Managing Risk in Alternative Energy Product Development

[1] Burcu Tan, [1] Edward Anderson, [2] Geoffrey Parker

[1] University of Texas, McCombs Business School
1 University STA B6000,
Austin, TX 78712-0201, US
Burcu.Tan@phd.mccombs.utexas.edu
Edward.Anderson@mccombs.utexas.edu

[2] Tulane University, Entergy Tulane Energy Institute
A. B. Freeman School of Business
9 McAlister Dr.,
New Orleans, LA 70118, US
gparker@tulane.edu

We will explore how to value using modern financial techniques the development of new alternative energy technologies (AETs) given uncertainty. Uncertainty in developing AETs derives from: (1) the reduction in installation cost of new generation capacity as experience with the technology is gained, i.e. the learning curve (2) oil and natural gas price cycles; and (3) other macroeconomic and geopolitical forces, particularly the behavior of national oil companies (Aramco, PDVSA, PEMEX, etc.). Evaluating a new AET properly requires representing these uncertainties as well as an investment valuation approach that works well under high uncertainty. In particular, we propose to adapt the real options methodology to value the potential return from developing alternative energy technologies using stochastic system dynamics models representing the uncertainty in both the learning curve and the fossil fuel price cycles. The proposed algorithm to accomplish this valuation leverages the prior work on real options valuation in the decision analysis literature.

Keywords: Alternative energy technologies, product development, learning curve, real options

1. Introduction

According to the International Energy Agency in its *2006 World Energy Outlook,* "The world is facing twin energy-related threats: that of not having *adequate* and *secure* supplies of energy at *affordable prices* and that of *environmental harm* caused by consuming too much of it." Oil prices began 2007 near record levels. In the long term, the situation will likely worsen. World oil demand is projected to increase by 50 percent by 2030, driven by economic growth in China, India, and other non-OECD countries. Meanwhile, geopolitical factors such as the Iraq war and the strike by PDVSA (Venezuela's national oil company) as well as ultimately finite fossil fuel reserves will constrain supply. Overhanging these economic issues is the specter of environmental harm, particularly the potential for global warming. Global carbon dioxide emissions are projected to increase to 40 billion tons annually by 2030, a 55% increase over today's level.

One natural suggestion to reduce the impact of these issues is to develop alternative energy technologies, such as, for example, wind power. However, developing these technologies has proven problematic. When new technologies are launched, generally they lack the cost efficiency their conventional counterparts enjoy, and their viability depends on the performance of the conventional technology. Alternative energy technologies target the electricity generation market whose price dynamics largely follow natural gas prices (Figure 1). Furthermore, the major alternative energy technologies like wind and solar power are used as intermediate load plants, for which the dominant, conventional technology is combined-cycle natural gas plants. Hence, natural gas price -or equivalently[1] oil price- is one major determinant of how competitive and viable alternative energy technologies will be.

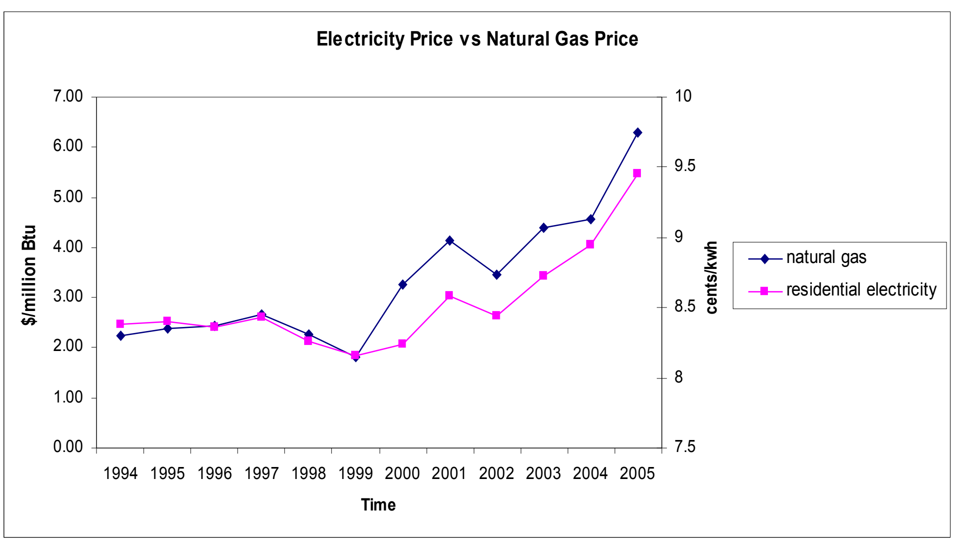

Figure 1: Electricity Price vs. Natural Gas Price

[1] Natural gas and crude oil are substitutes in consumption and complements in production. Hence, economic theory suggests a strong relation between their prices. This relationship has been subject to extensive analysis. Oil prices are found to influence the long-run development of natural gas prices but are not influenced by them (Villar et al., 2006).

Yet, these prices are highly stochastic and influenced by geopolitical or macroeconomic short-term factors as shown in Figure 2.[2] For example, the current peak in oil prices appears due to a confluence of long-term economic growth in Asia as well as the PDVSA Strike and the Iraq war.

