ECONOMICALLY OPTIMAL TIMING

OF INSECT CONTROL

IN FOOD PROCESSING FACILITIES:

A REAL OPTION APPROACH

By

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
December, 2018

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ACKNOWLEDGEMENTS (Optional)

At the outset, I would like to thank my advisor Dr. Brian D. Adam, for his patience and guidance. I enjoy very much working under him and it was an excellent learning experience for me. I appreciate him for teaching me how to think about a problem, how to get a new idea to solve the problem and how to validate my idea. I would also like to thank him for helping me out with great patience in writing this dissertation, for guiding me and giving me tips on structure, grammar, sentence and words. These lessons will benefit me all my life.

I would like to thank my committee members, Dr. Wade Brorsen, Dr. Brian Whitacre and Dr. Shu Yan for their timely advice, discussions and feedback. I often get inspiration and knowledge improvement from their intellectually challenging courses.

Then, I will thank my husband Zhenan He for his totally understanding and supporting. He always supports and encourages me to work hard in my research field. I am forever grateful to my parents for their love, financial and moral support and encouragement. Last but not the least; I would like to present such hard work as a gift to my son Daniel He in the name of love.

Name: SULING DUAN

Date of Degree: DECEMBER, 2018

Title of Study: ECONOMICALLY OPTIMAL TIMING OF INSECT CONTROL IN
FOOD PROCESSING FACILITIES: A REAL OPTION APPROACH

Major Field: AGRICULTURAL ECONOMICS

Abstract: Insect control is a key concern for handlers of grain and grain-based products during the storage, processing, and packing processes. Insect infestations and insect fragments in food products can cause both direct and indirect economic losses. The most significant economic damage from insects in food processing facilities is contamination of food, which can lead to rejection of shipments, treatment cost, insect fragments in food, consumer complaints and loss of consumer goodwill. However, the potential damage is hard to quantify. The cost is large but the probability of occurrence may be low.

Food processors must balance costs of insect control and risks of failing to control insects, while choosing from a set of imperfect insect control methods. An economical insect control strategy must make effective use of available information to optimize the timing of insect control methods, both chemical and non-chemical.

In this study, real option models are used to value insect control treatments and pick the optimal timing to treat insects. Daily temperature is the stochastic variable which is the main source that causes uncertainty about insect population and the corresponding potential damage.

Results found that the real option approach can reduce costs compared with using an economic threshold approach. The optimal treatment time signaled by a real option approach is earlier if temperatures are expected to increase, due to the higher probability of damage. Conversely, the optimal treatment time is likely to be later if temperatures are expected to decrease. Thus, the real option approach, by taking into account probabilities of future temperature movements, can reduce treatment cost by postponing treatment if temperature is likely to decrease, and can reduce insect damage loss by accelerating treatment if temperature is likely to increase.

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CHAPTER I

INTRODUCTION

1.1 Background

Insect control is a key concern for handlers of grain and grain-based products during the storage, processing, and packing processes. Insect infestations and insect fragments in food product can cause product damage (Larson et al. 2008), and both direct and indirect economic losses.

The most significant economic damage from insects in food processing facilities is contamination of food, which can lead to rejection of shipments, treatment cost, insect fragments in food, consumer complaints and loss of consumer goodwill. Insect infestations inside processing facilities and resulting product discount cause millions of dollars of economic losses each year (Harein and Meronuck 1995).

Conventional structural fumigations with methyl bromide or sulfuryl fluoride have often relied on calendar-based applications with limited evaluation of overall pest population dynamics (Campbell et al. 2010), which can cause both unnecessary treatment costs and more rapid evolution of insect resistance to the fumigants. Meanwhile, consumers prefer food products without pesticide residues.

Moreover, the most widely used and effective fumigant, methyl bromide, is no longer available because it has been designated an ozone depleter under the Montreal Protocol. Thus, food producers and processers face a challenge to control insects effectively with judicious use of a greatly reduced arsenal of chemicals.

Integrated pest management (IPM) programs attempt to reduce use of insecticides by using non-chemical treatments along with information to reduce frequency of chemical treatments and to optimize their timing. However, food suppliers may be hesitant to adopt such programs because of the potential increased costs if they fail to control insects adequately.

Estimating these costs is difficult because insect populations, insect movement and potential damage are difficult to predict, and although the probabilities of catastrophic costs from insect infestations (e.g. recalls) are low, they are not zero. Theoretically, economic thresholds (ET) can be used to make this decision, but in practice, economic thresholds are difficult to implement because of the uncertainties.

Time of treatment is an important decision in insect control. There is a need for a decision model that can optimize the frequency of using chemical treatments in a food processing facility, to minimize the combined costs of treatment itself and costs resulting from insect infestation.

A manager of a food processing facility faces the dilemma that postponing a treatment (such as fumigation) in order to reduce the frequency of using insecticides, risks allowing insect population to increase to an amount that causes economic damage. Conversely, fumigating too early may allow the remaining insect population to rebound sufficiently that another expensive fumigation is necessary earlier than it would have been.

Managers need economic guidelines to make insect control decisions that fully consider treatment costs, effectiveness, and costs of failing to control insects. Few studies have examined cost-effectiveness of strategies for insect control in food processing firms (Ramaswamy et al. 2000). The

high cost of insect control, combined with the high cost of failing to control insects, make such analysis economically important.

A real option approach that has been used in other contexts can reasonably be considered to this problem, because it can make the assessment of the costs of failing to control insects more manageable and easier to evaluate, interpret, and explain, particularly focused on strategies that reduce chemical use in food processing firms.

One of the benefits of real option approach is that the model considers those uncertainties as flexibilities and it places a monetary value on them. The decision maker receives benefit from that flexibility, a benefit that decreases in value as the time value decreases. In addition, a real option approach considers all information available to the manager at that date, including predictions about the future. One contribution of this study is the use of a real option approach to put a dollar value on the risk involved in the decision of when to treat for insects in a food processing facility.

