y_a)\frac{x_i - x_a}{\Delta x} \tag{3.20}$$

where $TI_{i,t}$is the technology input change by source of natural gas,

$$x_a = n\Delta x \tag{3.21}$$

and n is chosen such that

$$n\Delta x < x_i \leq (n+1)\Delta x \tag{3.22}$$

and

$$y_a = \underset{y}{\rightarrow}(n+1) = \underset{y}{\rightarrow}(n+1) \tag{3.23}$$

$$y_b = \underset{y}{\rightarrow}(n+2) = \underset{y}{\rightarrow}(n+2) \tag{3.24}$$

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[11] The values 3.73, 2.63, 4.73 were calculated for coalbed methane, conventional gas and shale gas, respectively. Optimizing the cost of exploration, marginal cost for each natural gas type, discovery delay, the desired reserve to production ratio and price in earlier versions of the NGPM based on minimizing the squared difference between historical and simulated proven reserves for coalbed methane, conventional gas and shale gas returned these marginal cost multipliers.

[12] The values of the marginal cost multiplier were determined using and optimization solver within Powersim Studio based maximizing the fit of the calculated as compared to the historical proven reserves for conventional, shale gas and coalbed methane.

where the values of n for y_i are chosen based on the bounding values adopted from Naill (1973) in the base case using this linear interpolation. [13] This interpolation factor allows the model to utilize input that adjusts the cost of exploration based on the fraction of unproven reserves remaining (x)[14]. The initial costs of exploration were determined to be \$2.22e-3, \$2.90e-3 and \$5.77e-4 per cubic foot in order to match historic proven reserves.[15] This is one method to initialize the model which then determines the appropriate price feedback to match historic proven reserves under the base case demand, return on investment, and other key driver levels and trends. The model calculated the optimized initial levels for discovery delay (years), the desired reserve to production ratio and marginal cost multiplier for each of the three natural gas types.

Figure 3.7 illustrates the cost of exploration multiplier behavior used in the cost of exploration to represent the assumption of an increasing cost of exploration until a new resource is developed.

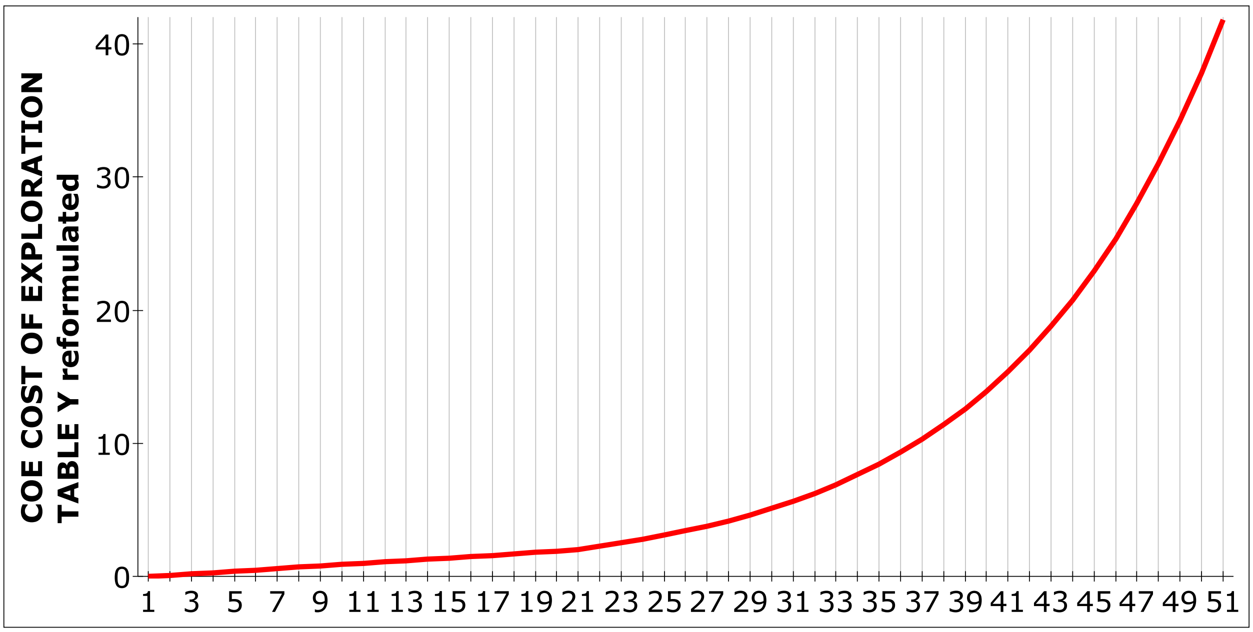

Figure 3.7. Cost of Exploration multiplier table used to represent increasing costs across the time between when new resources are developed.

The percentage change for the marginal cost of the resource ($PCMAR_{i,x}$) accounts for an exogenous, rapid price decline for shale gas in 2012 in the base case.

$$ROI_{i,t} = NGP_{i,t}/TC_{i,c} \tag{3.25}$$

[13] Base case uses a table function that employs the following trend to represent a cofactor to develop an increasing cost of exploration as the ratio starting value of assumed resources relative to the actual resources available increases to represent an increasing cost of exploration through time until a new source is included.
[14] Where the initial value of the unproven reserves for coalbed methane, conventional gas and shale gas in the base case are: 196.54, 2,112.86 and 46.58 tcf, respectively.
[15] The values of the initial costs of exploration required to more accurately match proven reserves were determine using the optimization tool within Powersim Studio.

The investments in research and development for exploration ($R\&DP_{i,t}$) is a function of the ($ROI_{i,t}$) such that as the return on investment increases, so do the expenditures on exploration and extraction technologies and efforts:

$$R\&DP_{i,t} = GRAPH\left(RPR_{i,t} \mathbin{/} DRPR_{i,t}, 0.2, 0.2, PIIP_i\right) * ROI_{i,t} \tag{3.26}$$

where $GRAPH$ is a table function that returns the values of a horizontal extrapolation beginning at 0.2, using 0.2 increments while incorporating feedback from the reserve to production ratio ($RPR_{i,t}$) that itself is a function of proven reserves divided by the average usage rate.

Additionally, the desired reserve to production rate ($DRPR_{i,t}$) serves as the denominator of the starting point of the graph which is collectively the ratio ($RPR_{i,t} \mathbin{/} DRPR_{i,t}$), and the percent invested in exploration table ($PIIP_i$) is the assumed, corresponding result to the horizontal extrapolation represented by this ratio taken from an assumed lookup table.[16] Figure 3.8 illustrates both the return on investment multiplier and the percent invested in exploration tables' magnitude and behavior. The return on investment behavior represents an increasing return initially when the price is above total cost, but then a plateau effect occurs to represent a situation when price may be lower than total cost and return on investment is reduced. Similarly, the percent invested in exploration behavior represents a situation where capital investments are reduced in instances of lower revenues driven by lower prices.

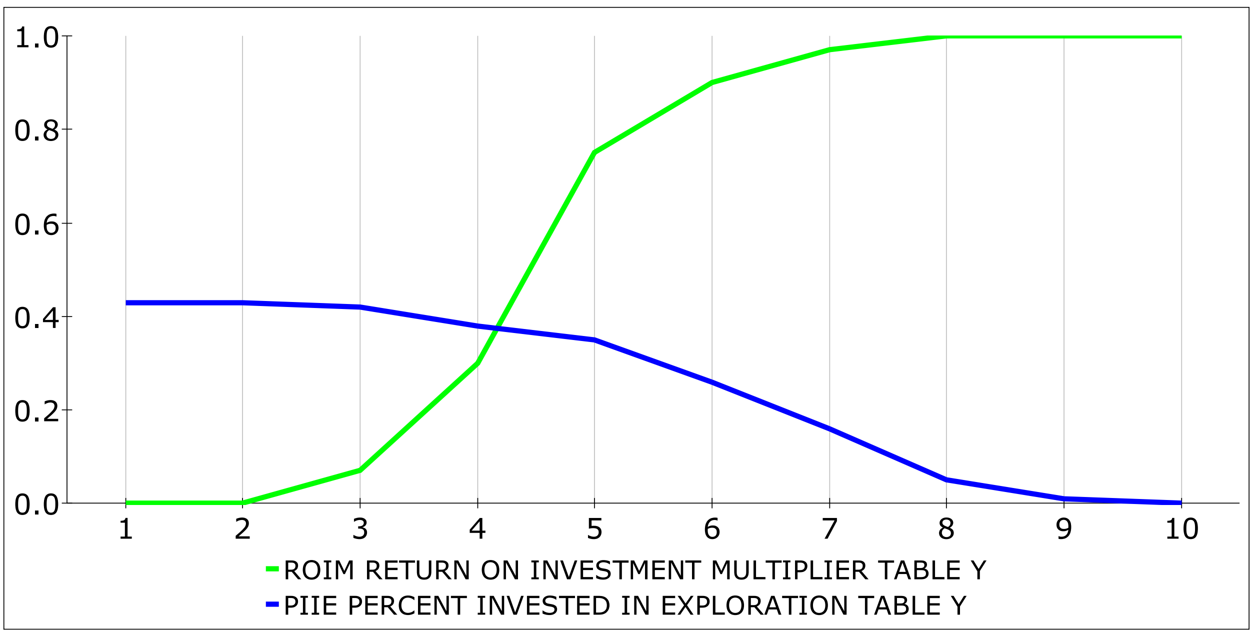

Figure 3.8. The return on investment and percent invested in exploration behaviors employed with the model framework.

[16] The ten points on the exploration GRAPH function's interpolation for the given input ratio values from the reserve to production ratio to desired reserve to production ratio relationship. The initial instance of the desired reserve to production ratio is an assumed 15.13 years.

The initial functional form of the research and development for exploration includes the added ability to alter the values in the assumed lookup table to test different scenarios as needed for the percent invested in R&D as appropriate.

3.2.4 Market Demand & Natural Gas Source Substitution

The market demand module includes many drivers including the demand multiplier, the price of natural gas, the reserve to production ratio, proven reserves, and the usage rate of natural gas. Figure 3.9 outlines the causal loop diagram illustrating the key variables that influence the market demand within the analytical framework.

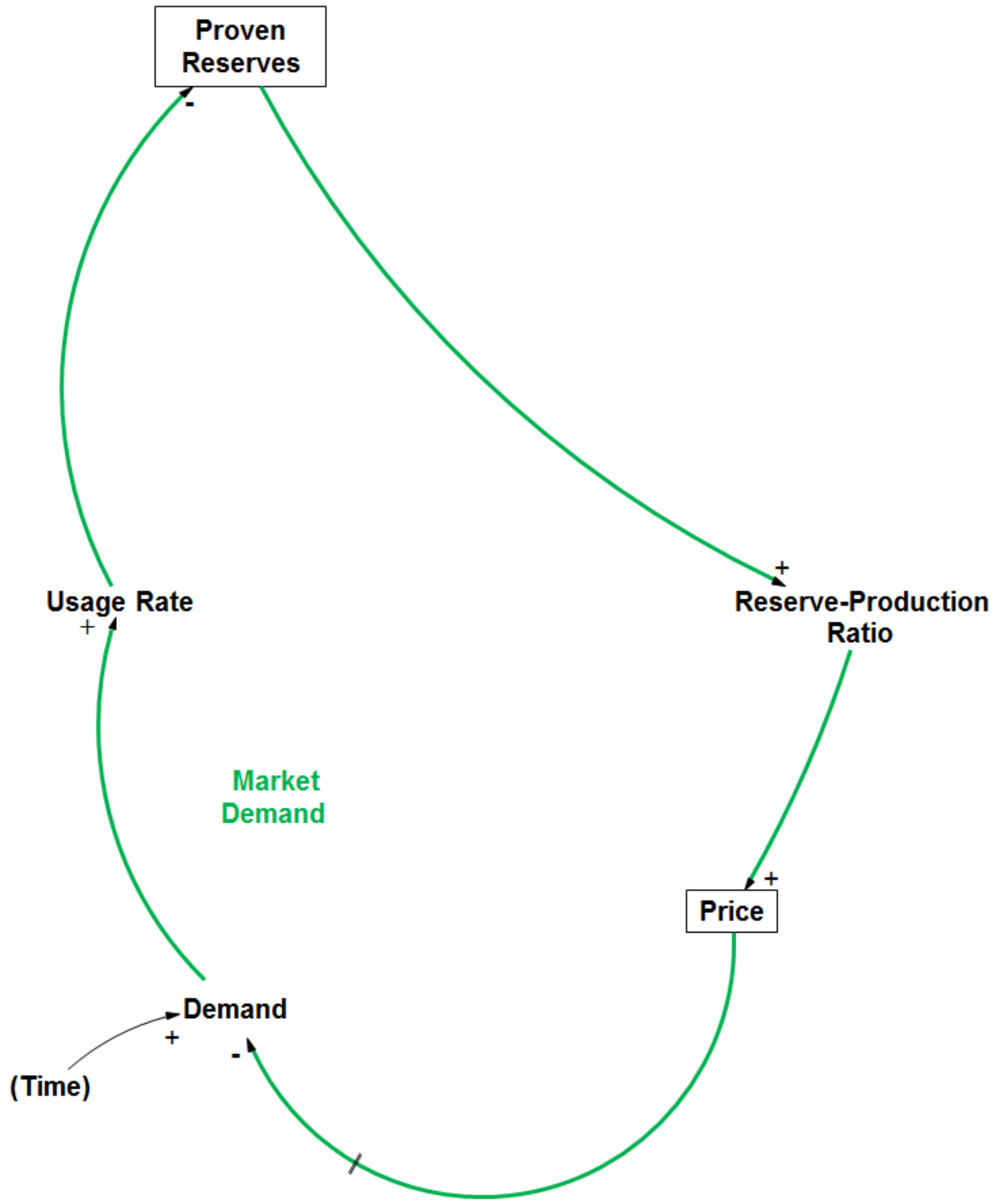

Figure 3.9. Market Demand Module.