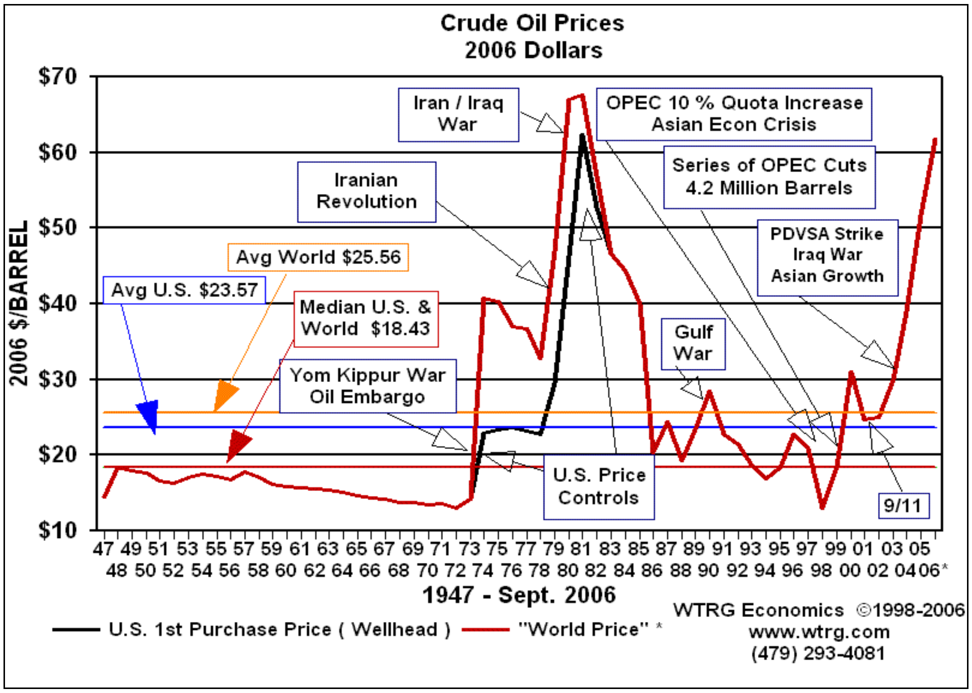

Figure 2: Real Oil Prices since 1947 including Macroeconomic/Geopolitical Shocks

One of the reasons for this underdevelopment is the difficulty in placing a value on the return from investing in projects employing them. Not only are fossil fuel prices highly stochastic, but so is the cost of developing new technology. The bulk of most AETs' cost structure lies in their non-recurring costs. These costs typically experience—like most other technologies (Argote 1999)—a steep reduction in cost with each doubling of the cumulative capacity installed. However, the steepness of this "learning curve" as well as its final "plateau" are generally uncertain *ex ante*. For example, consider the case of concentrated solar power (CSP), a highly promising renewable technology that uses parabolic mirrors to concentrate sunlight to heat fluids that can drive electricity-generating turbines (Figure 3). A number of CSP initiatives were begun in the 1980s during a previous bubble in energy prices. However, when this bubble collapsed, so did the economic viability of the projects and most of the firms and suppliers involved are no longer extant. Hence, new CSP projects may find they have to "reinvent the wheel" by redeveloping tacit technological knowledge lost since the last concentrated solar power installation was completed in 1992. In contrast, wind power (Figure 5) managed to emerge from the 1980s sufficiently viable that it has continued to grow apace and can now (as of 2004) generate electricity more cheaply than fossil fuels.
However, it too is experiencing similar uncertainties in its learning curve because windmill architecture is still in flux.

[2] From the website of WTRG economics. http://www.wtrg.com/prices.htm

Concentrated Solar Power

- Enough electric power for the entire US economy can be generated by covering a 100 mile square of Nevada with parabolic trough systems
- Preferred techological architecture still in flux
- Learning curve approximately 30%
- No new installations since 1992.

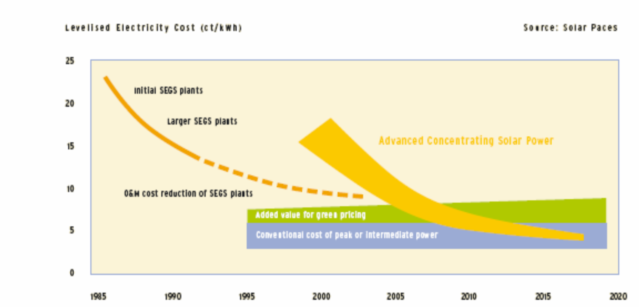

Figure 3: Concentrated Solar Power Summary Facts

Of course, broadly speaking, we are not interested in CSP or wind power *per se* but in determining whether any technology invested in during the onset of a fossil fuel price bubble can be expected to gain a sufficient "escape velocity" to survive a future, probable collapse in fossil fuel prices. The system dynamics methodology has demonstrated its capability of generating models that can plausibly track both fossil fuel prices (Sterman 1981; Naill et al. 1992; Morecroft et al. 1992, Davidsen et al. 1990, etc.; see Ford (1997) for a list of early SD work on electric power) and technology "learning curves" (Anderson and Parker 2002).