In the option models, we need to define a stochastic state variable. The key factor is insect population, which directly causes the potential economic loss. However, the insect population is hard to define and monitoring traps may not provide sufficient data. An insect growth model is an alternative, in which insect population usually depends on weather information. If there is a deterministic relationship between weather and insect population, it is proper to stochastically model weather patterns and then to predict insect population.

However, few studies have simulated weather when using a real option model to study pest management. In fact, few studies have attempted to quantify risk involved in insect control decisions. There have been no studies of insect management decisions in food processing facilities using a real option framework. This study will add knowledge to the areas of insect control in food processing and applications of real options. These results will provide guidance to help the managers of food processing firms make better insect control decisions.

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1.2 Objectives

The general objective is to determine optimal timing of insect control treatments in food processing facilities using a real option model.

The specific objectives are:

1) Determine the value of deferring insect treatment using a real option approach instead of making an immediate decision by economic threshold criteria.

2) Determine the value and optimal time to treat insects.

3) Determine the effect of timing flexibility on the value of an option for insect treatment.

1.3 Outline of work

In chapter II, we summarize literature on stored products pest management in the food processing facilities. We introduce the concept of integrated pest management. We compare tools for making decisions about insect treatment, such as economical threshold and real option models.

In Chapter III, we review the theory and framework of the option pricing and decision making concepts. We summarize the methods to calibrate empirical data into a stochastic process. Then we study the specific structure of different real option models that is useful to make a decision about insect treatments. The models are option to abandon, timing options and optimal stopping models.

In chapter IV, we explain the procedures. We analyze the empirical weather data. We estimate insect population, the corresponding potential damage loss, and the cost of treatment. We

specify different types of real options to evaluate different problems: 1) what is the value of an option to delay in determining optimal timing, compared with the conventional economic threshold approach to determine timing? 2) during a given time interval, what is the optimal time to treat insects; 3) define the optimal time as until when is the best time for us to hold this option to wait? We use both binomial lattice model and Monte Carlo integration to evaluate those problems.

In chapter V and VI, we summarize the results and get the conclusion. In addition, we discuss several limitations and possible future implementations based on our study.

CHAPTER II

LITERATURE REVIEW

2.1 Insect control in food processing facilities

Flour mills provide most stored-product insect pests with relatively mild temperatures and plentiful food sources. Stored-product insect species are found in moving mill stock Wagner and Cotton (1935), static mill stock, and inside the milling equipment (Dyte, 1965, 1966, Rilett and Weigel, 1956).

Campbell and Arbogast (2004) monitored stored-product insects inside and outside a flour mill by using commercial pitfall and sticky traps during a two-year period. They found 17 insect species, representing 12 families in 3 orders (Coleoptera, Hymenoptera and Psocoptera).

Tribolium castaneum, the red flour beetle, and Tribolium confusum, the confused flour beetle, are two of the major beetle pests of stored and processed products, especially of milled grain (Arthur and Campbell, 2008). These insects cause direct and indirect product losses through damage and consumption.

Insect activities directly cause grain quality loss in food processing by spreading and encouraging mold germination, adding to the fatty acid content of the grain, and leaving quantities of uric acid that cause grain rancidity (Mason and McDonough, 2012). For instance, the red flour beetle and the confused flour beetle produce pheromones and toxic quinone

compounds that can cause a foul odor and taste in the milled flour (Krischik and Burkholder, 1991).

Insects are a concern to the milling industry in two primary areas: internal feeding beetles in the whole grain before it is processed, contributing insect body fragments to flour, and external feeders infesting the structure and equipment within the mill leading to contamination of the product and potentially indicating unsanitary conditions within the mill.

New research shows insect fragments in food cause allergic reactions and they can potentially carry pathogens, especially those with antibiotic resistance genes (Channaiah et al. 2012). Although there is insufficient evidence to conclude that insect infestation necessarily causes human health problems, economic loss results from product rejection due to observation of insects or insect parts in food products, or product recalls because of health violations or consumer complaints.

In practice, the food company voluntarily recalls food products when it recognizes a problem and notifies the appropriate regulatory agency; or when the regulatory agency issues a request that the company initiate a recall. The direct cost can be calculated by multiplying the number of units of the recalled batch that are in distribution channels by the wholesale price of the product as recalled or rejected (Jarrell and Peltzman 1985).

Evidence also showed that food recalls influence product price and product demands, especially for a specific product line or brand. McKenzie and Thomsen (2001) found significant and negative responses in cash prices for recalled lean beef trimmings. Marsh et al. (2004) found statistically significant drops in demand for aggregate beef, pork, and poultry products due to recalls and Thomsen et al. (2006) found large and significant drops in sales of implicated branded frankfurters, which didn't recover to the pre-recall level for several months.

Moreover, there are indirect losses, such as the loss of goodwill or the loss of processing profit for a period of time in the event that the company's own inspectors discover an insect infestation in food products and are forced to shut down the processing facility and direct costs of extra insect treatments. Previous studies have suggested that industry bears significant costs from food pest or pesticide incidents that lead to product recalls.

Structural fumigation of food processing plants using methyl bromide to manage stored-product insects has been a major component of pest management programs (Fields and White 2002). However, methyl bromide has been designated an ozone-depleting substance under the Montreal Protocol, and it has been unavailable since 2005.

Data from the U.S. Environmental Protection Agency (EPA) provides evidence of the reduction of methyl bromide use. The amount of methyl bromide nominated for critical uses has been decreasing every year since its phase out in 2005, and the amounts nominated for 2011 were 135,299 kg. The nominations were further reduced to 74,511 kg in 2012 and 25,334 in 2013.

Many alternatives have been tested as replacements for methyl bromide. Dhana et al. (2008) tested physical control methods such as heat treatment. Extremely high ambient temperature (50℃ or above) in a flour mill can effectively kill insects within the mill and machinery (Roesli et al. 2003), but the costs of electricity and equipment used for treatment are much higher than for methyl bromide fumigation.

Adam et al. (2010a) compared the costs of fumigating a food warehouse facility using methyl bromide and one of its chemical replacements sulfuryl fluoride (sold as ProFume®). They found that sulfuryl fluoride fumigations are more expensive than methyl bromide fumigations. Sulfuryl fluoride is an economical alternative only if a low dose of chemical is adequate, a condition that depends on the type of fumigation to be conducted.