The usage rate ($\beta_{i,t}$) (the actual quantity of gas demanded) is a function of the usage rate potential (URP), the demand multiplier (DM_i), and the allocation percent (AP_i) of gas from each source. This section gives additional details salient to the base case run beyond the initial definition of the usage rate given in the earlier definition of proven reserves ($\rho_{i,t}$).

$$\beta_{i,t} = (URP * DM_i * AP_i) \tag{3.27}$$

where

$$URP = \begin{cases} (UR3 * e^{GC1} * t_{0+x} - t_0) & \text{for time <=1993;} \\ (UR3 * e^{GC2} * t_{0+x} - t_0) & \text{for 1993 >= time > 2007} \\ (UR3 * e^{GC3} * t_{0+x} - t_0) & \text{for time >= 2007} \end{cases} \tag{3.28}$$

such that the base time year (t_0) and the time of the simulation run (t_{0+x}) and the growth rates e^{GC1} , e^{GC2} , e^{GC3} based on data provided by the Energy Information Administration (EIA, 2013b) drive the URP, the demand multiplier DM_i is set such that if the price is below a given threshold, a one multiplier drives the DM_i, such as a linear growth rate based on an one set of conditions ($DM1T$), whereas if the price is equal to or greater than a given price, another set of conditions can be employed using the following formula.

$$DM_i = IF\big(P_i \geq 0.001, GRAPH(P_i, 0.001, 0.001, DM2T)\big), \\ GRAPH(P_i, 0, 0.001, DM1T)) \tag{3.29}$$

The base case demand multipliers ($DM1T, DM2T$) are approximations adapted from Naill, 1973[17]. Figures 3.10 and 3.11 illustrate the CLD for the usage rate, and the magnitude and behavior of the demand multipliers, respectively.

[17] The DM1T multiplier table base case values were adapted from Naill, 1973, but are adjustable for custom scenario analysis based on new demand elasticity information as it becomes available.

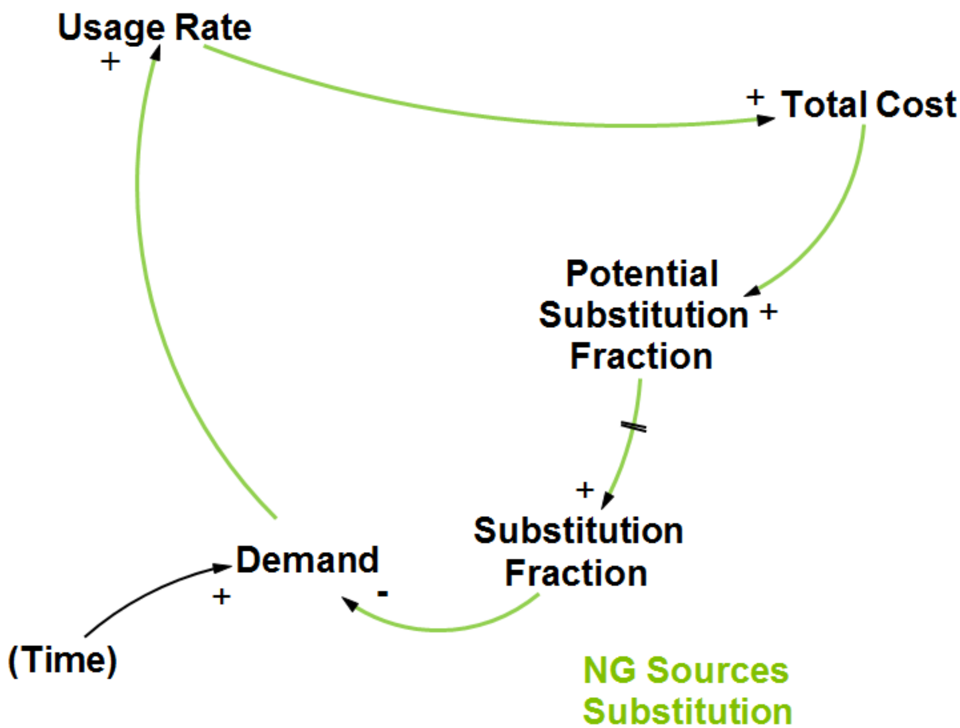

Figure 3.10. Natural Gas Sources Substitution Module.

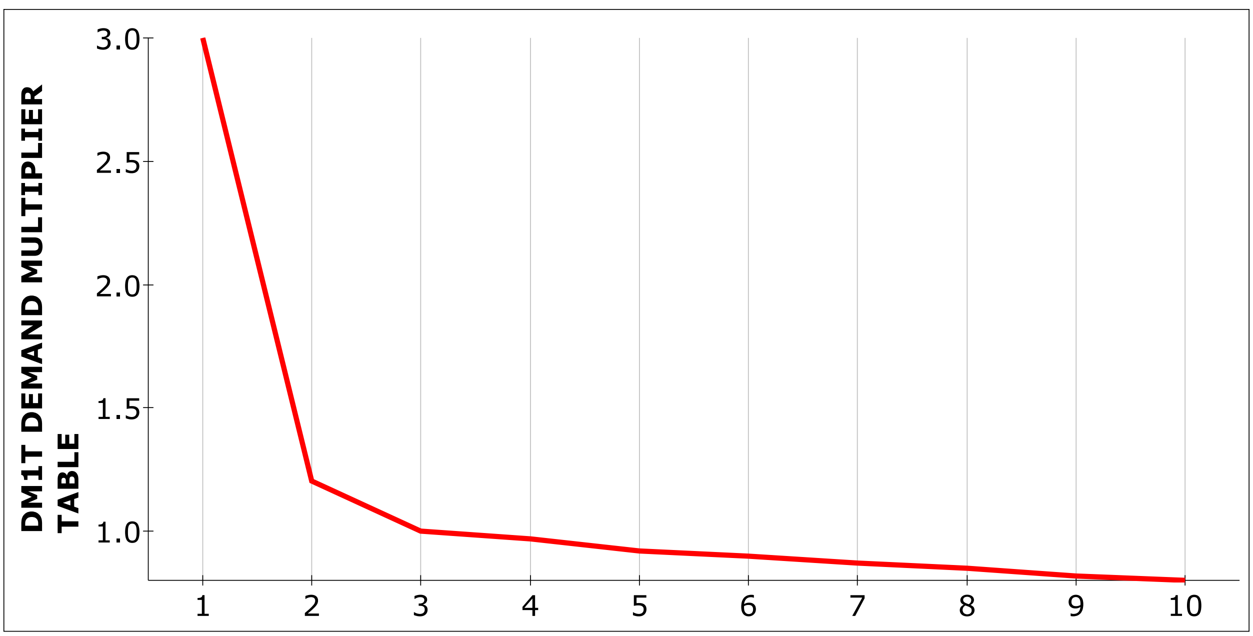

Figure 3.11. The base case demand multiplier tables used to drive demand behavior based on the relative, endogenously-developed price within the given scenario.

The allocation percent (AP_i) changes over time due to varying costs per source of natural gas. The base case usage percent $(BCUP_i)$ using cost as a driver is a key component, along with a regulatory intervention (RI_i) variable that allows for regulations to enhance or inhibit the production of proven reserves.

$$AP_i = \frac{(BCUP_i * RI_i)}{\sum(BCUP_i * RI_i)} \quad (3.30)$$

where

$$RI_i = GRAPH(RLF_i, 0, 0.1, RIT) \quad (3.31)$$

such that the reserve life fraction per source (RLF_i) and the regulatory intervention table (RIT), the latter of which is a customizable decreasing influence to signify a potential to slow (or increase) depleting proven reserve, drive the regulatory intervention factor.

The reserve life fraction per source employs the reserve to production ratio (RPR_i) and the regulatory intervention threshold (RIR) which uses 8 years in the base case.

$$RLF_i = RPR_i / RIR \quad (3.32)$$

3.3 Model Results

The base case scenarios for each of the three types of natural gas production vary greatly depending upon the historical levels of production and recent exploration enhancements. First, the model was developed and the base case results compared favorably to the historical data presented in Figure 3.12.

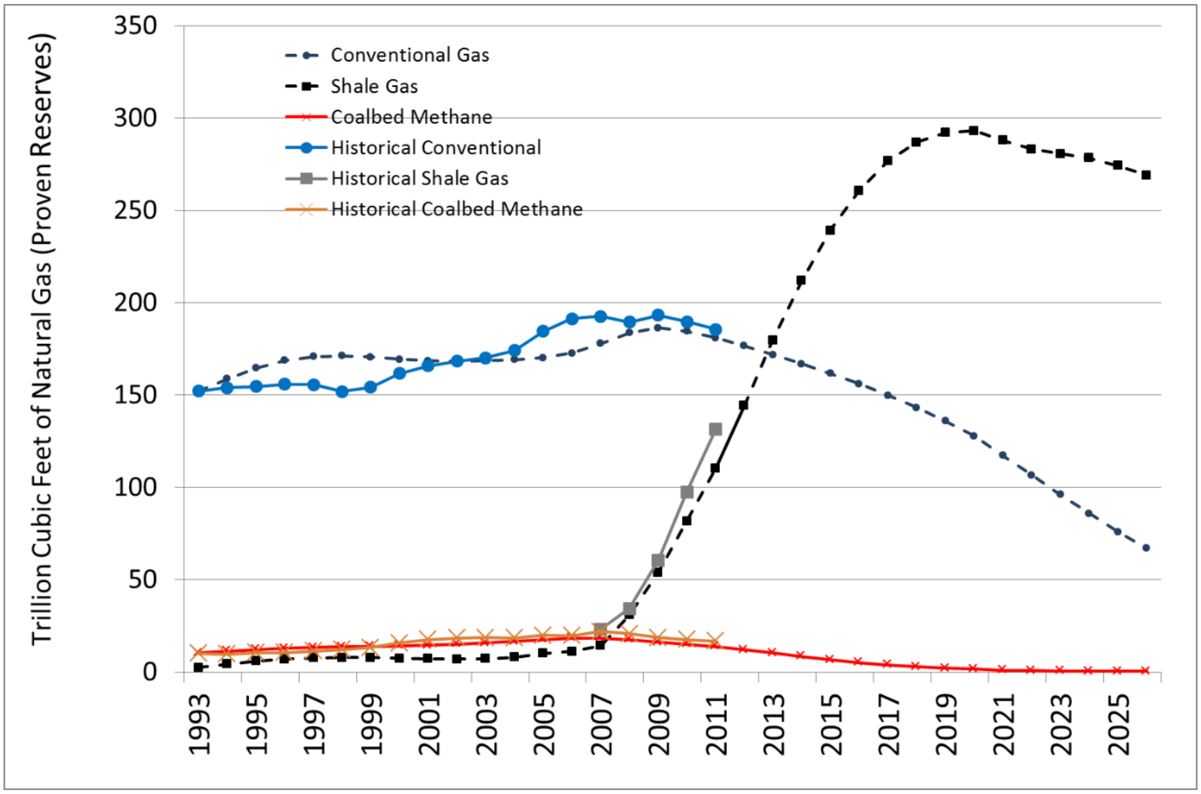

Figure 3.12. Conventional, shale gas and coalbed methane historical data and base case model projections (Note: historical data, 1993−2011; projections from 2012−2025).

The usage rate of natural gas by type has been changing over the last decade, and is projected to increase for conventional gas unless additional shale gas reserves are brought online with new price pressures. Figure 3.13 illustrates the historical and projected usage rate for conventional natural gas, coalbed methane and shale gas.