However, even once an appropriate SD model is built (as described in Section 2), evaluating whether to proceed with an AET project still remains difficult because the rate at which a firm implements such a project is an ongoing decision. Within certain constraints, such a project can be accelerated, decelerated, or abandoned at any time depending on the evolution of fossil fuel prices and the cost of the AET capacity. The standard method for evaluating projects with such managerial flexibility is the real options approach (Dixit and Pindyck 1994). Standard real options models of the underlying project to be evaluated remain highly unrealistic, generally depending on black box models of price and cost evolution such as Brownian motion. However, implementing real options evaluation approaches in system dynamics, while not unknown (Danner et al. 1999), remain problematic for reasons described in Section 3. To circumvent these issues, we propose instead to transform an appropriate system dynamics model first into a decision tree using the methodology of decision analysis (Clemen 1997), in a manner similar to that discussed in Osgood (2005), prior to valuation. We then use the methods developed in the Decision Analysis (DA) literature (e.g. Brandao et al. 2005) to evaluate decision trees with the real options methodology (Brandao et al. 2005). Section 4 presents this approach, combining SD, DA, and real options methodologies, in detail, as well as some limitations to this approach. Finally, Section 5 briefly concludes the paper.

2. Toward an Appropriate System Dynamics Model for AETs

Below, a sector diagram of a proposed SD model for evaluating AETs is presented:

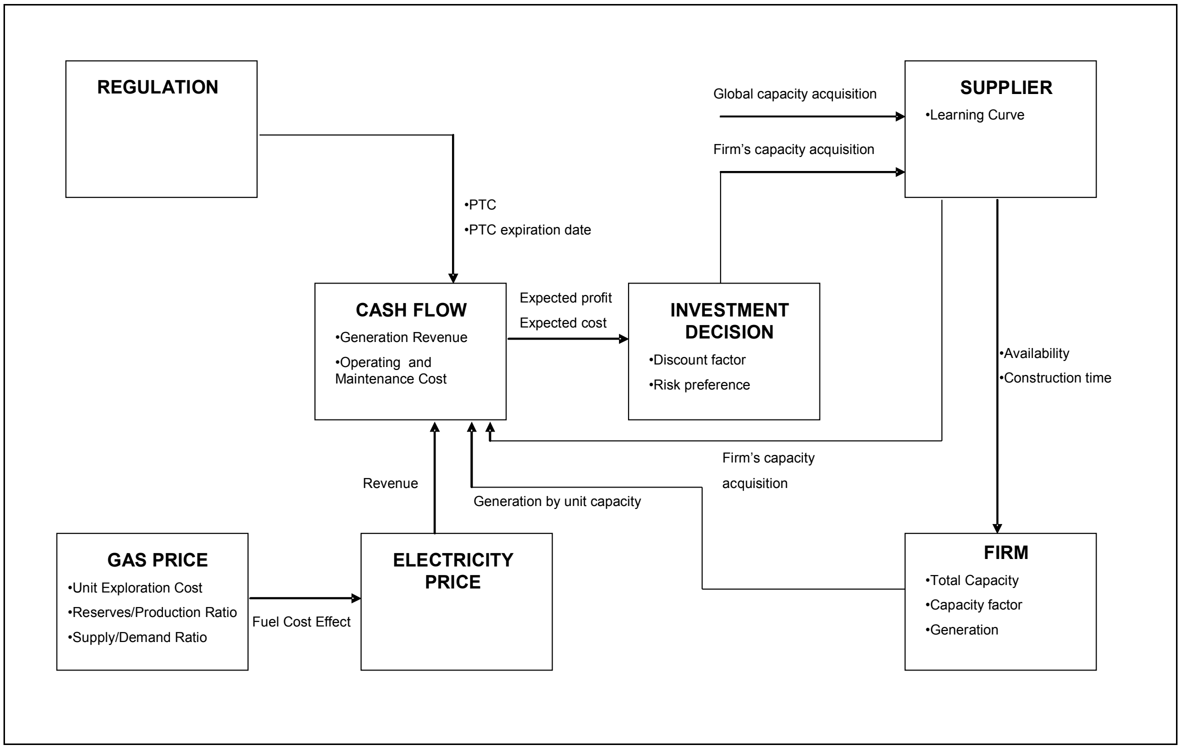

Figure 4: Sector Diagram of the SD Model

Cash flow and investment decision sectors lie at the heart of the model. Revenues accrue based on the electricity price and generation; whereas costs are incurred with capacity acquisition and through operating and maintenance. State and/or federal regulations play a key role in determining the profitability of an investment project. For example, the production tax credit (PTC) and its expiration date have been major determinants of wind capacity investment.

Implicitly, there is a supply-chain structure in the model: The supplier, which installs the equipment for the energy plant (e.g. windmills), and the generating firm, which evaluates the investment opportunity. The supplier enjoys a reduction in its installation costs as the firm acquires more capacity. Hence, the more the generating firm invests, the lower the costs it will face in his future investments[3]. The supplier also takes some advantage of global technological improvements, which is approximated as the impact of a "global" capacity acquisition level.

The model is built for a medium scale firm, which is a price-taker. As described in Section 2, electricity price dynamics largely follow the dynamics of natural gas price. Gas price sector is kept exogenous to the model based on the fact that no alternative energy technology is

[3] Similar feedback relations in this context have been modeled in Ford (2006) and Vogstad (2004).

likely to affect the gas price dynamics within the time horizon of the model (less than 10 years). The essential feedback mechanisms that determine the gas price and learning curve dynamics are depicted in the causal loop diagram in Figure 5.