Many studies have shown that aerosol treatments using a combination of synergized pyrethrins and insect growth regulator (IGR) methoprene are efficient methods to control stored-product insects in food processing facilities. Aerosols are targeted to specific locations, and do not require prior removal of all food and shutting down the whole facility.

When the manager decides to adopt aerosols as an insect control method, he must install a network of pipes with nozzles in areas within the facility that might be targeted. Once this network is installed, the manager can use a computer in the control center to spray the chemical in the targeted locations at the appropriate time.

By targeting specific locations based on monitoring information, chemical use and shutdown costs can be reduced. However, spraying only targeted areas may reduce efficiency of insect control because aerosol is only effective on exposed insects. It is easy for insects to escape to neighboring areas that have not been treated (Jenson et al. 2010).

Sanitation programs have been emphasized in stored product pest management. Earlier studies suggested that sanitation can reduce or eliminate insect populations by eliminating the insects' resources. Arthur and Campbell (2008) found that adoption of sanitation when using pesticides with less penetration ability than fumigants (such as aerosols) can reduce amount of insecticide needed.

However, sanitation by itself is unlikely to sufficiently control insect population. Williams et al. (2015) argued that financial investment in better sanitation is not a requirement to improve the facility cleanliness and pest management effectiveness, but that employees' knowledge and awareness of the pest management program is a better indicator of sanitation's impact on facility pest management.

All these insect control techniques have advantages and disadvantages. Different flour mills with different structures, surroundings, climate, and insect species may require different

types of insect control techniques. Sometimes, more than one technique is necessary to control an insect population. Choosing an effective and economical strategy is a difficult and important problem.

2.2 Integrated pest management concept

IPM is a balanced use of multiple control tactics – biological, chemical, and cultural – as is most appropriate for a particular situation in light of careful study of all factors involved (Way 1977). Thus, unlike calendar-based treatment, IPM approaches stress judicious use of pesticide with the objective of maximizing its efficiency. After obtaining information on insect population, chemical efficacy, treatment cost, and risk of failure to control insects, integrated pest management tactics can help managers to make better decisions regarding insect management strategies (Fields and White 2002).

Uncertainty about insect population is a significant barrier to decision-making about insect control. Two major parts of the uncertainty are uncertain insect growth and uncertain insect movements, both of which are due in part to variable weather and conditions in a facility's surroundings.

This uncertainty can lead to unnecessary treatments, which increases costs and environmental impacts, or failure to make treatments when needed, increasing both risk of failing to control insects and cost of extra treatments. There are many ways to obtain information about insect population, including sampling or monitoring information, expert systems, consultants, and the predictions of computer simulation models (Hagstrum and Flinn 2012). However, there is much risk in these approaches.

Pheromone trapping programs have been widely used to monitor insect population and distribution in food processing (Flinn et al. 2010). The common four types of traps are: light traps, aerial traps, surface traps, and bulk grain traps (Toews and Nansen 2012). Those traps have corresponding food odor or pheromone as attractants for capturing insects.

Due to stored product insects' habits, that they often are sedentary during the day and active at night when they search for food, mates, and shelter (Toews et al. 2003), pheromone traps are important as a method to estimate insect population. Long-term monitoring can provide more information about insects present than an estimate based on visual inspection (Hagstrum and Subramanyam 2000), which could not provide numerical data for decision support (Toews and Nansen 2012).

Campbell and Arbogast (2004) pointed out some other advantages of pheromone trapping programs, which are that they can detect insect immigration, provide earlier warning of potential problems, and detect insect levels in inaccessible areas within the structure of the building. In addition, a pheromone trapping programs is a good method for applying spatial analysis of stored product insect density. Spatial mapping of insect counts can be used to characterize the relationships among sample data points and then interpolate values between points in the food processing facilities (Campbell et al. 2002). Spatial analysis recognizes that sample points that are closer together are more correlated than sample points that are farther apart, which are assumed as completely independent in conventional statistical approaches (Toews and Nansen 2012).

However, pheromone trapping to assist insect monitoring may provide inaccurate information on insect population (Campbell et al. 2002). For example, since pheromones attract insects, the counts of insects in pheromone traps may overestimate the actual population. In fact, many studies have argued that there is not always a tight correlation between captures of stored product insects and insect population densities (Campbell et al. 2002, Hagstrum et al. 1998,

Nansen et al. 2004a, Nansen et al. 2004b, Toews et al. 2009, Toews et al. 2005a, Toews et al. 2005b, Vela-Coiffier et al. 1997). There are many biological and environmental effects, including pheromone lure age or trap replacement interval (Toews et al. 2006), environmental conditions such as sanitation level or dust accumulation (Nansen et al. 2004a, Nansen et al. 2004b, Roesli et al. 2003), trap position and indoor conditions such as air temperature, air movement, light, and photoperiod (light and dark cycles) (Toews and Nansen 2012).

When Campbell et al (2002) used pheromone trapping with contour mapping and mark-recapture to assess the spatial distribution and movement patterns of some species of stored-product insects, they found that decisions about trap type, trap location and the number of traps were difficult because different choices for these variables could lead to different estimates of spatial distribution of pest infestation.

Although risk of inaccuracy exists, pheromone trapping is still one of the most efficient and cost-effective tools available for monitoring stored-product insect density for many pest control studies. Pest management professionals can combine practical, economic, and ecological considerations based on their experience to minimize the riskiness (Toews and Nansen 2012).

As an attempt to improve on monitoring strategies, using information from a variety of sources, entomologists have developed models for estimating insect population using computer simulation programs (Arthur et al. 1998, Flinn and Hagstrum 1995, Flinn et al. 2004, Hagstrum et al. 1998, Hagstrum and Subramanyam 2000, 2006, Skovgard et al. 1999, Smith 1994, Sporleder et al. 2004). Such simulations use information on the relationship between temperature and humidity conditions in the food processing facility environment and insect life cycle history to predict insect population growth rate (Hagstrum and Subramanyam 2000). Testing of at least some of these models have showed that for a number of important species the predictions of adult insects have tended to follow trap catch estimates fairly well (Flinn et al. 2010).