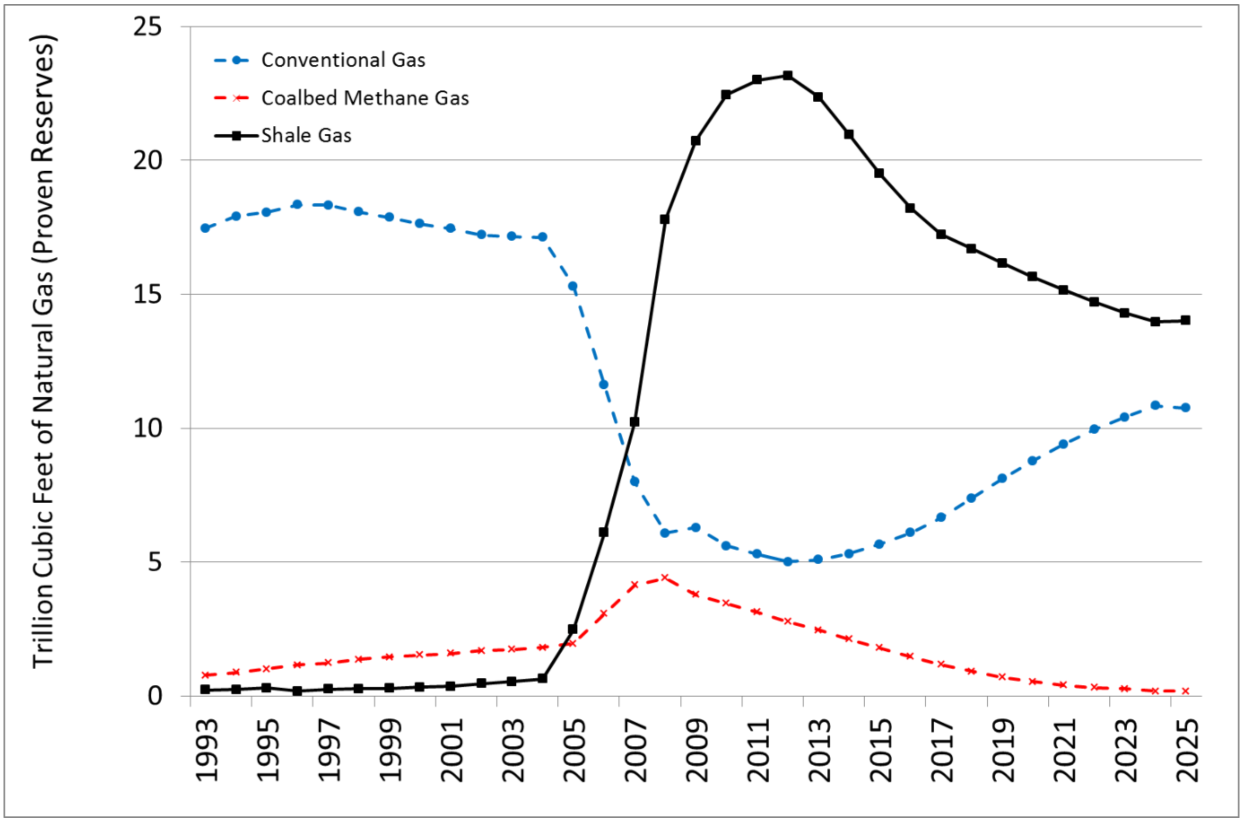

Figure 3.13. Historical and projected usage rate from the Natural Gas Production Model (NGPM) for natural gas in the U.S. (Note: historical data, 1993−2011; projections from 2012−2025).

3.3.1 Scenario Analysis

The results from the Shale Gas-specific production scenario analysis for the geoscience, technology and market modules for shale gas are presented in Figure 3.14. The shale gas production results shown on the left-hand axis represent the proven reserves for the base case, $50/ton carbon dioxide tax and a one-time 25% increase in demand scenario results in addition to the on the annual usage rate of natural gas on the right-hand side axis. The carbon tax increases the total cost to produce natural gas. This increase in the cost increases the price of natural gas to the consumer, which thereby decreases their annual consumption accordingly. Similarly, without additional increases in technology to reduce the cost of production or increase the supply available to the market, a one-time 25% increase in demand results in a temporary market shortage that increases the market price. This increase in price leads to a slightly lower usage rate by the customers. However, the feedback within the model's structure assures that with the initial increase in demand and subsequent increase in price, this brings more shale gas to the market thereby tempering the net effect of the decline in usage rate for the initial increase in demand.

Figures 3.14 through 3.24 illustrate several salient model results including proven reserves, percent allocation amongst the different types of natural gas, total costs, price responses, discovery rates, reserve to production ratios and usage rates. Figures 3.14 to 3.17 focus on the scenario results and are the core findings of this analysis.

The effects of a \$50/tonne CO_2 tax include decreasing the proven reserves in the coming decade due to a potentially negative incentive to explore and extract additional supplies of natural gas. This could reduce proven reserves. Additionally, the carbon tax would have a modest effect to decrease the amount of demand for natural gas *ceterius paribus*. That is, these scenarios do not take into account cross price elasticity with other types of energy supply substitutes including coal, renewables, and energy use efficiency (effectively increasing the necessary supplies) technologies.

Next, the effects of a 25% increase in the demand for natural gas in 2020 would increase the production reserves in the coming years. The effect could be more pronounced in longer model forecasting runs, but it does appear in Figure 3.14 via an increase in the demand (usage) rate after the 2020 timeframe.

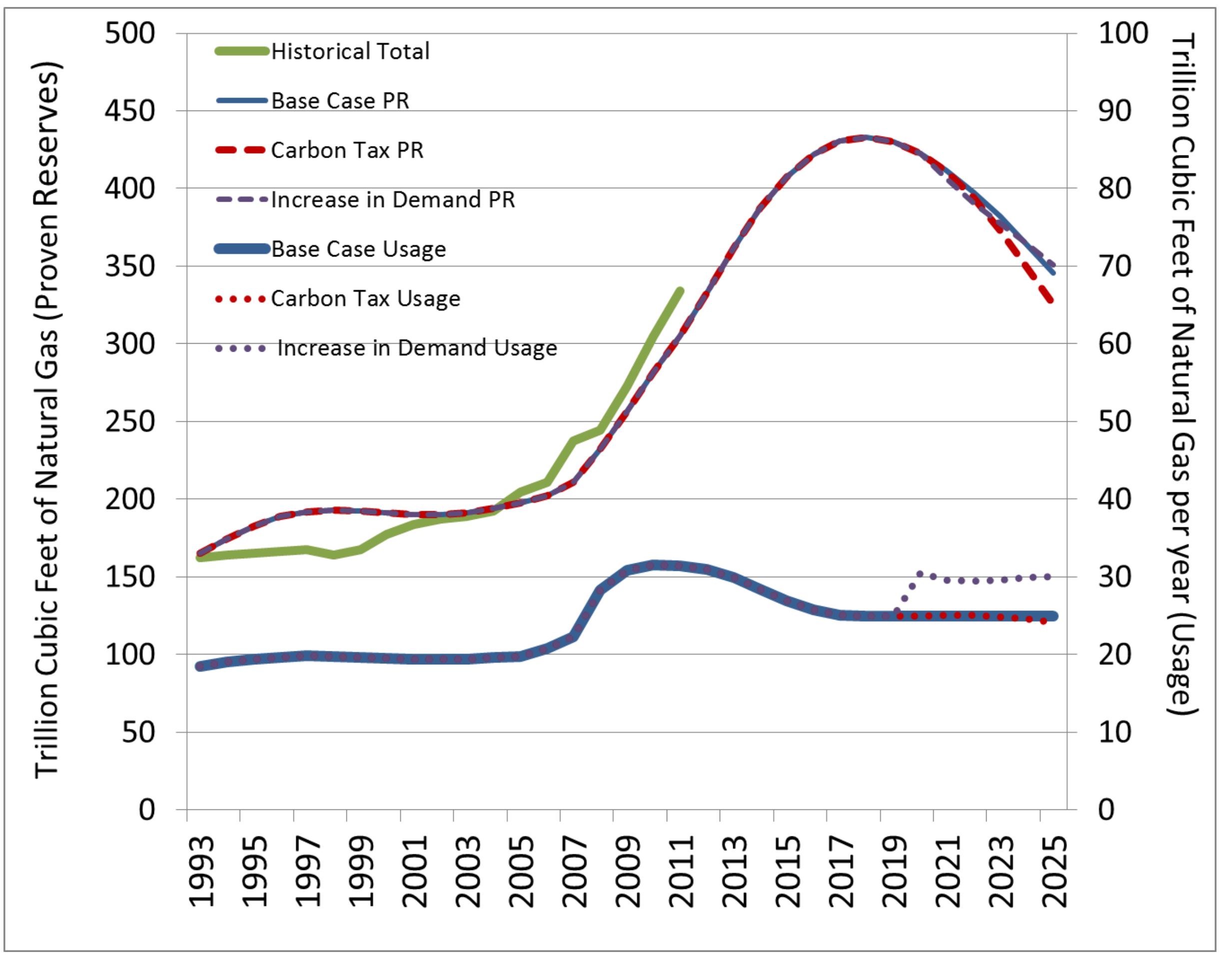

Figure 3.14. The effects on total U.S. natural gas proven reserves and natural gas usage rate for a \$50/ton CO_2 and a one-time, 25% increase in demand in 2015. (Note: historical data, 1993−2011; projections from 2012−2025).

Figure 3.15 offers a more detailed illustration of the effects of the core scenarios on the proven reserves and usage rates for shale gas. It is worth noting how the simulated proven reserves (staring from the initial model conditions based in 1993) match the historic proven reserves reasonably well in the 2010 timeframe. This adds some confidence the model framework captures a sizable portion of the driving factors for shale gas proven reserves development – a key goal of this study. Implementing a CO_2 tax results in a pronounce decrease in the proven reserves due to the interaction of the feedbacks including increasing the cost of exploration and the price elasticity of demand for natural gas. The increase in demand by 25% is more readily apparent in the shale gas results of Figure 3.15 than the totals shown in Figure 3.14. This is due to the fact that the proportion of natural gas coming from shale gas increases dramatically as compared to conventional or coalbed methane-based supplies in the scenarios. The simulated proven reserves (staring from the initial model conditions based in 1993) match the historic proven reserves reasonably well in the 2010 timeframe.

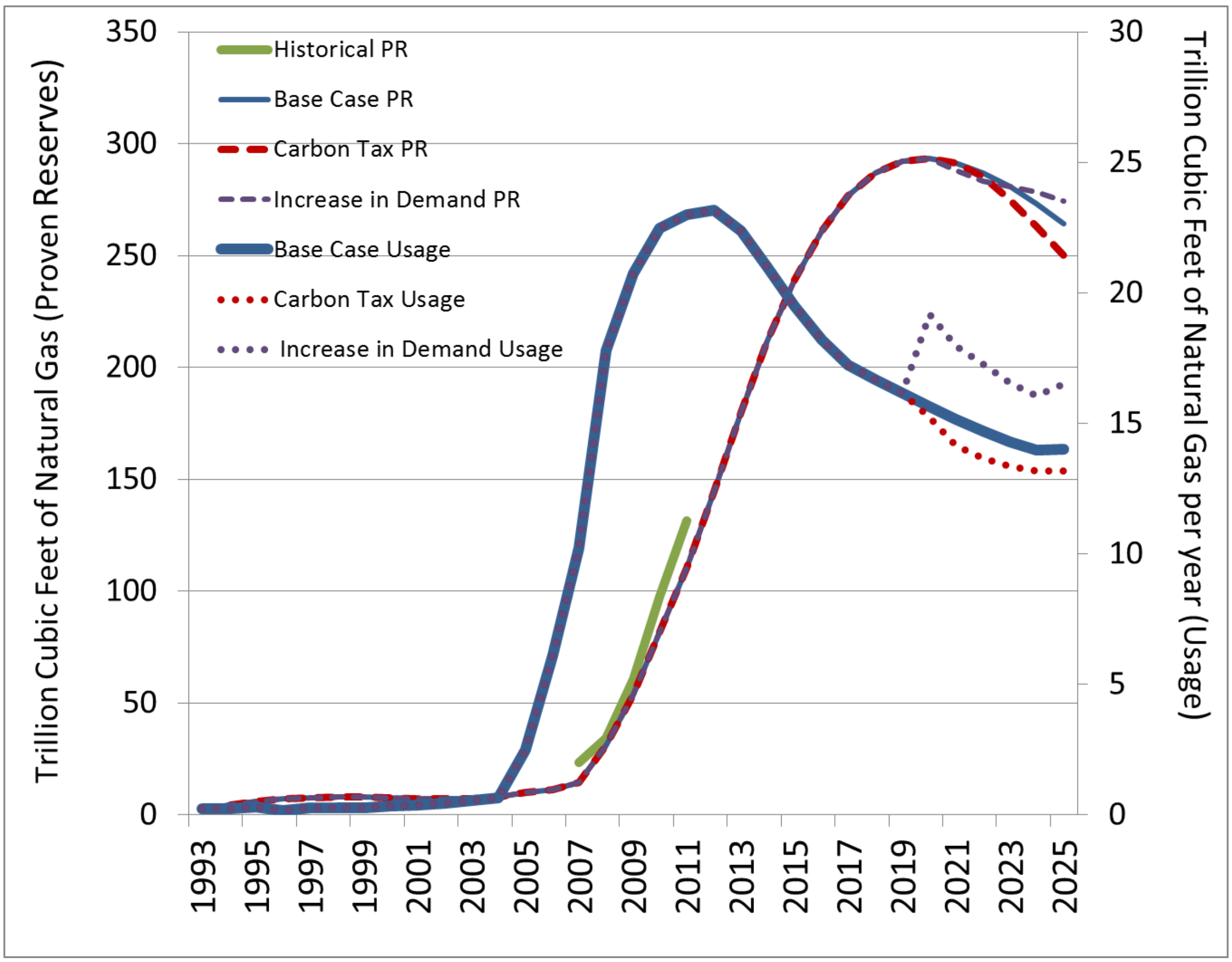

Figure 3.15. The effects on shale gas proven reserves and natural gas usage rate for a $50/ton CO_2 and a one-time, 25% increase in demand in 2015. (Note: historical data, 2007−2011; projections from 2012−2025).

The base case, carbon tax scenario and increase in demand scenario affected the proven reserves forecasts for conventional natural gas less so than for shale gas. However, the changes in usage are more pronounced due to the influences of these scenarios. The usage for conventional gas may increase due to overall usage only decreasing slightly as illustrated in Figure 3.14, yet shale gas represents a notable decrease and the overall usage has to be met. The differences between these types of natural gas ramping up or down relative to the scenarios is also greatly affected by the delay time for discovery between the types of natural gas being different, and the larger scale of proven reserves for shale gas when compared to conventional gas between Figures 3.15 and 3.16.