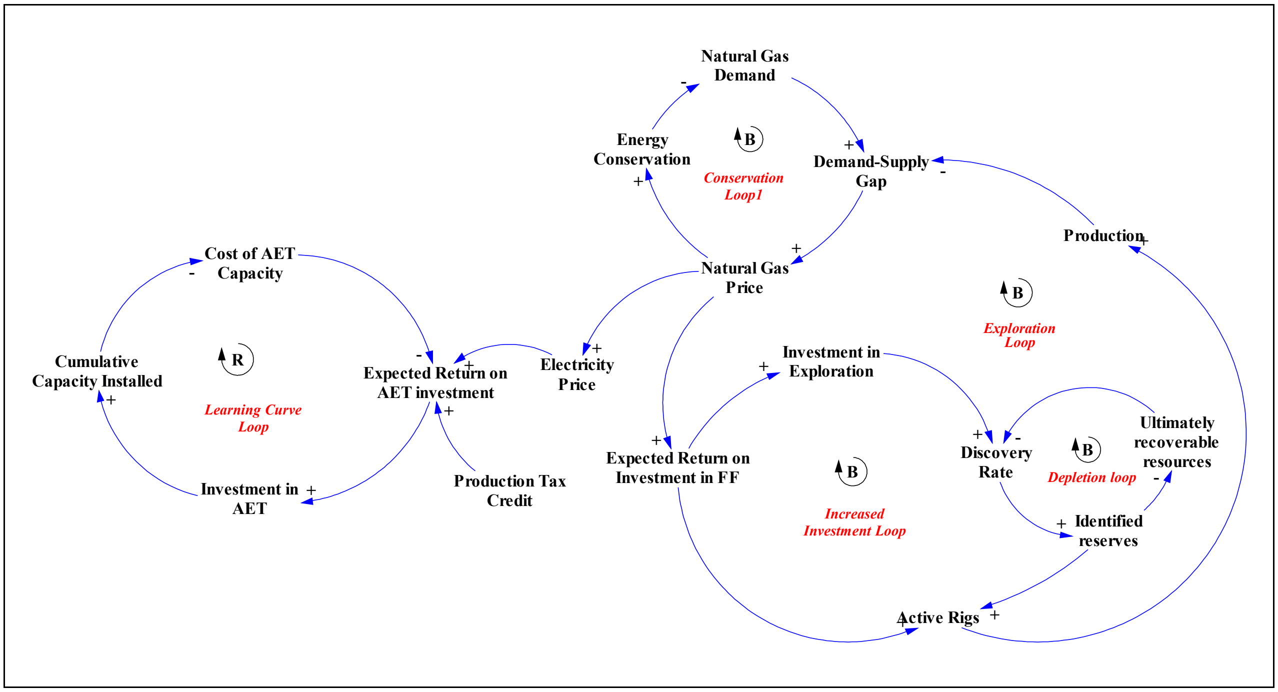

Figure 5: Causal Loop Diagram of the SD Model

Note that the particular SD model we have just described does not lie at the core of this paper. Other models may very well describe the phenomenon of AET technology better. Our focus is rather on developing the methodology to evaluate an AET capacity investment project with both a reasonable gas price model (i.e. better than a mean-reverting Brownian motion model, which is standard) and an endogenous learning curve for the alternative energy technology.

3. System Dynamics, Real Options, and Decision Analysis

Problems with Real Options Valuation

Traditionally in many real life projects, investment opportunities are evaluated using discounted cash flow (DCF) analysis. However, the adequacy of this rule is challenged when a project's expected cash flow profile is facing significant uncertainties and when the management has the flexibility to respond to these uncertainties. For example, a standard DCF approach would be unable to account for the managerial flexibility to accelerate, delay, or abandon a project. Hence DCF analysis systematically undervalues the projects with high uncertainties and accompanying managerial flexibilities. In such projects, the use of real options valuation approach is recommended.

A real option is the right but not the obligation to take a certain action in the future depending on how uncertainties evolve. Real options valuation approach interprets managerial flexibility as “options on real assets”, which can be valued similarly to financial options (Dixit and Pindyck 1994). It allows strategy changes based on how some uncertainty has been resolved, which makes it an effective method of risk management.

Despite its conceptual appeal, real options valuation is not widely used in practice. This is attributed mostly to the mathematical complexity of the traditional valuation techniques, which make the solution process obscure (Triantis, 2005), and to the restrictive and typically unrealistic assumptions upon the interactions and distributions of the system’s random variables necessary to provide a tractable solution. Some progress toward model “realism” has been made with the adaptation of the decision analysis (DA) methodology to real options problems (e.g. Brandao et al. 2005), which we shall return to later.

Real Options Valuation and System Dynamics

Real options valuation traditionally models the uncertainty by assuming an input distribution or a stochastic process. For example, generally, the price of electricity is assumed to follow a geometric Brownian motion and commodity prices (e.g. natural gas) are assumed to follow a mean reverting geometric Brownian motion process. Yet, as already discussed above, fossil fuel prices are not a stationary stochastic process, even in terms of the long-term mean. Hence, conventional black-box stochastic processes are insufficient to capture the subtleties such complexity introduces. Modeling the essential structure that produces this complex price behavior via system dynamics methodology potentially improves the reliability of the ultimate valuation. One particular benefit of using system dynamics in this context is its ability to model path-dependence, which is critical to obtain the learning curve effect.