In 2010, Flinn et al. (2010) developed a model for the red flour beetle in wheat flour mills that can be used to predict population growth of red flour beetle as a function of inside air temperature. The model uses a distributed delay to simulate variation in developmental time, manage survivorship, and model insects through various life stages. Their model could be very useful to develop optimal integrated pest management strategies for food processing facilities.

One of the advantages of the Flinn et al. (2010) model is that the input was as simply as hourly inside air temperature in the facility, which managers can measure more easily than insect density for decision making. Another advantage is that their model can predict the effects of various structural treatments and subsequent population rebound, which provides enough information for other insect treatment decision-making studies.

However, since monitoring data with pheromone trapping is the main source of information about insect life history to calibrate the insect simulation models, some of the same risk of inaccuracy experienced with trapping data exists in these models. Mitigating this, though, since the insect growth models are based on insect physiology and many studies of insect growth determinants, they likely are less susceptible to random errors than relying solely on strictly empirical monitoring data.

In addition, IPM strategies are costly. Cost of monitoring programs includes cost of traps and labor costs of gathering traps and identifying and counting insects. There might also be risk of losing floor traps because of ongoing plant activities, including sanitation, leading to both economic costs and costs in term of information loss (Campbell et al. 2002).

Successful IPM programs need to define the balance between the costs of doing additional IPM and the gains in information obtained and the potential economic benefits of reducing the amount of chemical use (Campbell et al. 2002). There may also be benefits to

society of IPM, such as environmental benefits, although individual firms do not realize these benefits and may not include them in their decision criteria.

The costs and benefits of these various IPM strategies in food-processing facilities have not been critically evaluated, optimally integrated, or compared with those for sulfuryl fluoride fumigations or high-temperature treatments (Zhu et al. 2009).

Previous studies by Adam et al. (2010a, 2006, 2010b) estimated and compared costs of grain damage and insect treatments for both IPM and chemical-based strategies in stored grain facilities. Evaluation of insect damage cost and efficacy will be more difficult and costly in a food-processing facility than in the more homogeneous environment within stored grain facilities because of the variety of processing activities which results in a wide range of insect growth conditions.

Food suppliers may be hesitant to adopt alternative components of an IPM approach that uses less chemicals when facing those uncertainties, and they need accurate information about cost and effectiveness of available IPM alternatives to make good insect control decisions. They need direct evidence of cost and benefit, including costs of failing to control insects, in order to adopt IPM strategies.

2.3 Critical and economic threshold for insect controls

A standard criterion is required to help managers make treatment decisions with the available information. The threshold concept, introduced by entomologists, is the critical insect population at which a specific treatment should be taken (Saphores 2000).

Stern et al. (1959) defined economic threshold as "the density at which control measures should be determined to prevent an increasing pest population from reaching the economic injury

level" (p. 86). The economic injury level is "the lowest population density that will cause economic damage, which is the amount of injury that justifies the cost of artificial control measures."

It is hard to build a standard model for an economic threshold because the economic injury level may vary by locations, seasons, or a manger's scale of economics value (Stern et al. 1959). Conventional cost-benefit analysis identifies the economic threshold as the point where the benefits from the treatment are merely equal to or greater than the costs (Ndeffo-Mbah et al. 2010).

However, those economic models of pest control are mostly too theoretical because they rely on perfect information about pest population (Saphores 2000). In other words, economic threshold decision making models are based on assumptions of certainty (Mumford and Norton 1984). Managers, however, face considerable uncertainty when they are making decisions. A model that explicitly includes uncertainty is necessary.

One approach is to use Bayesian decision theory (Luce and Raiffa 2012, Mumford and Norton 1984). The earliest application of Bayesian decision theory to pest control decision making was introduced by Carlson (1970). This method recommends that managers use probabilities to weight several levels of outcomes and then to make a decision based on the expected outcomes. The probabilities usually were predicted based on historic information. In decision-making situations in other contexts, binomial trees, first introduced by Cox and Miller (1965) and Cox, Ross and Rubinstein (1979), were widely adopted to express the magnitude of outcome changes over time by steps.

Most of the studies only consider one point of time of benefit and cost to make a current decision. However, sometimes time plays an important role in the decision making (Guthrie 2009). For example, if a current insect population is below the economic threshold, instead of

making the instant decision, either treat or not, there might be another choice: wait until a later time to see if treatment is necessary.

For the problem of managing insect populations in food processing, insect population may be reduced by future cold weather. In that case, even though the insect population reaches the economic threshold, a current treatment may not be essential because the potential damage could be eliminated below the criteria level after a population reduction by cold weather.

If an insect treatment can be delayed and still effectively eliminate potential damage, this would likely enable a manager to delay subsequent treatments, reducing costs because the frequency of the treatments is reduced in the long run (Ndeffo-Mbah et al. 2010).

When they included "delay" as an alternative choice in their study, Ndeffo-Mbah et al. (2010) argued that treatment should be undertaken when the benefits exceed the costs by a certain amount and not if they are merely equal to or greater than the costs as standard net-present-value (NPV) analysis suggests. Their study showed the evidence of model that including "delay" leads to a reduction in fungicide use.

As a result, future actions or insect population states may influence current decisions. A dynamic decision model that can consider future actions conditions will be more proper for insect treatment problems.

Real option models may be a possible solution because they allow future treatment as a choice. When future treatment becomes a part of the choice set, the decision model should contain more information, which is not only about different possible outcomes but also about timing. Real option models should be a good method for an optimal timing problem such as identifying the best time to apply insect treatment.

2.4 Real options

A real option, which is derived from the term "option" in financial markets, is the right, but not an obligation, to exercise a certain real action in the face of uncertainty (Cheah and Jicai 2006). Myers (1977) coined this term, and Zeng and Zhang (2011) argued that many corporate investment assets, particularly growth opportunities, can be viewed as call options. Therefore, techniques developed for financial options can be extended and adapted to "real-life" decisions.