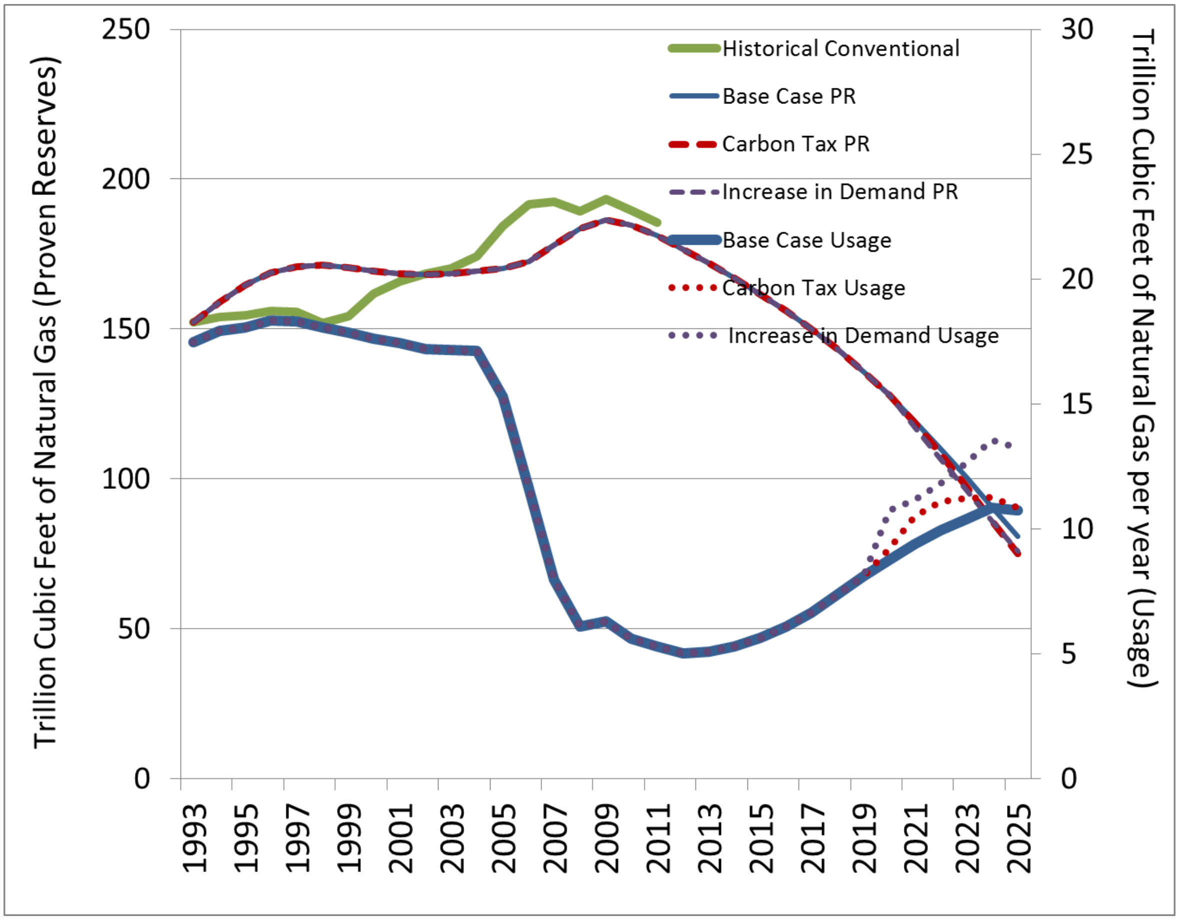

Figure 3.16. The effects on conventional gas proven reserves and natural gas usage rate for a \$50/ton CO_2 and a one-time, 25% increase in demand in 2015. (Note: historical data, 1993−2011; projections from 2012−2025).

Coalbed methane proven reserves are substantially smaller than that of shale gas or conventional natural gas. As shown in Figure 3.17, the simulation results match the general increase, peaking and falling behavior of historic proven reserves, but the agreement between the two is less focused than that of conventional or shale gas proven reserves. As such, the scenarios for carbon dioxide taxes and increasing demand are challenging to discern in the 2025 timeframe – largely due to the very small projected volume of natural gas proven reserves.

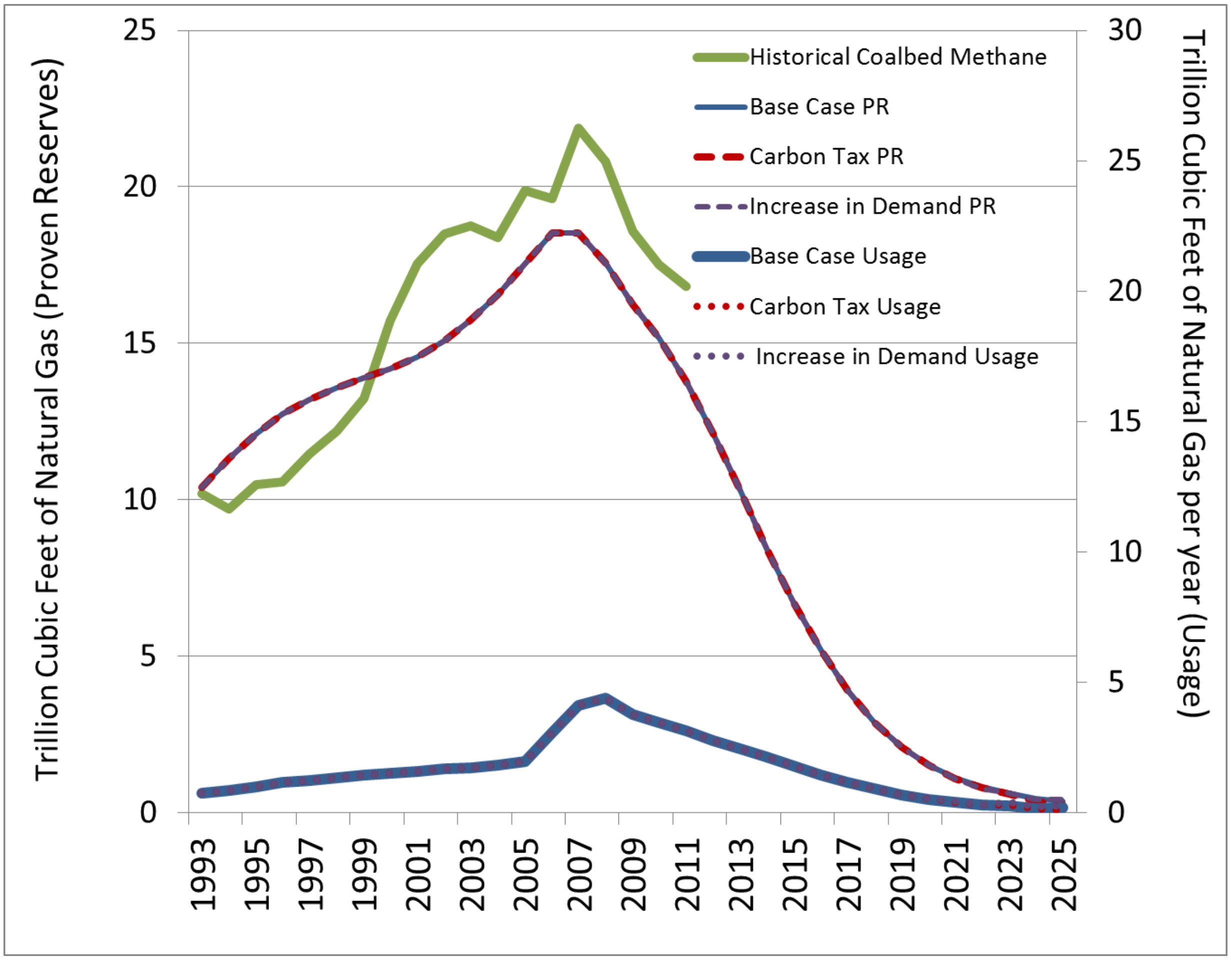

Figure 3.17. The effects on coalbed methane gas proven reserves and natural gas usage rate for a \$50/ton CO_2 and a one-time, 25% increase in demand in 2015. (Note: historical data, 1993−2011; projections from 2012−2025).

The NGPM calibrates the required costs to match historic proven reserves by minimizing the difference between the two subject to this condition.[18] Additional conditions include calibrating the discovery delay (years), the desired reserve to production ratio (years) and marginal cost for each individual type of natural gas. The growth constant required to match historic usage rate (demand) is also calibrated by the optimization tool.

The optimization tool calibrated the model's natural gas costs required to exhibit the historic behavior of proven reserves. This was done for two reasons. First, cost data is often proprietary, and these values are used largely to initialize the model which then builds upon its systems behavior to calibrate to historical proven reserves. Second, the amount of proven reserves remaining and demand profile drive the need to explore and develop new resource that further decrease the cost of exploration. In the last decade, a dramatic drop in the cost of exploration and extraction due to technological change for shale gas extraction (hydraulic fracturing) drove

[18] The Powersim Studio optimization tool solves to minimize the squared difference between the historical values relative to the simulated results (e.g., proven reserves, price and production).

the cost and hence market price down to historically low prices with substantial swings due to speculative price signals and Hurricane Katrina.

Shale gas historically had a relatively low volume of proven reserves given the recent surge in exploration and extraction efforts in the U.S. over the last decade.

The shale gas total cost initial are calibrated to be very low given the very limited market penetration of the technology and the optimizer's goal to minimize the difference between the historic and simulated proven reserves in the subsequent years.

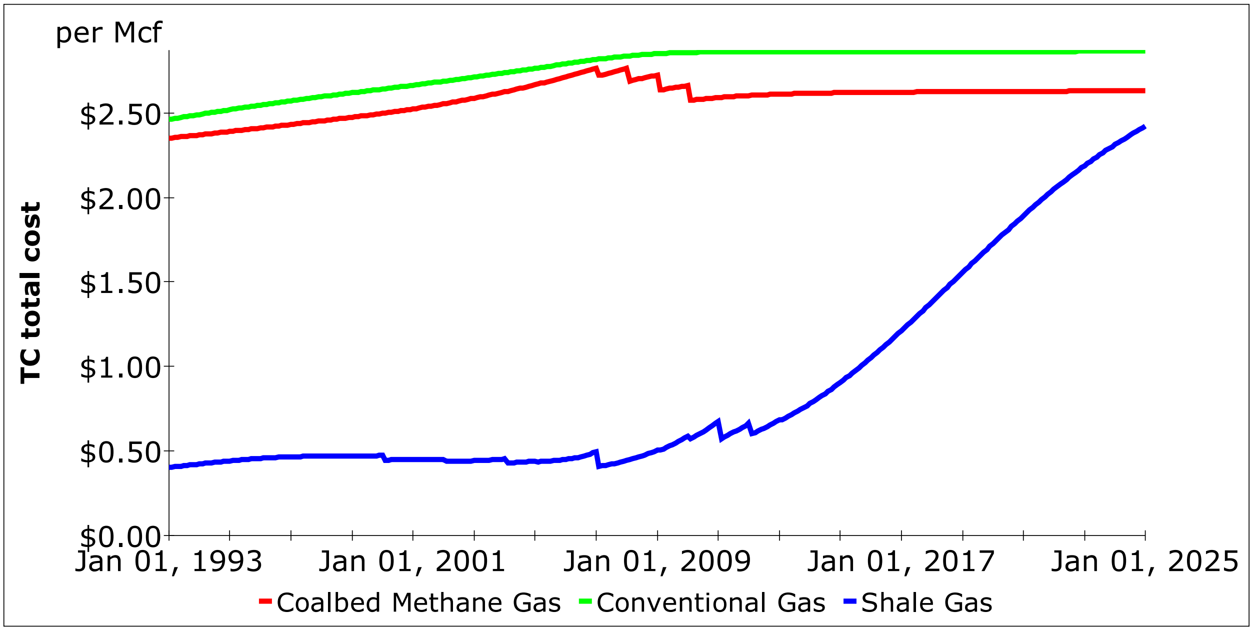

Figure 3.18. Total Cost of exploration driven by the reserve to production ratio, and used to calculate the weighted averages market price of natural gas.
(Note: The initial values were determined by optimizing the values required to match historical proven reserves data to the simulated results.)

Figure 3.19 illustrates historic well head natural gas prices and the weighted average of the 'cost plus' pricing developed in NGPM (EIA, 2015). For some context, the price of natural gas in the U.S. is driven by many factors. Many of these are included in the NGPM. However, in the summer of 2005, hurricanes along the U.S. Gulf of Mexico caused several billion cubic feet of natural gas to be shut in. This effectively delayed the ability to get that natural gas to market, causing a short term shortage in the supply chain and increased the spot market of natural gas to reach $15 per million BtU, roughly double those prices seen in the spot market in 2004 (Mastrangelo, 2007).