Using system dynamics also makes it possible to add multiple sources of uncertainty without increasing the complexity of the problem significantly. Furthermore, the ability to describe the distribution of uncertainty around SD variables is straightforward given the SD methodology’s emphasis upon the use of concrete variables that correspond tightly with observable and “real” phenomena (Sterman 2000), such as modeling the revenue from a windmill installation as the product of the variable electricity cost (i.e. natural gas price), the amount of energy generated per windmill, and the number of windmills. In this example, one can represent the randomness from weather as a random distribution in wind speed, which then directly affects the energy per windmill. Given that, in the context of our problem, it is the multiple—and possibly interacting—sources of uncertainty that make difficult to develop proper project valuations, the concreteness and flexibility offered by system dynamics in defining both endogenous, non-linear systems and separate stochastic effects is a clear advantage. Finally, system dynamics provides clearer insights into the drivers of the option value and the effect of a certain strategic action (Johnson et al. 2006; Danner et al. 1998). In view of these potential benefits, one objective of this research is furthering system dynamics as a new tool in real options valuation, following the work of Johnson et al. (2006) and Ford et al. (2005). However, using a real options approach to track sequential—let alone continuous—decision processes is difficult using standard techniques.

What is difficult to capture in System Dynamics is optimizing a sequential decision process, e.g. capturing a generating firm's making a decision in 2008 upon whether to accelerate, maintain, or suspend a project, which presupposes knowing what will be best choice at the decision points in 2009, 2010, etc. given the conditions pertaining at those times. The way to solve these problems typically involves backwards induction. As a short example of backwards induction, consider a simple project with decision points in 2009 and 2010. A firm would first calculate the best decision possible for 2010 given any potential set of economic and firm conditions. The firm would then be able to map each set of conditions in 2010 with a best decision under that set of conditions. Once all the potential 2010 decisions are mapped, then for all sets of conditions that could exist in 2009, the firm would make its 2009 decision. This 2009 decision would be based both upon the set of 2009 conditions as well as upon the knowledge that the 2009 decision will lead to a probability distribution of a set of economic and firm conditions for 2010. Importantly, however, the firm in 2009 knows *ex ante* how each of these potential 2010 conditions is already mapped to an appropriate decision for 2010. Because this is the very managerial flexibility that the real options approach seeks to capture, modeling such a decision process and the backwards induction necessary to "solve" it is crucial to evaluating AET—and many other sorts of—projects. However, the forwards integration nature of system dynamics simulation evaluation algorithms is incompatible with backwards induction. In principle, this is not insurmountable; backwards induction solutions to many system dynamics-like problems can be seen in any standard dynamic programming text, such as Bertsekas (2005). But another approach may be simpler than directly mating backwards induction to system dynamics and yield some important ancillary benefits.

Decision Analysis

In contrast to system dynamics, decision tree analysis (or simply decision analysis or DA) is an intuitive approach commonly used to model sequential decision processes (Clemen 1997) and is designed to be compatible with backwards induction. In view of these benefits, there have been studies working on ways to apply decision tree analysis to real option valuation problems (See Brandao et al. 2005 for a review). In particular, decision trees can be used to model a discrete approximation of project uncertainty and managerial flexibility with only a few adjustments to the traditional decision tree analysis in order to make a theoretically sound real option valuation. For example, using the replicating portfolio method makes it possible to obtain the correct discount rates for the project and capture the market information about risk in valuing the project. DA is also appealing because DA models are simple to explain to non-practitioners. However, the stochastic distributions of cash flows resulting from DA typically are difficult to determine in practice because they result in part from non-linear mappings of mutually interacting stochastic, endogenous variables such as numbers of windmills, etc., which are what system dynamics is good at representing.

4. The Proposed Valuation Algorithm

Because of the complementary advantages of system dynamics and decision analysis in representing stochastic models and decision processes, we propose the following methodology that hinges upon first formulating a system dynamics model and then transforming it into a corresponding decision analysis tree. Backwards induction is then used upon the decision tree to obtain a real options valuation of the project. To illustrate the details of this procedure, consider the extended example below, which is a simplified AET project.

We illustrate the proposed solution procedure with another simple example based on the one discussed earlier when discussing backwards induction. Suppose that we have built a simplified *stochastic* system dynamics model that captures the essentials of capacity investment, fossil fuel price and learning curve dynamics. Further suppose that the horizon of a particular investment problem is two years. In each year—say 2009 and 2010—the manager has to decide how much to invest in new capacity. For simplicity, she can only choose between three rates of capacity expansion: high, moderate, or none at all ("suspend"). Depending on the firm's decisions and on how the fossil fuel price and capacity cost uncertainties evolve, the cash flow at the end of each of the two years may be high, nominal or low. (The "low" level may possibly be negative). This decision problem can be represented with the decision tree in Figure 6.

Basic components of a decision tree are as follows: Square nodes are the *decision nodes*, which represent the decisions to be made at a particular time, like "invest high or suspend". Circular nodes are the *chance nodes*, which represent the uncertainties underlying the project. Triangular nodes are the *terminal nodes* that depict the final outcome of a particular scenario after all decisions have been made, all uncertainty has been resolved and all payoffs are received. Branches leaving a decision node represent the decision alternatives. Branches leaving a chance node represent possible outcomes of uncertain events[4]. Time flows from left to right.

[4] For visual clarity, a limited number of terminal nodes and branches are shown in Figure 9.