During 1980-1990, after the first proposal by Myers (1977), this topic began to attract academic interest on theories and applications of the real options analysis (Amram and Kulatilaka 1998, Borison 2005, Ross 1978, Trigeorgis 1993). Attention to real options spread to industries, which considered the real option approach as a potentially important tool for valuation and strategy. Beginning in the oil and gas industry and extending to a range of others, the real option approach has been frequently applied to technology adoption decisions (Purvis et al. 1995) and capital investment decisions (Anderson and Weersink 2014, Stokes et al. 2008).

One of the advantages of a real option approach is that it values the decision maker's flexibility in choosing to exercise an action now, wait until a later date to exercise, or not to exercise at all. The decision maker receives benefit from that flexibility, a benefit that decreases in value as the time value decreases.

Another advantage of a real option approach is that it considers all information available to the manager at that date as well as new information revealed in the future. This distinguishes it from static decision making, in which the manager's action at every future date depends only on information available to the manager at the current date (Guthrie 2009).

Using a real option analysis, as opposed to traditional economic analysis such as net present value, can provide a decision maker wider information about choices that can be made,

such as measuring the value of delaying the investment choice until a later time, especially when facing some uncertainties (Copeland and Tufano 2004).

Dixit and Pindyck (1994, 1995) and Ross (1995) both pointed out traditional investment decision-making, which ignores the value created by the delay of investment decisions, may result in wrong investment decisions. McGrath et al. (2004) showed that a real option analysis helped to identify the source of variability and the effect of risk on an investment project's valuation. The higher variability suggested the stronger possibility that actual value might deviate from the expected future returns.

Stokes et al. (2008) found that real option analysis allowed a better comparison between investing to convert a dairy farm's technology to a new methane technology or not investing. In this way, they could more fully consider the advantages of reducing the uncertainty of fluctuating energy prices by using energy produced on the farm.

Many business decisions can be mapped into underlying financial options. For example, the opportunity to invest in the expansion of a firm's factory, or alternatively to sell the factory, is a real call or put option, respectively. Luehrman (1998) shows an example of how the characteristics of business opportunity can be mapped onto the template of a call option (Table 2.1).

Table 2.1 Mapping an Investment Opportunity onto a Call Option

Investment Opportunity	Call Option
Present value of a project's operating assets to be acquired	Stock price (S)
Expenditure required to acquire the project assets	Exercise price (X)
Length of time the decision may be deferred	Time to expiration (t)
Time value of money	Risk-free rate of return (r_f)
Riskiness of the project assets	Variance of returns on stock (σ^2)

Source: Luehrman, 1998

In financial options, European options can only be exercised at maturity (Hull 2009). This type of financial option can be mapped into a simple real option model, for example, whether to treat insects now or two weeks later. American options allow option holders to exercise the option at any time prior to and including the maturity date (Hull 2009). This type of financial option can be mapped into a more complex real option model – for example, which date (now or two weeks later) is the best time to treat insects.

A Bermudan option is a type of exotic option that can be exercised only on predetermined dates, typically every month. Bermudan options are a combination of American and European options; they are exercisable at the date of expiration, and on certain specified dates that occur between the purchase date and the date of expiration. Bermudan options may fit insect treatment models well because food-processing managers may acquire insect information every other week or every month to make decisions, rather than every day.

Similar to a financial option, time is a major factor that gives the real option value. Since the future is uncertain, a real option has time value because of the probability that some event will happen in the future with the result that the option is "in the money." But real options are not

typically traded as securities, and do not usually involve decisions on an underlying asset that is traded as a financial security (Amram and Howe 2003).

Studies of real options have been broadly extended into decision making of many other areas. Odening et al. (2005) noted that three conditions must exist to make a real option meaningful: 1) uncertainty of returns from an action; 2) irreversibility of the action; and 3) flexibility with respect to time of action. Real options analysis can reasonably be used in any problem that satisfies those three properties.

All three of the conditions hold in the insect treatment application considered here (Saphores and Shogren 2005). First, uncertainty arises in the evaluation of the insect population. The future insect density and future damage is stochastic due to fluctuations in weather and the surrounding environment. Second, irreversibility arises in pest damage and insect control expenditures. Finally, insect control can be delayed under appropriate conditions. Thus, a real option approach can be used for this study. The choice to conduct a treatment for insect control can be compared to an investment opportunity and modeled as a call option.

Some studies have used a real option approach in pest management decisions. Saphores (2000) formulated an optimal stopping model for applying pest control measures when the density of a pest population varies randomly. Saphores and Shogren (2005) generated a compound stopping option model to control exotic pests under conditions of uncertain pest density.

Richards et al. (2006) created a hypothetical "bug option," showing that such an option could improve risk-return results for insuring insect damage in a cotton farm. Ndeffo-Mbah et al. (2010) compared a real option approach with conventional NPV approach for optimal timing of crop disease control. Their model measured the benefits of delaying control and the value in waiting.

A timing option is a real option focused on determining how long to delay a decision (e.g., 'wait until when' to exercise the option). There are many kinds of timing option, such as deferring, abandoning, expanding, staging, or contracting a capital investment project. (Guthrie 2009, Mun 2002, Trigeorgis 1996). The insect control problem considered here can be considered as a variation on an option to abandon an existing project.

The real option model is proper for a "when" to treatment an insect problem because it value timing. When the value of the project contains both the current value of insect treatment and the value of treatment at a future time, the model can describe the value of waiting, a time value.

The value of waiting reflects the benefits gained from holding the option and wait until sometime later. While waiting, the uncertainty may be reduced with better information. If time value becomes zero, waiting is no longer valuable. Several previous studies have used "optimal timing to treat" options (Ndeffo-Mbah et al. 2010, Saphores and Shogren 2005), and that principle is still proper for the problem of insect treatment in food processing.

2.5 Stochastic process

Unlike prices or log prices of futures markets for a finance option, the stochastic state variables in most real option models are physical variables. For the problem of insect treatment in food processing facilities, the stochastic variable is insect population, which causes uncertain insect damage. Many previous studies about pest management using real option methods treated the state variables as pest population or pest density.