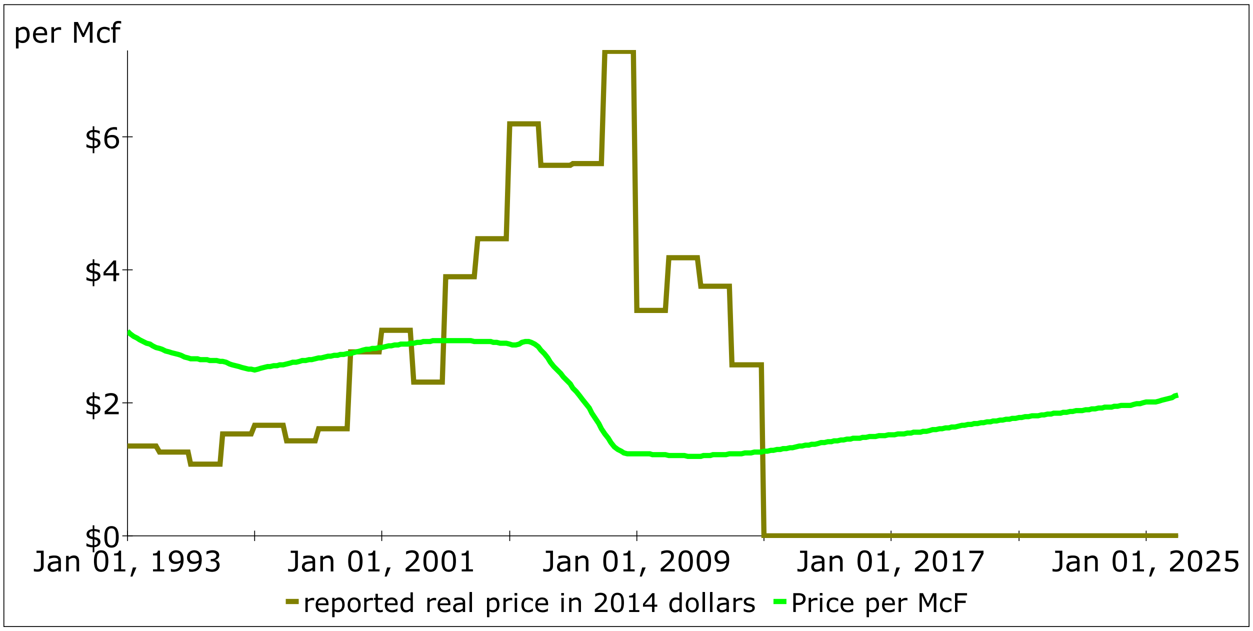

Figure 3.19. Base Case, endogenously-derived price. Historic data adapted from the EIA (2015).

Figure 3.20 illustrates the simulated discovery rate for coalbed methane, conventional and shale gas. Shale gas discovery rates increased substantially over the last decade, and the simulated results (2012–2025) continue this trend. The feedback in NGPM balances the discovery rates, with their respective time delays to from investment to discovery for each natural gas type, to meet the expected demand, expected reserves to production ratios and allocation percent forecasts based on EIA data during the 1993–2012 time period, and then transitioning as smoothly as possible to the simulated, forecasted data (EIA, 2013a).

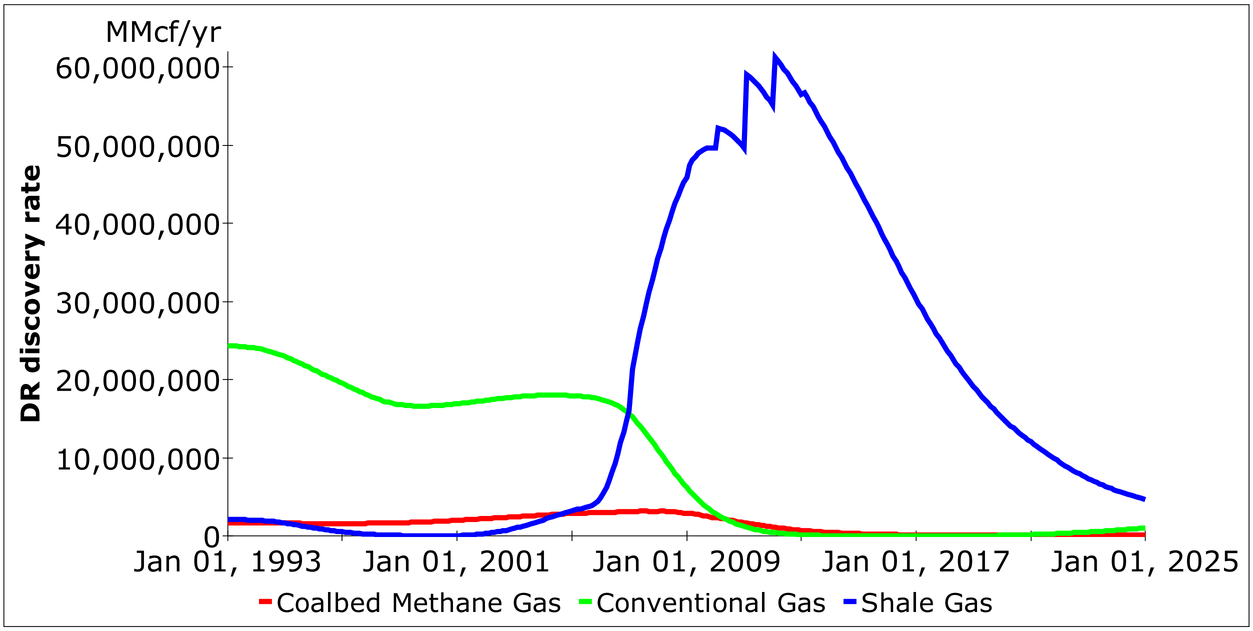

Figure 3.20. The calculated discovery rate of natural gas by type based on underlying cost, demand, investment and desired reserve to production ratios.

Figure 3.21 illustrates the simulated reserve to production ratio that influences percent invested in exploration, reserve life fraction remaining, weighted average of the reserve to production ratio by natural gas type, and the total cost calculation. Conventional natural gas has a historically stable reserve to production ratio due to longer field development times than seen in recent shale gas plays. Coalbed methane gas plays traditionally take a longer time to develop and utilize. Shale gas, however, at the scale seen in the last decade have a markedly faster development rate and production decline. The rapid increase and decline in the historical timeline of the NGPM illustrated in Figure 3.21 is due to the initial lack of proven reserves and subsequent development of those proven reserves. In the latter half of the NGPM run, the shale gas reserve to production ratio increases due to the higher demand for shale gas. A higher demand for shale gas due to its lower relative cost to conventional and coalbed methane gas, increases production. These dynamics cause the shale gas reserve to production ratio to increase across the simulation forecast period.

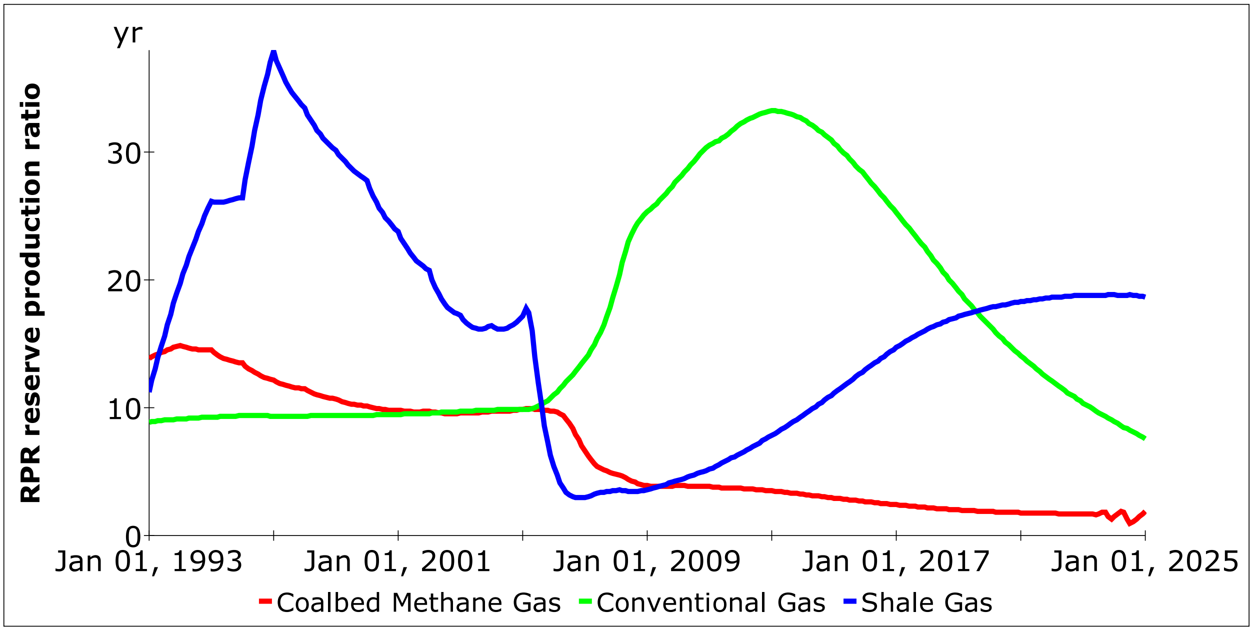

Figure 3.21. The reserve to production ratio by natural gas type.

The historic allocation percentages used in the NGPM are based on the Annual Energy Outlook (AEO) (EIA, 2013a). Figure 3.22 illustrates the percentage allocation of natural gas demand met by coalbed methane, conventional and shale gas. The notable changes are the extremely high percentage of conventional gas in the 1993–2012 timeframe, and then the simulated exchange of shale gas to become the dominant type of natural gas used to meet demand.

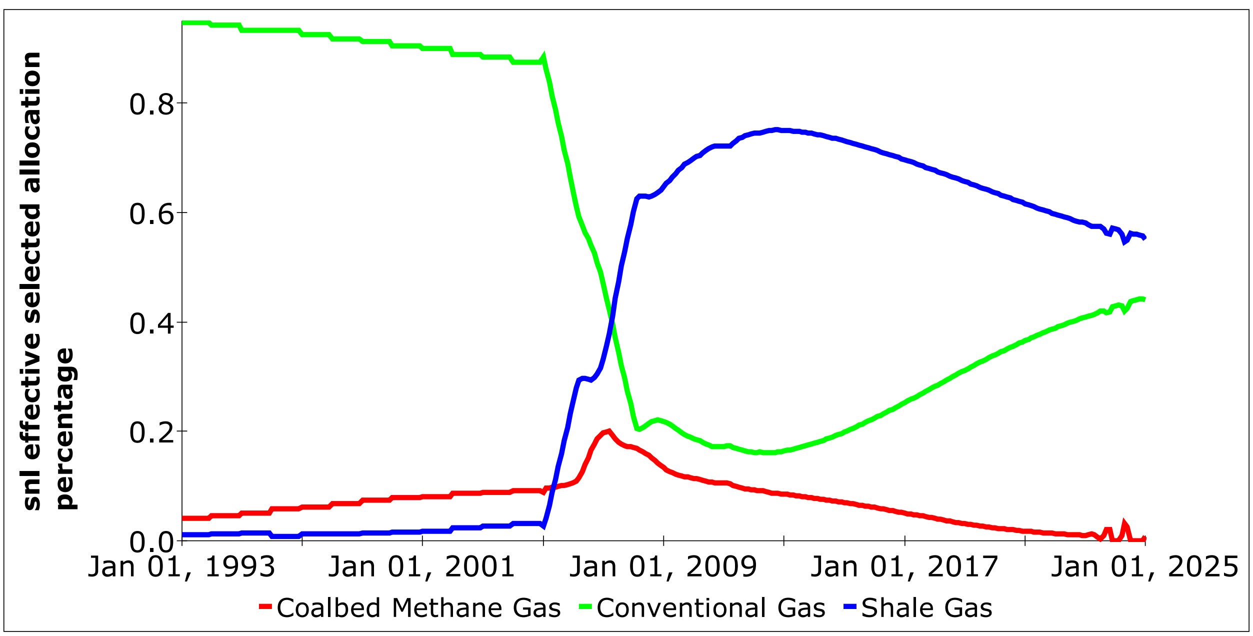

Figure 3.22. The allocation percentages are driven by the underlying price behavior, demand response behavior and total cost initialization to match historic proven reserves data to validate the underlying structure of the model framework.

The multitude of variables required to balance and reach a type of steady-state solution within the system dynamics framework posed several optimization challenges. The model largely tries to minimize the offset between the historic and simulated data for the proven reserves for the three types of natural gas analyzed. The majority of the simulation runs would either match the simulated and historic wellhead price at the expense matching the proven reserves or the usage rate and the proven reserves. This resulted in a lower matching of the proven reserves than if usage rate were allowed to fluctuate freely, including in the 1993-2012 historic timeframe. The latter was deemed unacceptable given historic usage rate data were known, and the NGPM has the ability to manage multiple optimization and tuning variables per run. Figure 3.23 illustrates the best case available to match the historic price, proven reserves by natural gas type, and usage rate. The usage rate for conventional gas matches historic up to the point the smoothing algorithm begins the transition from historic EIA-based data to simulated results in 2005.