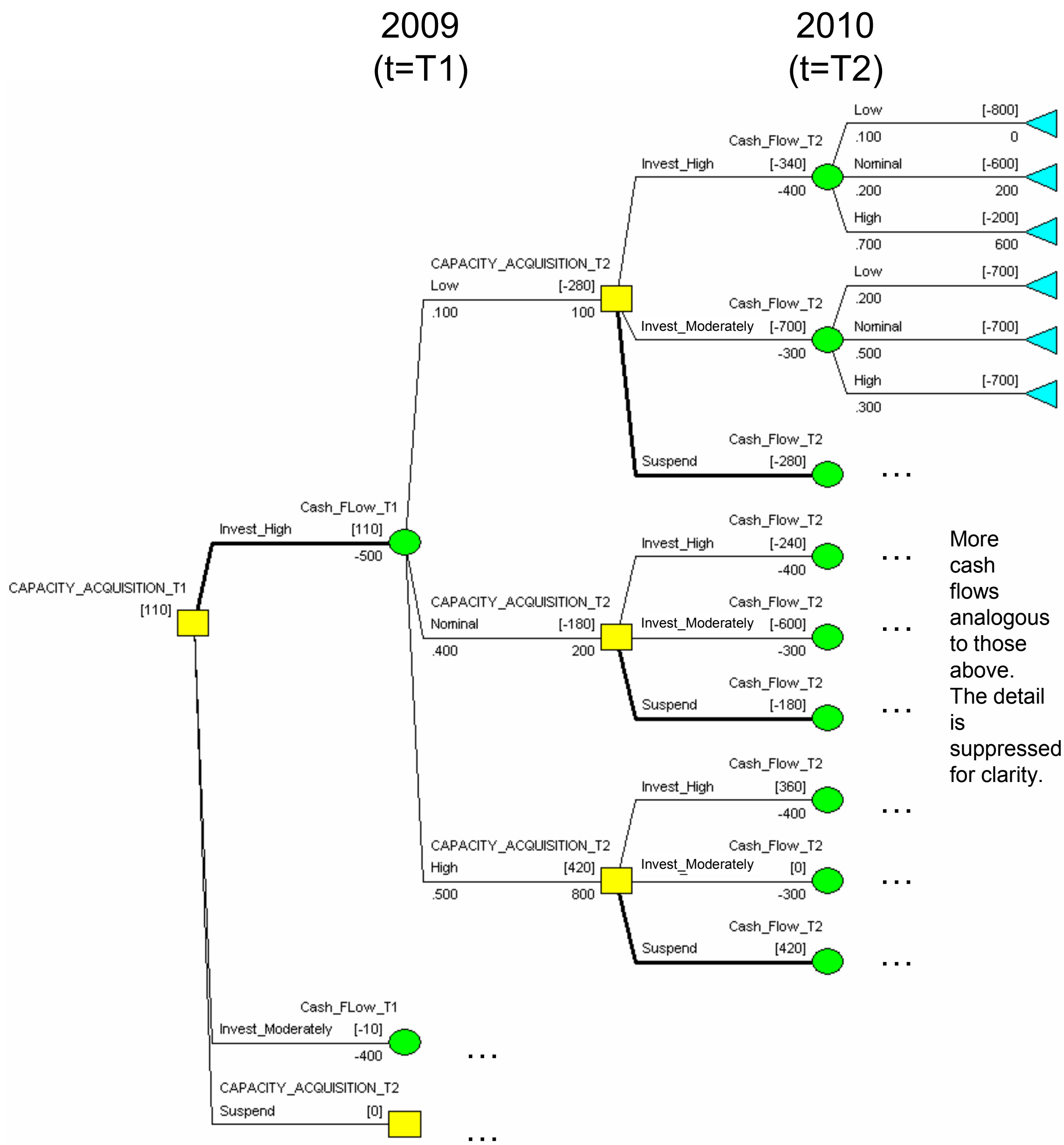

Figure 6: Decision Tree and Outcome Distributions

In traditional decision analysis models, probabilities are assigned to each branch leaving a chance node. These exogenously assigned probabilities are generally either the (subjective) beliefs about the likelihood of a specific "event" represented by the chance node or the risk neutral-measures derived from these (subjective) beliefs. However, since we endogenously account for the uncertainties within an SD model, we will use a different approach in this study: Chance nodes will represent the distribution of the cash-flows at time *t* (either 2009 or 2010), which will be from the stochastic SD model for each combination of decisions in 2009 and 2010. Each possible sequence of decisions is referred as a *decision rule*. A decision rule is a function that specifies the sequence of actions given any possible history of events. In this example, the horizon of the investment problem, T, is 2 and the number of decision alternatives at any decision node, n, is 3. At each time period, the manager can choose any of the 3 alternatives: invest high (H), invest moderately (M), suspend (S). This results in 9 decision rules as can be seen from the table below. Note that it is straightforward to impose these rules in the SD model with a few additional if-else type equations.

Rule ID	**Decision in 2009**	**Decision in 2010**
1	H	H
2	H	M
3	H	S
4	M	H
5	M	M
6	M	S
7	S	H
8	S	M
9	S	S

Table 1: Decision Rules for the Example Problem

In order to value the project, first we need to run Monte Carlo simulations of the SD model for each decision rule in Table 1. Each Monte Carlo run gives a cash flow distribution for the associated terminal node. We determine the value of the probability distribution of cash flows for each terminal node by finding the value of an appropriate security or a portfolio with the same risk-return profile[5]. The value of the twin security or replicating portfolio can then be substituted for the value of the terminal node. This implies that the associated probabilities will also be endogenously determined. Such an approach is particularly useful here because we are path-dependent with respect to the cumulative investment up to time t.