Carlson (1970) estimated crop disease density when defining the optimal control of peach rot. Ndeffo-Mbah et al. (2010) estimated epidemics disease density when defining the optimal

chemical control for crop disease. Saphores and Shogren (2005) studied exotic pest population when defining the optimal biologic control. Most of those studies have mentioned that the uncertainties of pest or disease are associated with weather. However, none of them treated weather as a stochastic variable, while in most cases weather is the key source of the uncertainty.

Collecting weather data is much easier than measuring insect population in a food processing facility. Past weather information might be more accurate, since risk of inaccurate monitoring of traps exists and the risk is very hard to define (Campbell et al. 2002). If we treat weather as the stochastic variable, and use computer simulation programs from to estimate insect population from Flinn et al. (2010), insect population then becomes deterministic based on the stochastic weather.

Many studies have shown that weather follows a mean reverting process with strong seasonality patterns in both mean and the variance (Bellini 2005, Benth and Šaltytė-Benth 2005, Dornier and Querel 2000, Roustant et al. 2004, Wang et al. 2015). They also found that weather data such as temperatures are temporally dependent. While the other studies from Carlson (1970), Ndeffo-Mbah et al. (2010) and Saphores and Shogren (2005) modeled the pest density process as a Brownian motion stochastic process, they did not consider mean reversion. Furthermore, insect population might be even more nonstationary than weather.

Another adavantage of estimating weather as the stochastic variable is that this model allows the ability of some extensions such as adding more specific stochastic components other than weather on insect population. By doing so, we can easily trace the source of the uncertainty rather than process insect numbers directly.

The real option approach has not been used in the context of insect management decisions in grain/food processing facilities. Moreover, few studies have considered the economic impact from stored product insects recognizing the large effect of weather on insect populations.

A study to develop a decision model for insect control based on a real option approach could fill this vacancy in the literature.

CHAPTER III

THEORY AND CONCEPTUAL FRAMEWORK

3.1 Insect control and damage cost

When a manger faces an insect treatment decision in a flour mill, the choice for extra fumigations adds treatment costs but can potentially reduce damage cost. On the other hand, fewer fumigations can save treatment costs but insect population can also grow, increasing damage. As the number of insect treatment increases, cost of potential insect damage and cost of insect treatment move in opposite directions (Figure 3.1). Managers want to minimize the total of treatment cost and damage cost to maximize their profit.
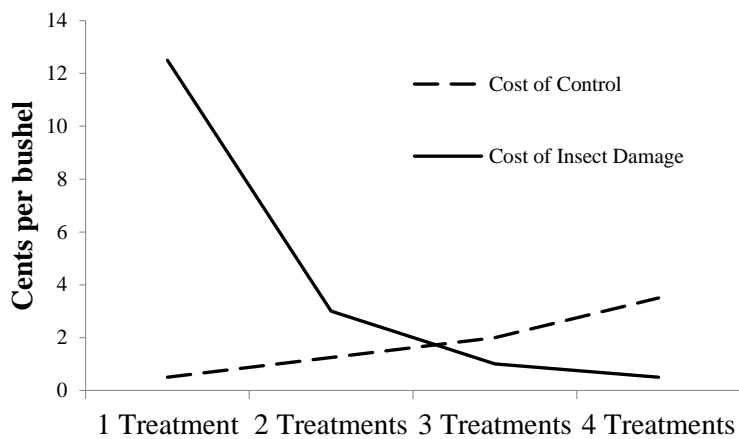
Figure 3.1 Cost of control vs cost of insect damage

Taking the production process and all prices as given, the objective of the manager can be specified as

(3.1)
$$\min_{TR_{jlt} \in \{0,1\}} E(C) = \sum_j \sum_l \sum_t TR_{jlt} * TC_j + E(\widetilde{D}),$$

$$s.t. \ \widetilde{D} = f(\widetilde{I_{lt}}),$$

$$\widetilde{I_{lt}} = g(\widetilde{W}_t, I_{lt-1}, TR_{jlt}),$$

where $E(C)$ is the expected total cost, TR_{jlt} is the choice variable when $TR_{jlt} = 1$ representing adopting a treatment, where $j = 0, ..., J$ represent different types of treatments, $l = 0, ..., L$ represent the treating spots for a treatment, $t = 0, ..., T$ represent treatment dates, TC_j is the treatment cost (\$) for each type, $E(\widetilde{D})$ is the expected value of damage loss from insect infestation as a function of insect population $\widetilde{I_{lt}}$, $\widetilde{I_{lt}}$ is the insect population at location l and time t, which is a function of vector of weather factors $\widetilde{W}_t$, such as temperature, humidity and , insect population I_{lt-1} at location l and time $t - 1$ and the total number of treatments $\sum_j \sum_l \sum_t TR_{jlt}$.

With an economic threshold approach, the optimal policy is to apply an insect treatment as soon as insect population reaches a critical value, denoted ET. It can be written as, $TR_{jlt} = 1$, when $\widetilde{I_{lt}} \geq ET_{lt}$. The threshold separates "low" and "high" values of insect population. For the "high" values, if action is not taken immediately unacceptable damage loss occurs.

In practice, the economic threshold is hard to implement because of random factors, especially uncertain insect population. Insect population is dynamic and fluctuates; the numbers may reach the threshold at some point but may drop below the threshold later. The conventional threshold model would lose that part of information, which is important to make the optimal decision.

In contrast, a real option approach takes into account various risk factors while considering information about the future. The model puts a value on treating or waiting to treat, so it can be used to determine the optimal time of insect treatment. The corresponding insect population at that optimal time determined by the real option approach will be called in this study the critical threshold ET^*, which may be more accurate than ET because it contains more information.

Timing in real option models, in general, is about "when to act" in the decision-making. The action makes the event switch from one state to another state; usually the change is irreversible. In an investment context in timing decision, the decision maker desires to make a potential future cash inflow be sufficient to offset initial project cash outflow. The manager might consider different kinds of options for different types of actions, such as option to switch, option to expand, option to defer or delay and option to abandon.