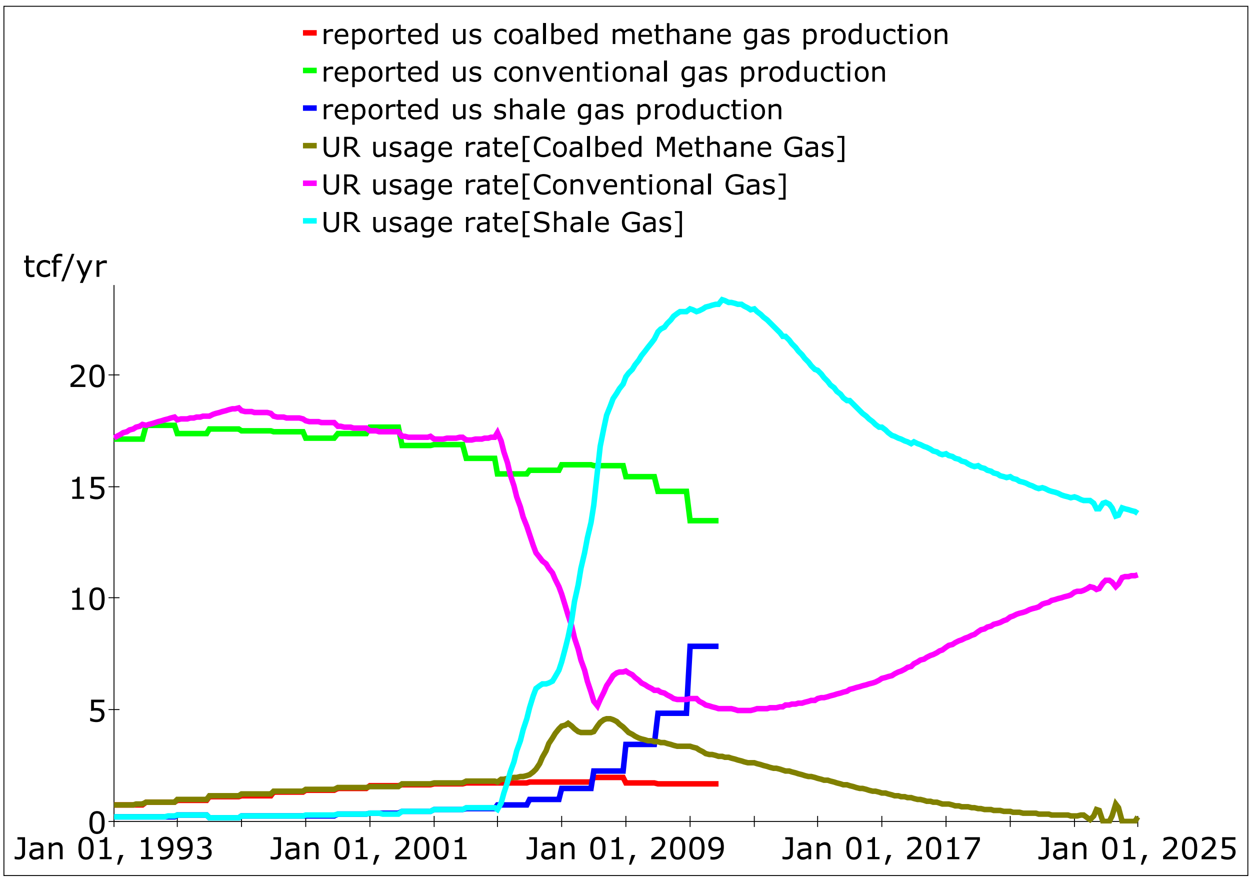

Figure 3.23. The usage rate results under the base case assumptions.

Figure 3.24 illustrates the cumulative usage (quantity demanded) of natural gas over the model's timeline. Conventional gas continues to remain a sizable portion of the natural gas supply, followed by shale gas growing its share substantially over the last decade. Coalbed methane traditional comprises a small portion of the overall natural gas supply, and the forecast is for it to remain so in the coming years.

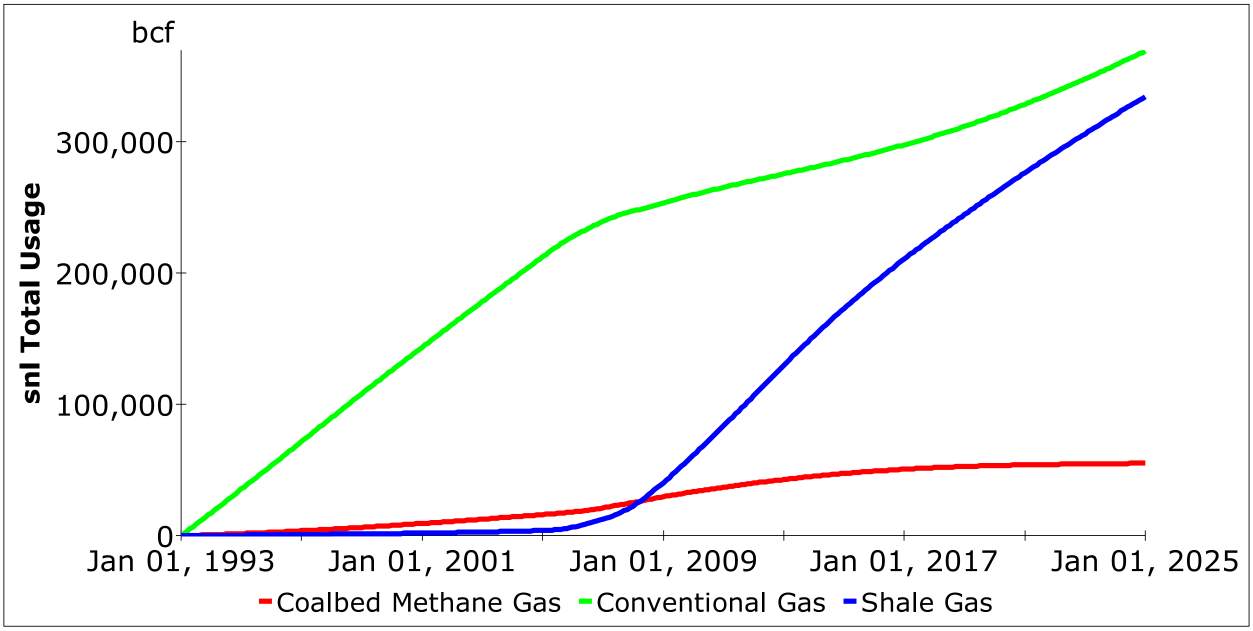

Figure 3.24. The usage employed by the NGPM by natural gas type.

3.4 SD Discussion

The model successfully develops natural gas price endogenously based on a cost-plus relationship building from technological change, and the buildup over time of a desired reserve to production ratio based on feedback from the demand for natural gas and exploration for new sources of natural gas. With the base case, environmental CO_2 tax and increased demand scenario, various policy analyses may be analyzed for their effects on proven reserves of natural gas in the years to come. Modeling the complex relationship between the geoscience, economic and engineering nature of the natural gas extractive industry in a system dynamics framework offers several advantages. First, nonlinearities across time of relationships such as technological change, demand and supply elasticities, and threshold analysis are easily replicated using the model framework developed for the NGPM. Second, the evolving, feedback-rich nature of these complex interactions can be easily represented in the NGPM along with identifying how to calibrate against historic data in the face of great uncertainty in the future of natural gas markets. Third, modeling potential disruptive events in markets can be analyzed using the NGPM. However, forecasting these events, such as notable Hurricane damage, will prove challenging.

3.5 SD Conclusions

The Natural Gas Production Model offers several key insights to how sensitive the U.S. natural gas market is to increasing shale gas production. New shale gas plays are being rapidly developed and may replace many of the traditional, conventional gas supplies for the economy. However, the geological characteristics of shale gas are vastly different from conventional gas. For example, where shale gas plays may only last a year or two before losing production potential under current technology solutions, conventional gas plays are developed and maintained to produce for several years to several decades. It is these diverse interactions that affect the true production capacity of natural gas in the U.S. to meet demand in the decades to come. Future research may look to include stochastic, disruptive events to help evaluate the magnitude of their effects on the market price of natural gas, include new technologies to enhance production while maintain a competitive cost structure, and additional policy scenarios that may enhance or curtail different types of natural gas production.

4. CONCLUDING DISCUSSION

This project developed two models to represent non-equilibrium approaches to analyze shocks and policy impacts affecting U.S. natural gas markets. The agent-based modeling approach offers an updated, and novel method to model supply, demand and various storage actors within the U.S. natural gas pipeline network. It also allows one to test a regional and national impact scenario if an LNG export terminal were placed in the Gulf Coast region of the U.S. Working results indicate the price of natural gas may initially increase due to this type of export terminal utilizing the supply available at the time of the terminal development. Over time, however, the price impacts become less inflationary due to more supplies being produced from the existing actors and the potential for growth in the pipeline infrastructure thereby allowing even more supply areas to come online.

Similarly, a system dynamics-based model and subsequent analysis illustrates how multiple feedback loops and interactive effects can affect the proven reserves for coalbed methane, conventional and shale gas in the U.S. An illustrative scenario indicates that environmentally-focused policies such as a CO_2 tax would decrease the incentive to explore and develop new proven reserves, and the usage rate (demand) may decrease due to the higher cost of natural gas, *ceteris paribus*.

Future research for both models could include factors such as natural and anthropogenic impact scenarios such as hurricanes and intentional disruptive attacks to infrastructure and markets. The agent-based model framework could be extended to include several more types of agents such as economic sector-specific agents, different types of supply agents according to the type of natural gas they produce and the region in which they produce (as it relates to pipeline congestion costs), and more detailed storage of NG in the northeastern U.S. The system dynamics-based modeling approach could include more details on historic, exogenous disruptions such as hurricanes and apply those using a probabilistic assessment to forecast future natural and anthropogenic-caused impacts to the NG infrastructure.

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APPENDIX A: NATURAL GAS SYSTEMS MODEL, SUGGESTIONS FOR FUTURE RESEARCH

A.1: Additional Agent Behavior Suggestions and Future Research

Introduction

The goal is to create a tool for policy-makers which allow them to understand how actions they can take might influence the operation and development of the US natural gas system. Policy consequences are the outcome of many interacting processes, including resource discovery and development, transmission system operation and growth, and consumers' gas usage rates. Some of these processes are well understood, but many are not, and others (such as future technological developments or specific changes in environmental drivers) cannot be known. Policy outcomes cannot be accurately predicted by any model, however sophisticated. A model including the driving processes and their interactions is still useful as a means to systematically explore the range of possible outcomes, measure the potential power of contemplated interventions to shape that development, and look for surprising bad outcomes.

We first review developments in the natural gas industry over the last 30 years. These developments have generally led from a highly-regulated and centrally controlled system to a system whose behavior and development is determined by a large number of independent decision makers, each pursuing their own specific interests. We next discuss the general characteristics of agent-based computational economic (ACE) modelling, identifying those characteristics that make such models well-suited to exploring possible system trajectories. Finally we discuss some possible definitions for agents composing such a model. The flexible design of the basic NG modelling framework allows for library alternative models of agent behavior to be developed over time; the agent definitions proposed here are not intended to exclude other possibilities.

A History of Change – How Regulation Influenced the Modern NG System

The Federal Energy Regulatory Commission (FERC) is an independent regulatory agency charged with the regulation of certain aspects of the energy industry in the United States, including the regulation of natural gas transportation. Until 1985 the NG industry was vertically separated into production, pipeline transportation, and distribution. FERC Order Numbers 436 and 636 altered both the purchasing and transportation of natural gas and associated contracts. FERC Order 436 made it possible local distribution companies (LDCs) to terminate long-term contracts they had with pipeline companies. LDCs could now directly establish long-term purchasing contracts with NG producers. Prior to 1985 pipeline owners would enter long-term contracts to purchase NG from producers; pipeline owners would then sell the transported NG to distributions companies (or local distribution companies known as LDCs).

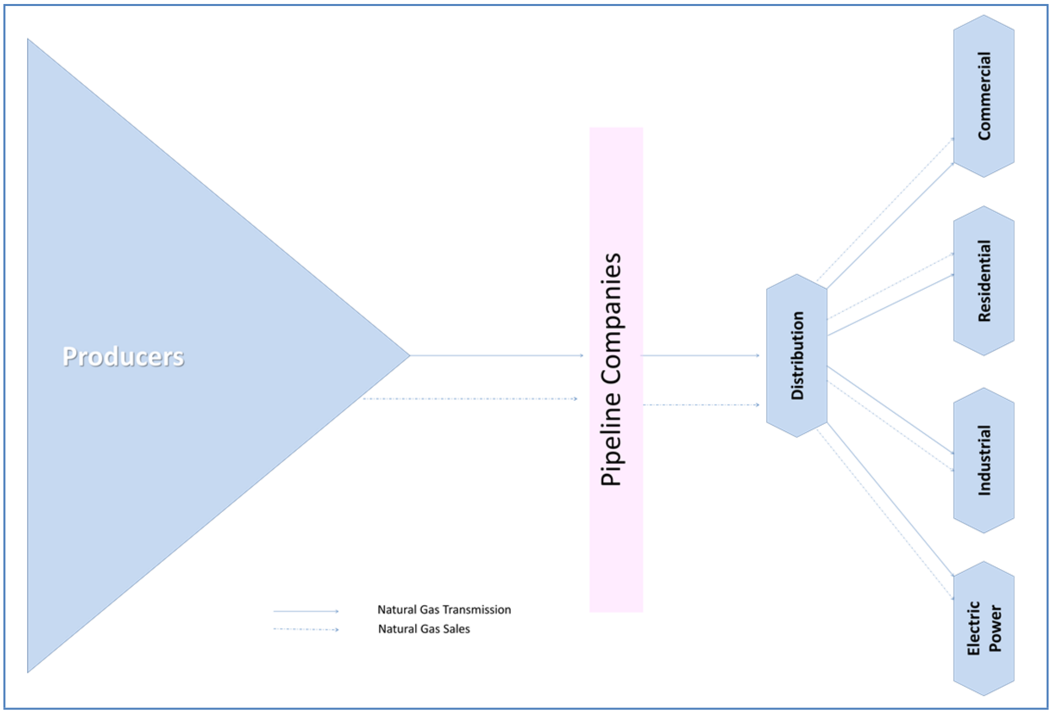

Figure A1. Abstraction of United States Natural Gas Market Prior to Regulatory Prior to 1985

Effects of Regulatory Changes on Pipeline Transactions

Subsequent to Federal Energy Regulatory Commission (FERC) order 436 pipeline owners remained in long-term contractual obligation to NG producer to purchase established levels of NG. With local distribution companies (LDCs) no longer contractually obligated to purchase from pipeline owners, pipeline owners were experiencing significant financial losses. Within two-years FERC Order No. 500 was established, which states pipeline companies could pass on transition costs associated with FERC Order No. 436 to NG producers, LDCs, and consumers.