After obtaining the market adjusted value for each terminal node, we begin with evaluating the decisions at the final period 2010 and move backwards using backwards induction as described earlier (Bertsekas 2005). At each decision node, the better of the two decisions can be chosen based on that valuation and the worse "pruned off" so that the value of the better decision can be substituted for the "cash-flow" at time 2010. We can then begin to evaluate the impact of decisions made at period 2009 using the valuations for each of the period 2010 random outcomes as described above. We could then, in principle, continue in this manner for additional previous periods, determining the random distribution of cash-flows for the potential decisions made, valuing those cash flows, "pruning" the inferior decision branches, and then proceeding to the next previous period. This will continue until the first period of the project. At that point, we will obtain a final valuation for the project as a whole. This valuation will incorporate not only management flexibility but also the market or "true" valuation of the risk involved in the project.

[5] In this context, an appropriate place to look for such securities could be natural gas futures market.

In summary, consider the generalization in Figure 7 of the example just described. Using this method, we can gain all the advantages of a system dynamics model while still obtaining an appropriate real options valuation.

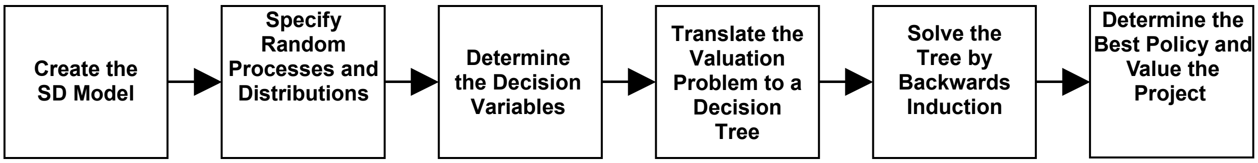

Figure 7: Steps of the Proposed Algorithm

Step 1-Create the SD Model: Build a deterministic SD model of AET capacity investment, fossil fuel prices, and learning curve dynamics.

Step 2-Specify Random Processes and Distributions: Model the underlying uncertainty of the project within the SD model. In this case, there are multiple sources of uncertainty: those determining the gas price realization and those determining the learning curve effect realization.

Step 3-Determine the Decision Variables: Determine the decision alternatives of the project manager, which are invest high, invest moderately, or suspend in the simple example[6].

Step 4- Translate the Valuation Problem to a Decision Tree: The next step is constructing the decision tree based on the decision alternatives determined in the previous step. Identify the decision rules and modify the SD model (if necessary) so that different decision rules can be imposed by the analyst in each run. The most difficult portion of this step is to create a reasonable number of "bins" for each chance node and each decision node to discretize the continuous ranges of each variable. If too few are chosen, the decision rule's approximation to optimality will be low and the real options valuation, inaccurate. If too many are chosen, the computations involved will become prohibitive.

Step 5-Solve the Tree with Backwards Induction:

5.1-Run a Monte Carlo simulation of the SD model for each decision rule and obtain the cash flow distribution of each terminal node in the tree.

5.2-For each terminal node, find a twin security or a replicating portfolio from the market that has the same risk-return profile. Use the market value of that security as the value of that terminal node.

5.3-Determine the best decision at the last period T. Given the best node at T, proceed backwards to obtain the best node at T-1 (backwards induction). Repeat this step recursively until evaluating the first decision node.

Step 6-Determine the Best Policy and Value the Project: Determine the highest payoff policy. The expected value of the project is obtained from this decision rule.

Note that it is possible to value a specific option associated with each decision node by rebuilding the tree without that option, reiterating Step 5 and obtaining the value. An

[6] Suspend decision in the first period corresponds to a deferral option. Invest high or low in the second period corresponds to an expansion option at the decision nodes that follows invest high or invest low in the first period.

estimation of the expected value of that option is the difference between the value of the project with the option and without the option.

One limitation of this solution procedure is the seemingly unavoidable “curse of dimensionality” should T or the number of decisions alternatives at each node (n) or both boost. For {T=2, n=3}, one must evaluate 9 decision rules. For {T=10, n=3}, this number would be 3^{10}=59049. As the number of nodes and periods increases, the number of computations will quickly become prohibitive. However, reducing the number of nodes and periods will make the algorithm less accurate. Thus, a difficult trade-off presents itself to the modeler. Fortunately, when more fidelity is required, decision analysis literature does offer some approaches to fight against the dimensionality problem. One possible approach is adapting the Least Square Monte-Carlo (LSM) approach developed by Longstaff and Schwartz (2001) to solve the tree. It has been numerically shown that the size of the problem with LSM approach grows much more slowly than in the backwards integration algorithm just described.

5. **Conclusion**

There is a clear need for the development of alternative energy technologies, given the energy threat the world is facing. However, even the most promising of these technologies remain underdeveloped. One of the reasons for this underdevelopment is the difficulty in placing a value on the return from investing in projects employing them. The valuation procedure proposed in this paper aims addressing this problem. The viability of an alternative energy technology is largely determined by fossil fuel prices and alternative energy development costs, both of which are highly stochastic. The system dynamics methodology has proven capable of modeling fossil fuel prices and technology learning curves. Similarly, the real options valuation approach has proven to be the appropriate valuation scheme for capital investments that are subject to high uncertainties. Hence, adapting real options approach to value the potential return from developing these technologies and representing the uncertainties by stochastic system dynamics models is one potential way to value more accurately the development of new alternative energy technologies. In particular, the algorithm proposed in this paper offers a structured way to do this by taking advantage of the intuitiveness of decision tree methods.