An option to switch provides flexibility to use cheapest future inputs or the most profitable future outputs mix as alternatives from current input or output when the relative prices of the inputs or outputs fluctuate over time. An option to expand enables management to accelerate the rate or expand the scale of production with a follow-on cost if and when market conditions turn out to be more favorable than expected.

An option to defer or delay enables management to defer investment until a later time. The option to defer investment is analogous to an American call option on the net present value of expected operating cash flows of the completed projects where the exercise price (strike price) equals the investment outlay (Trigeorgis 1996). The choice to invest early forgoes some of the benefits of deferring the choice for a better situation later, so the manager receives value by deferring if there is still time value left (Luehrman 1998).

Management may abandon a project if the anticipated required expenditure exceeds the value from continuing the project, so that the net revenue from continuing is negative. In "option to abandon" models, the expense of abandonment is offset by the salvage value from eliminating the bad parts (Guthrie 2009). The option to abandon can be valued as an American put option on the current value of the project with an exercise price equal to the salvage value (Trigeorgis 1996).

This study on insect control decisions will focus on the option to defer and the option to abandon. Suppose the problem starts after the application of the last fumigation, when insect population is controlled sufficiently and the probability of infestation is low. Deferring treatment reduces the frequency of treatment so that it reduces the total cost of treatments (Figure 3.1). Meanwhile, insect population grows while deferring treatment so that the probability of insect infestation loss increases.

The "option to treat" insects can be thought of as an option to abandon. The cost of treatment is analogous to cost of abandonment, and the insect damage cost is analogous to the cost of continuing a (losing) investment project. The cost of insect treatment is offset by the salvage from eliminating the insect damage. When the treatment is applied, treatment cost is incurred and probability of infestation is reduced.

Assume the objective for the manager is to minimize the expected total cost in the presence of uncertainty. The objective is to determine the optimal time to treat insects in a food processing facility. In order to accomplish this, a real option approach will be used. The following paragraphs describe how a real option is evaluated and how a real option model can help make timing decisions, and then putting those concepts to the insect problem.

According to the classic option formula, the option value is

(3.2)
$$V_t = E(V_T) * e^{-r(T-t)},$$

where V_t is the option value at time t, V_T is the option value at the expiration time T, r is a discount rate. By deferring insect treatment to time T, the management foregoes a cost of potential insect damage, D_T, and insect treatment cost, TC. Thus, the value of an option to defer insect treatment is

(3.3)
$$V_T = \min(TC - D_T, 0),$$

For the option to abandon (option to treat insect), the management pays $D_T + \min(TC - D_T, 0)$ at abandonment. Thus the value of the option to treat insects is

(3.4)
$$V_T = \min(D_T, TC).$$

When value of treatment is less than treatment cost $(D_T < TC)$, the option is out of the money. In contrast, the option is in the money if value of treatment is greater than treatment cost $(D_T > TC)$. While waiting to treat, value of treatment increases as insect population grows. Therefore, the "out-of-the-money" situation increases its probability of moving "into the money." When insect population grows sufficiently high, potential infestation loss occurs and treatment is necessary. At that point, the option has no value remaining.

If the real option is in the money (has intrinsic value) but has no time value, the processer would "treat now." If the option is out of the money but has time value, the processor would "wait to treat." If there is no probability of an "out-of-the-money" option moving into the money, the processor should "never treat." Thus, the optimal timing to apply fumigation is when the option value is "in the money" and the time value goes to zero (Table 3.1).

Table 3.1 The Relationship Between Option State and The Decision

	Time value > 0	Time Value = 0
In the Money: $D_T > TC$	**Wait to treat** until time value goes to 0	Treat **now**
Out of Money: $D_T < TC$	**Wait** to treat	**Never** treat

The key to estimate the value of the option is to evaluate the $E(V_T)$ in equation (3.2) which includes two parts: 1) the expected of value of the treatment, $E(D_T|D_T > TC)$ and 2) the probability of "in-the-money" occurs, $P(D_T > TC)$. The distribution of uncertain variable DL_T becomes very important.

The Black-Scholes model, which is the basic formula for calculating the value of a European call/put financial option model, can also be used for real options. However, insect population as the key dynamic variable may not be able to be directly observed, as prices or assets are. There might be some adjustment to adopt the real option models into the insect problem. Next, we would discuss the option finance pricing models for both European and American options and timing options.

We will first describe the assumptions, derivations and the formula of Black-Scholes models. Secondly, we will introduce the binomial tree, applying it to an empirical real option state variable process. Third, we will describe details in using timing options to solve an optimal timing problem. For each section, we will map the above concepts into the insect treatment problems, specifically addressing the adjustments needed to adapt real option concepts to insect treatment problems.

3.2 Black-Scholes model

The Black-Scholes model applies when the nonstationary state variable is modeled by the logarithm of a geometric diffusion process and it explicitly assumes that the variable process is continuous. The formula of a Black-Scholes model for a European call option is (Black and Scholes 1973, Merton 1973)

(3.5)
$$F(S,t) = c(S,t) = S_t N(d_1) - Y e^{-r(T-t)} N(d_2),$$

where

$$d_1 = \frac{1}{\sigma\sqrt{(T-t)}} \left[\ln\left(\frac{S_t}{Y}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t) \right]$$

$$d_2 = d_1 - \sigma\sqrt{(T-t)}$$

where

$F(S,t)$ is the price of a derivative as a function of time and stock price,

$c(S,t)$ is the price of a European call option,

$N(\cdot)$ is the cumulative distribution function of the standard normal distribution,

$T - t$ is the time to maturity (expressed in years),

S_t is the spot price of the underlying asset,

Y is the strike price,

r is the risk-free rate (annual rate, expressed in terms of continuous compounding) and

σ is the volatility of returns of the underlying asset.

Table 3.2 shows how to map an insect treatment opportunity (parameters on equation (3.2)) onto a financial call option (parameters on equation (3.5)). If an insect treatment model

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follows the same assumptions as the Black-Scholes model does, it is easily to directly use the

Black-Scholes formula by understanding this transformation.