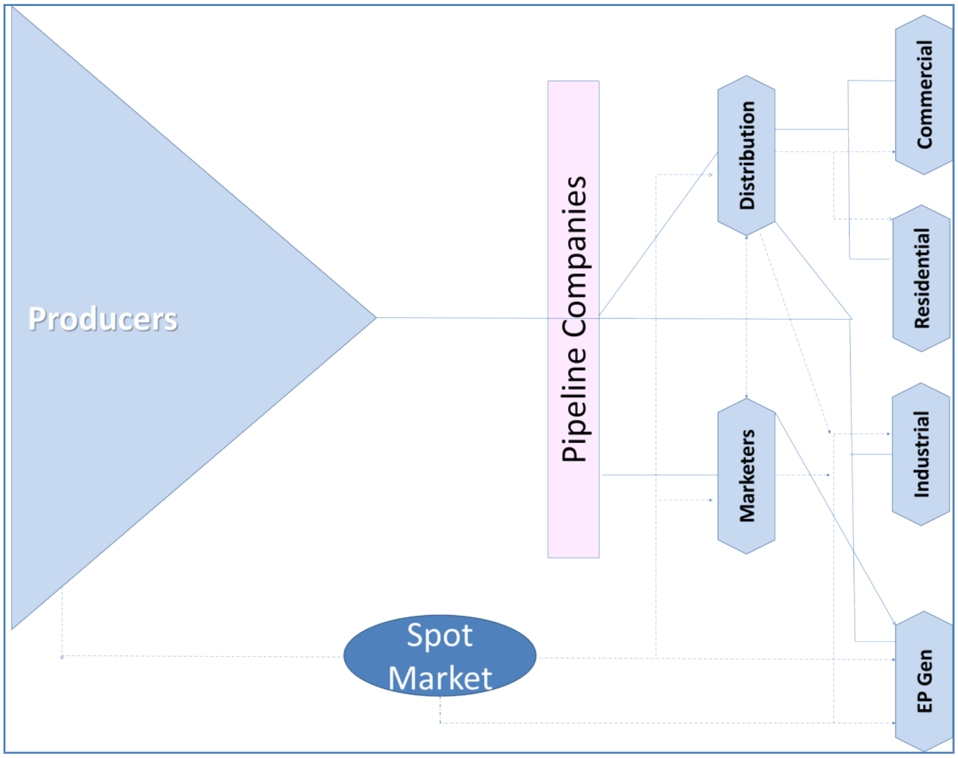

Figure A2. Abstraction of the United States Natural Gas Market Post 1985 Regulatory Changes

Previous to 1992 there was often a single price for NG, interstate transmission pipeline owners could sell a bundled product of transported and commodity natural gas for one price. Pipeline owners served as both transporters and traders of natural gas. FERC Order No. 636 unbundled these products, meaning these previously bundled transactions were now individual transactions. Interstate pipeline owners were restricted to only sell the transportation component and never own the NG being transported on the interstate pipeline[19]. Pipeline owners were now required to offer open access of their pipelines to other market participants: marketers, producers, LDCs (end users). FERC Order objectives were aimed at transitioning away from a vertically separated industry system to one founded in "open access" markets. These loosening of regulations were designed to establish a wholesale NG market that was more a free competition market than a tightly regulated market.

Agent-Based Computational Economic Modelling Approach

The model is intended to allow policy makers to anticipate the behavior of the natural gas system under the disaggregated decision-making regime created by deregulation, as well as to anticipate its possible response to changes in that regime.

Our approach links economic theory and agent-based computational economic modeling (ACE) of the natural gas system. The approach defines principles of action for the diverse decision-makers in the system. Their economic interactions are constrained by physical infrastructure, such as production fields, storage facilities, and transmission systems. The basic NG network system model represents these physical constraints. Starting with a basic network model design

[19] http://naturalgas.org/regulation/market/

allows analysts to define alternative models for agent behavior, and to examine the outcomes of their interactions with other agents in determining the system's operational state and growth. The following ACE characteristics distinguish these models from traditional economic models,: heterogeneity, explicit space, local interaction, bounded rationality[20].

Heterogeneity – imbuing agents with different characteristics or attributes. Each agent can have different preferences, contracts, budget constraints, sophistication, etc.).

Explicit Space – physical location specification can be represented on a network structure. This allows for physical location and neighbor interaction to influence agents or influence network structure.

Local interaction – network structure that connects the agents to each other can be specified. Analytic models either assume partial equilibrium in a single market or general equilibrium was with the Walrasian[21] markets.

Bounded or distributed rationality – It can be argued that individuals have difficulties in determining and following an optimal behavior and are actually characterized by some type of bounded rationality. ACE's can model information acquisition and decision-making explicitly, allowing the effects of non-optimal hypotheses to be explored (Gigerenzer and Selten, 2001). Non-equilibrium behavior –Because the system's behavior results from local interactions among agents with incomplete information, reaching a global equilibrium can take time, and equilibrium may never be reached. This is in contrast to neoclassical economics, in which agent's actions are assumed to be in equilibrium with the pattern they create.

ACE does not displace neoclassical economics; it is an emerging approach to economic analysis with the promise of offering insight into economic and social systems in situations that are too complex to be tractable with traditional models. ACE differ from classical and neoclassical theory in that agents can learn through explicit rules governing what an agent knows, remembers, and how information is processed from one time period to the next.

The usefulness of ACE lies in the flexible modelling techniques that can assist in understanding market dynamics with a view to evaluating regulatory impacts or formulating suitable regulatory frameworks. This is an important feature for a commodity such as natural gas with hourly, daily, monthly bidding, and whose markets are subject to regulatory influence.

Model Components

[20] L. Tesfatsion and K.L. Judd, editors. Handbook of Computational Economics., Volume 2: Agent-Based Computational Economics of Handbook in Economics 13. North-Holland, 2006.
L. Tesfatsion. Agent-based computational economics: A constructive approach to economic theory. In Tesfatsion and Judd [2006], Chapter 16, pages 831–880.

[21] A Walrasian equilibrium for this model is a set of prices such that supply is determined by all firms maximizing profits, demand is determined by all end users maximizing utility subject to a budget constraint given by the value of their endowments, and excess demand for all goods is zero.

Below we define the agents and interaction structures that we believe would constitute a useful model for policy analysis. The definitions include both those currently implemented and those slated for implementation.

Agent definition includes a description of the roles agents of that type play in the system. Each role includes a list of the actions they can take (outputs) and the information and influences they receive (inputs). Generally these are mediated by an interaction structure of some kind. Most agents are involved in short-term (day to day) activities as well as in longer-term (year-to-year) activities. For example, day-to-day activities might involve meeting consumption requirements of existing plant and equipment, while long-term activities include deciding whether to expand or close existing facilities. This can be described as two roles for the agent, or as two aspects of the same role. For each role one or more formal models can be defined. Model definitions enumerate the inputs obtained from the appropriate interaction structures, the state variables and parameters that characterize the agent, and the outputs the agent generates.

Interaction structure definition includes a description of the kind(s) of agents the structure connects, and the kinds of information, transactions, or materials they exchange using the structure. Interaction structures usually correspond to collections of physical equipment, institutional arrangements, legal constraints, and conventions. They are likely to have a single role in the system (e.g. transmitting NG), however they may have both short-term behavior that manages interactions and long-term behavior that changes capacity, connections, or interaction rules. One or more models can be defined for the interaction structure. Inputs and outputs include information from the agents using the structure, but may include other information such as conditions in the environment. State variables and parameters may include things like network topology and regulatory constraints.

Interaction structures may or may not have associated agents responsible for either their short-term behavior or long-term behavior. If an infrastructure model includes agency, the responsible agent can be defined in the Agent Definition section. That agent's state variables, parameters, inputs, and outputs will include aspects of the model of the interaction structure that it controls.

Interaction Structures

The basic constraint on interaction among model agents is the NG transmission system. Two basic strategies are available for modelling economic interactions: using supply/demand curves to represent the outcomes of possible negotiations, or explicitly representing negotiation of individual transactions. While agents are considered to be autonomous, their specification has to reflect the rest of the model and its interaction structure. In this case, for example, treating the agent as a price taker works when the relevant market price (either local or global) is determined by an external process, which presents the agent with the resultant market price and thus determines the agent consumption. If, on the other hand, price and quantity determination involves negotiation and contractual arrangements with specific other counterparties, then the agent behavior has to be augmented with the ability to search for counter parties, and to enter into such contracts. Just as importantly, the model then has to reflect those contracts in the determination of the flows.

Gas Allocation Model – short-term network dynamics

The Gas Allocation Model (GAM) was originally purposed as a network description of the natural gas pipeline system. It was employed to study and understand infrastructure disruptions, propagations of disruption, indirect effects, and mitigation. For this effort GAM will serve as the foundation on which the agent-based model will be built.

GAM was developed as a capability to estimate the physical availability of natural gas rather than to predict actual flows of natural gas in the pipelines and market dynamics. Entities represented within the GAM model represent storage, pipelines, and customer classes. GAM was selected as the foundational model for the ABM/ACE because it met the overall modelling requirements: flexibility, represents a level of useful detail, individual pipeline representation, and allows for changing demand and supply; detailed below.

- Must include a representation of the U. S. natural gas pipeline system and the associated locations, directional flows, and flow capacities of the pipelines
- Must include the ability to represent individual receipt and delivery points for natural gas that add and remove, respectively, natural gas from the pipeline system
- Must be able to include a representation of natural gas storage facilities
- Must be able to report daily flows on the pipelines
- Must be able to report daily quantities of natural gas removed from and added to the natural gas pipeline system for individual receipt/delivery points (RDPs)
- Must be able to track daily inventory levels at natural gas storage facilities
- Must be able to represent modifications to the system that might be evaluated as mitigating measures, such as increasing pipeline capacity or storage volume.

The original GAM model was not intended to be used for exploration of market evolution since it does not represent *human factors* such as: contracts/contracting individual firm decisions, regulators, and regulation. The extension of GAM to include ABM/ACE will primarily be focused on the representation of *human factors*.

The natural gas system within GAM is structured as a network model because of the interconnectedness of the natural gas transmission system. Networks are defined generally by nodes and edges/links that connect two nodes. Each process that produces, injects, consumes, or exchanges NG within the natural system is defined as nodes in the network. To build the network structure around a particular process, edges/links are defined between each process and its output material or materials. The nodes and edges/links are visually represented in Figure A3. The varying thickness of the edges/links indicates increased pipeline capacities.

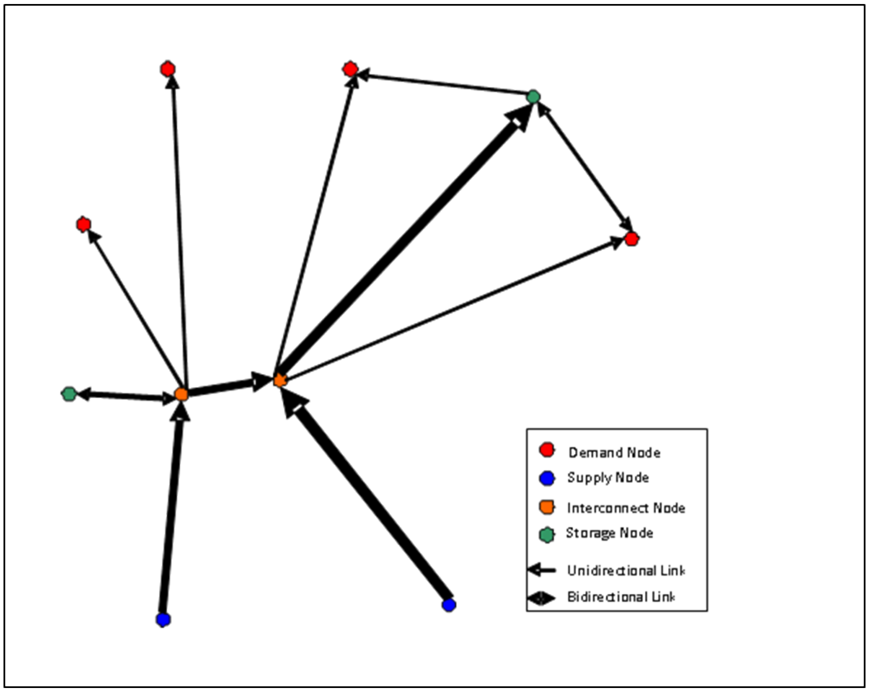

Figure A3. Network representation of a simple natural gas system.

Gas flows on the transmission system occur as a result of transactions conducted by agents in a number of markets and other interaction structures.