References

Anderson, Edward G., and Geoffrey G. Parker (2002). “The Effect of Learning on the Make/Buy Decision.” *Production and Operations Management* 11 (3): 313-339.

Argote L. 1999. *Organizational Learning: Creating, Retaining, and Transferring Knowledge.* Kluwer Academic: Boston, MA.

Bertsekas, D. (2005). *Dynamic Programming & Optimal Control, vol. I.* Athena Scientific, Nashua, NH.

Brandao, L. E., Dyer, J. S. and W. J. Harren (2005). “Using Binomial Decision Trees to Solve Real-Option Valuation Problems.” *Decision Analysis*, 2 (2): 69-88.

Clemen, R.T. (1997). *Making Hard Decisions: An Introduction to Decision Analysis*. Duxbury Press, Belmont, CA.

Danner, G.E., Agatstein, K. E., Angelahis, D.E., and O. Uhan (1999). “Strategic Value: Incorporating Real Options into System Dynamics Models.” *Proceedings of the System Dynamics Conference*, Wellington, New Zealand, 1999.

Davidsen, P. I., Sterman, J. D. and G. P. Richardson (1990). “A Petroleum Life Cycle Model for the United States with Endogenous Technology, Exploration, Recovery, and Demand.” *System Dynamics Review*, 6(1).

Dixit and Pindyck (1994). *Investment under Uncertainty.* Princeton University Press, Princeton, NJ.

Economist, The (2006). “Oil’s Dark Secret.” August 12, 2006, pp. 55-57.

Ford, A. (1997). "System Dynamics and the Electric Power Industry." *System Dynamics Review*, 13(1): 57-85.

Ford, A. (2006). “Simulating the Impact of Carbon Market on the Electricity System in the Western U.S.A.” *Proceedings of the 24th International Conference of the System Dynamics Society*, Nijmegen, Netherlands.

Ford, A., Vogstad, K. and H. Flynn (2007). “Simulating price patterns for tradable green certificates to promote electricity generation from wind.” *Energy Policy*, 35: 91-111.

Ford , D. and S. Sobek (2005). “Adapting Real Options to New Product Development by Modeling the Second Toyota Paradox.” *IEEE Transactions on Engineering Management*, 52 (2).

Johnson, S. T., Taylor, T. and D. Ford (2006). “Using System Dynamics to Extend Real Options Use: Insights from the Oil and Gas Industry.” *Proceedings of the System Dynamics Conference,* Nijmegen, Netherlands, 2006.

Longstaff, Francis A. and Eduardo S. Schwartz (2001). Valuing American Options by Simulation: A Simple Least-Squares Approach.” *The Review of Financial Studies* 14 (1): 113-147.

Morecroft, John D. W. and Kees A. J. M. van der Heijden (1992). "Modeling the Oil Producers: Capturing Oil Industry Knowledge in a Behavioral Simulation Model." *European Journal of Operational Research* 59(1): 102-122.

Naill, R. F. (1992). “A System Dynamics Model for National Energy Policy Planning”, *System Dynamics Review* 8(1): 1-19.

Naill, Roger F. Sharon Belanger, Adam Klinger, and Eric Petersen (1992). "An Analysis of the Cost of Effectiveness of US Energy Policies to Mitigate Global Warming." *System Dynamics Review* 8(2): 111-128.

Osgood, N. (2005). "Combining System Dynamics and Decision Analysis for Rapid Strategy Selection." *Proceedings of the 23rd International Conference of System Dynamics Society*, Boston, US.

Sterman, John D. (1981). *The Energy Transition and the Economy: A System Dynamics Approach* Ph.D. Thesis, MIT.

Sterman, J.D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World.* McGraw-Hill/Irwin: New York.

Sterman, J. D., G. P. Richardson and P. I. Davidsen (1988). "Modeling the Estimation of Petroleum Resources in the United States" *Technological Forecasting and Social Change*, 33: 219-249.

Stobaugh, R., D. Yergin, eds. (1983). *Energy Future- Report of the Energy Project at the Harvard Business School*. Vintage Books Edition, New York.

Triantis, A. (2005). "Realizing the Potential of Real Options: Does theory meet practice?" *Journal of Corporate Finance*. 17(2) pp. 8-16.

Villar, J. A. and F. L. Joutz (2006). "The Relationship between Crude Oil and Natural Gas Prices." *Energy Information Administration, Office of Oil and Gas*.

Vogstad, Klaus-Ole (2004). *A System Dynamics Analysis of the Nordic Electricity Market: The Transition from Fossil Fuelled Toward a Renewable Supply within a Liberalized Electricity Market.* PhD. Thesis, Norwegian University of Science and Technology.

Yergin, D. (2004). "Ensuring Energy Security." *Foreign Affairs,* 85 (2): 69-82.

Data References

American Petroleum Institute, Basic Petroleum Data Book: Petroleum Industry Statistics, Volume XXV, Number 2, 2005.

American Wind Energy Association, Economies of Wind Energy, Wind Energy Factsheets, 2006. www.awea.org.

Baker Hughes, Worldwide Rig Counts, 2006.

BP Global, Statistical Review of World Energy 2006, 2006.

Energy Information Administration (EIA), Department of Energy, US Data, 2006.

International Energy Agency (IEA), World Energy Outlook 2005, 2005.

International Energy Agency (IEA), World Energy Outlook 2006, 2006.

National Renewable Energy Laboratory, Concentrating Solar Power Research, 2006. http://www.nrel.gov/csp/publications.html