General Agent Description

Here we discuss the characteristics of the agents composing the system. Agents are described as independent actors playing specific roles in the system. Many companies combine several roles, for example LDCs often act as storage operators. For clarity of exposition, we do not discuss behavior of all possible compound agents

Agents receive information from their environment, and then integrate that information with past experience and with their objectives to select among some actions available to them. Agents differ in the kind of information available to them, their experience interacting with the system, their objectives, and the actions available to them. Agent types or roles are initially defined through these information and control flows. Given these interface constraints, many alternative models for the decision-making process used by each agent type can be defined. An important design goal for the model is to support alternative models for agent decision-making so that the implications of adopting different hypotheses for system behavior can be explored.

For each agent, two behavioral regimes are considered. Operational behavior includes decisions about the operation of existing infrastructure and equipment to achieve short-term goals. Long-term behavior includes decisions affecting capacity, especially investment in new infrastructure and equipment, and sales of assets to other agents.

Subsequent sections describe the information obtained by each type of agent from the environment and the kinds of actions the agent can perform. Operational and long-term behaviors are distinguished. For each agent type, possible models for their decision process are discussed. Below are factors considered in the definition of individual Agents.

Agent: Generic
Attributes
Decision and behavioral rules
Decision making
Ability to acquire and process information available, Memory
Resources
Rules to modify behavioral rules

Each Agent's interactions with other agents within the modelling environment are determined by these factors and the time-frame over which these interactions occur.

Implementing one or more models for each of these agent types would eventually produce the desired capability to map the possible consequences of a wide range of policies. It is much easier to understand each agent's contribution to the behavior of the system, and to verify its implementation, if agent types are added sequentially. Figure A4 proposes an implementation sequence for each agent type that allows for intermediate testing and analysis. Figure A5 shows a proposed sequence for introducing richer interaction structures. These development pathways are coupled because agents introduced in later stages (e.g. Traders) compose the key market interaction structures.

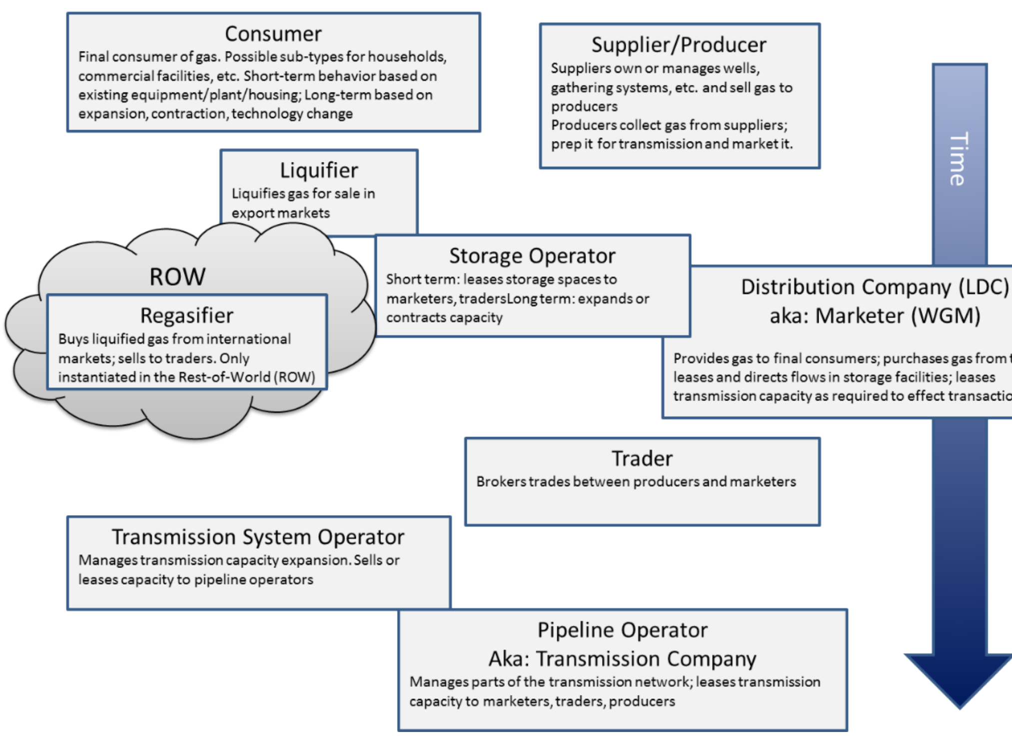

Figure A4. Possible sequence for developing/elaborating model agents.

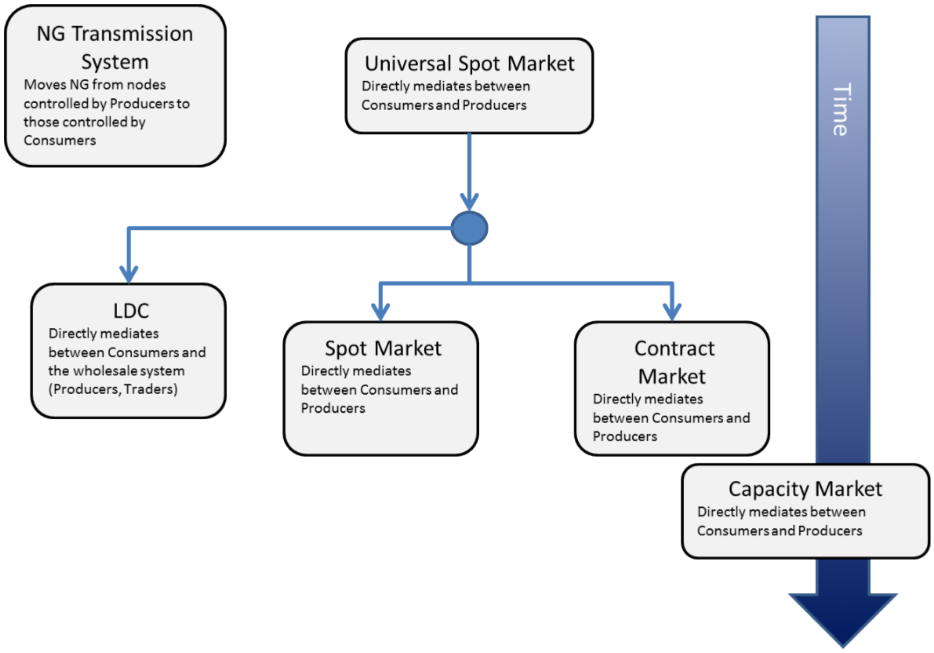

Figure A5. Possible sequence for developing/elaborating interaction structures.

Consumer Agents

This class generally represents all categories of final demand. Residential, commercial, industrial, power generation and other categories might be specified as sub-types, or might instead be defined by distinctive parameter value ranges within a common sub-type.

Inputs
Price: Consumers are assumed to be price takers. Different categories of consumer may see different prices and have access to different markets.

Time: Consumers' demand may be depend on many exogenous factors (e.g. temperature, electric power demand). This dependency can be modelled explicitly in the agent's decision-making logic, however it is assumed to be a function of time.

Outputs – Short-term
Consumption rate: Given the current price and time (along with any internal state information maintained by the decision-making model) agents consume gas a particular rate.

Outputs – Long-term
Investment/disinvestment in facilities. The amount and type of physical equipment fed by consumed gas is represented in some way in the agent's decision model. Consuming agents' long-term behavior does not act on the system directly, but is reflected in a change in consumption rate given the same operational inputs.

Models

In general, quantity demanded by a given agent i at time t at a given price p can be represented as $f_i^t(p,t)$, where treating time both as an index and as an explicit independent variable allows incorporating the changing functional form of demand curve (time as index) and treating the seasonality explicitly (time as independent variable). Both for the ease of understanding and due to data limitations, it is beneficial to split this specification into the short-term and the long-term components, where the short-term represents the given and fixed functional form that reflects seasonality and the long-term component reflects the evolution of the demand function over time.

Short-term

Perhaps the simplest way to represent short term behavior of consuming and producing agents is through a function that specifies the quantity demanded by a given agent i at time t at a given price p:

$$q = f_i^0(p,t) \ ,$$

where the functional form f_i^0 represents the demand for a particular period of time, say from t_1 to t_2.

Long-term

Consuming agents may grow or contract over time. A simple representation of the effect of long-term changes is consuming agents is via changes in the short-term demand curve:

$$f_i^0 -> f_i^1 \ ,$$

where the function f_i^1 represents the demand for a particular period of time, say from t_3 to t_4

Supplier/Producer Agents
This class represents supply and production processes as a single aggregated agent. Each is assumed to control a specific collection of wells, gathering systems, and other resources needed to bring produced gas to the transmission system.

Inputs
Price: Producers monitor market prices and may adjust production rates (and in the longer term investment rates) in response.

Time: Production may depend on many exogenous factors that vary seasonally, although this is generally a weaker dependency than consumption.

Outputs – Short-term
Production rate: Given the current price and time (along with any internal state information maintained by the decision-making model) agents produce gas a particular rate.

Outputs – Long-term
Investment/disinvestment in facilities. The amount and type of physical equipment used to produce gas is represented in some way in the agent's decision model. Producing agents' long-term behavior does not act on the system directly, but is reflected in a change in production rate given the same operational inputs.

Models
Supply may be modelled using price response functions analogous to the demand curve models described above to characterize consumers decision-making.

Storage Agents
The most basic function of a storage agent is to balance supply. For a defined time period storage can be used for day to day supply balancing, seasonal balancing and to mitigate shortages. Day to day balancing can be used in instances of price arbitrage. Seasonal balancing occurs when NG is stored during low demand seasons to capitalize on low NG prices and when NG is extracted from storage and sold to the LDC in high demand seasons. Storage can also buffer system response through times of shortage or surplus.

Inputs
Price: Storage agents may monitor prices and may adjust injection/withdrawal rates (and in the longer term investment rates) in response.

Time: Large storage fields are primarily operated to buffer seasonal demand, so that their operation is tied to the time of year.

Weather: Weather forecasts may be used to anticipate future demands

Capital costs: Influence long-term capacity investments

Outputs – Short-term
Production rate: Given the current price and time (along with any internal state information maintained by the decision-making model) agents produce gas a particular rate.

Outputs – Long-term
Investment/disinvestment in facilities. The amount and type of physical equipment used to store gas is represented in some way in the agent's decision model. Storage agents' long-term behavior does not act on the system directly, but is reflected in a change in storage capacity, injection rate, and withdrawal rate given the same operational inputs.

Models
The current implementation schedules injections and withdrawals at fixed times of the year. Storage can be made more adaptive by introducing a profit-maximizing decision rules based on

price forecasts, with the model of future price based on observations of the endogenous market price.

Pipeline Owner Agents
Pipeline Owners owns the physical assets that compose the transmission system. They lease these assets to transmission companies or other Agents under long-term contracts sufficient to provide acceptable return on their capital investment. Owners may themselves act as transmission companies, bet these roles are distinct.

Inputs
Price: Pipeline owners make long-term commitments and are therefore interested in trends in price and consumption rather than short-term price fluctuations.

Demand/supply forecasts: Projections of regional patterns of demand and supply are important elements of transmission planning

Capital costs: Influence long-term capacity investments

Outputs – Short-term
Pipeline owners are not involved in operational decisions

Outputs – Long-term
Construction of new pipelines
Investments to increase capacity of existing pipelines

Models
Pipeline owner behavior can be simply modelled as a gradual change in network capacity as a function of utilization, with the time constant associated with capacity growth dependent on capital cost.

Alternatively, a network-theory-based algorithm for network expansion with the goal of alleviating the existing bottlenecks might be used. Such an algorithm would not produce a concrete prediction of the possible future states of the network, but would create states of the network that could support the anticipated changes to supply and demand.

Transmission Company Agents
Transmission companies operate Interstate and Intrastate pipelines leased from owners. They in turn sell transmission capacity to traders, LDCs, and other wholesale users.

Inputs
Prices: Transmission companies sell wholesale transmission services, and so are indirectly interested in short-term price fluctuations and trends in prices.

Demand/supply forecasts: Projections of regional patterns of demand and supply are important considerations in setting tariffs.

Outputs – Short-term
Flow rates: Transmission companies move gas on the systems they control according to contracts they've made.

Tariffs: Rates charged for new contracts may be adjusted based on current utilization

Outputs – Long-term
Leases: Transmission companies lease assets from pipeline owners

Models
Transmission company tariff rates may be represented as fixed transmission costs on network elements. This approximation would reflect scarcity of transmission capacity without the complication of modelling individual contracts.

Traders

Traders buy gas from producers or storage and sell natural to LDCs who in turn sell and deliver to final demand consumers (electric power generation, residential, industrial, and commercial users). Sales can occur daily or yearly between traders and the LDC. In the interim the natural gas purchased by the Trader can be placed in Storage for a fee.

Inputs
Prices: Traders buy and sell wholesale contracts and are especially attentive to regional differences in gas price.

Demand/supply forecasts: Projections of regional patterns of demand and supply are important considerations in hedging.

Outputs – Short-term
Offered prices:

Local Distributing Companies (LDCs)

LDC's distribute gas to final end users

Inputs
Prices: Prices offered by traders.
Regulatory constraints: Prices charged to final consumers may be constrained by utility regulators

Outputs – Short-term
Contracts
Customer rates

Outputs – Long-term

Investments in distribution infrastructure
Contracts with storage operators

Future Direction
The current model has implementations for Consumer and Producer agents, and for the transmission network interaction structure and a global spot market interaction structure that represents all structures that intermediate between consumers and producers.

Figure A4 and A5 depict a possible elaboration sequence for the agents and interaction structures. This sequence was developed in consideration of existing capabilities, the need for incremental testing and evaluation, the complexity of added features, and uncertainty about the value of incorporating additional processes for resolving questions of interest.

A.2. Bibliography of Project Output

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