Table 3.2 Mapping a Treatment Opportunity onto a Financial Call Option

Treatment Opportunity	Financial Call Option
The value of the option to treat at time, V	The price of a European call option, c
Treatment cost, TC	Exercise price/ strike price, Y
The value of treatment, D	The spot price of the underlying asset, S
Some discount rate, r	The risk-free rate, r
Level of uncertainty about insect damage, σ	The volatility of returns of the underlying asset, σ

Before adapting the method of measuring option values as Black-Scholes model, we have

to understand more details about the assumption and the concept behind the equations. Following

are some important terminologies:

Brownian motion (Wiener process), describes a continuous-time stochastic process

(Brown 1828, Dixit and Pindyck 1994, Wiener 1923a, b), $dz = \epsilon_t \sqrt{dt}$, where ϵ is a random draw

from $\phi(0,1)$, a normal distribution with mean 0 and standard deviation 1. Wiener process has

with three important properties: the Markov property, independent increments, and changes that

are normally distributed (Dixit and Pindyck 1994).

Brownian motion with drift (-average change per unit time), a generalized Wiener

process that the drift rate and the variance rate can be set equal to constant (Dixit and Pindyck

1994), $dx = \alpha \, dt + \sigma \, dz$, where dz is the increment of a Wiener process with a drift rate of 0

and a variance rate of 1, α is the drift parameter, and σ is the variance parameter.

Geometric Brownian motion (Ito Process), a more complex feature in that the drift and

the variance coefficients are functions of the current state and time (Dixit and Pindyck 1994),

$dx = a(x,t)dt + b(x,t)dz$. The continuous-time stochastic process $x(t)$ is called an *Ito process*

(Itō 1944, 1951).

Ito's Lemma, in general to differentiate or integrate functions of Ito process (Dixit and

Pindyck 1994, Itō 1944, 1951). Suppose an Ito process $x(t)$ and a function of $F(x, t)$ that is at

least twice differentiable in x and once in t, Ito's Lemma gives the differential $dF = \frac{\partial F}{\partial t} dt +$

$\frac{\partial F}{\partial x} dx + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} (dx)^2$, or substituting dx, then $dF = \left[\frac{\partial F}{\partial t} + a(x,t) \frac{\partial F}{\partial x} + \frac{1}{2} b^2(x,t) \frac{\partial^2 F}{\partial x^2} \right] dt +$

$b(x, t) \frac{\partial F}{\partial x} dz$, which shows the change in $F(x, t)$ is normally distributed with mean

$\left[\frac{\partial F}{\partial t} + a(x,t) \frac{\partial F}{\partial x} + \frac{1}{2} b^2(x,t) \frac{\partial^2 F}{\partial x^2} \right] T$ and variance $[b(x,t) \frac{\partial F}{\partial x}]^2 T$.

The above provides the mathematical fundamentals for using the Black-Scholes methods

to evaluate the value of the options. To adapt it into an insect treatment real option problem, the

derivative form describes the uncertainty of the progression for treatment value, using a

Geometric Brownian motion process with some drift for the stochastic variables (Dixit and

Pindyck 1994).

The original Black-Scholes model provided theoretical support for valuing European

options assuming continuous variable in the stochastic process. The European options property

does not allow early exercises. However, the binomial trees with discrete-time random walks and

early exercises could be very useful tools for applied empirical problems such as insect treatment

decisions. A relevant question to be answered with this approach is, "Are the changes in the

random variable over any finite time interval still normally distributed?"

In the next section we review a finding that the Geometric Brownian motion can be

derived as the continuous limit of a discrete-time random walk (Cox and Miller 1965, Dixit 1993,

Dixit and Pindyck 1994). This implies that the same principle of the original Black-Scholes

model can be used for calculating the value of each node for an American option in binomial tree

models. Similarly, Bermudan options follow the same principle, except that the time frequency is

weekly or monthly.

3.3 Binomial trees

A multiplicative binomial process can deal with many stochastic problems, in which the binomial tree displays two possible outcomes of the stochastic variable and its corresponding probabilities at any point. This discrete random walk can represent Brownian Motion if the time period approaches zero.

Assume the length of each discrete time period is Δt. The variable x moves either up or down by the amount Δh with corresponding probabilities of p and q (where $q = 1 - p$) each time period (Figure 3.2). With initial value of x_0, the Δx from each period to the next is a random variable that can take on the values $\pm \Delta h$.
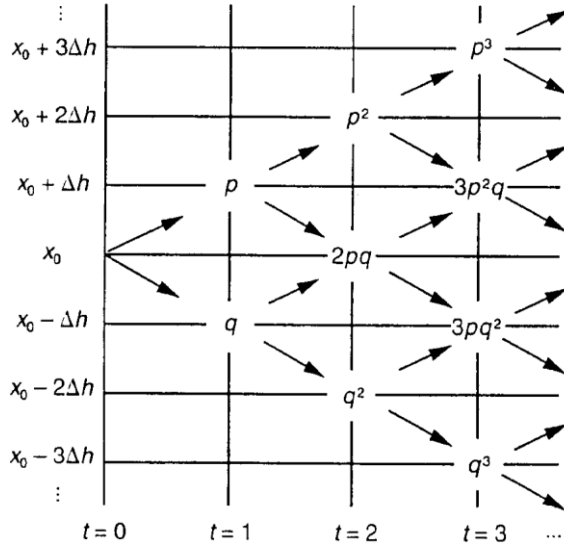
Source: Dixit and Pindyck (1994)

Figure 3.2 Random walk representation of Brownian motion

The value of probabilities p and q and the increments Δh and Δt can be set arbitrarily with α and σ, but the relationship Δh and Δt must satisfy $\Delta h = \sigma \sqrt{\Delta t}$ according to the Brownian

motion property. As Δt goes to zero, the distribution (binomial distribution) of cumulated change

$(x_t - x_0)$ converges to a normal distribution with mean αt and variance $\sigma^2 t$, where α is the drift

and σ^2 is the variance per unit of time as for Brownian motion (see more details in Dixit and

Pindyck (1994)).

As a result, Brownian motion is the limit of a random walk. The changes in x over finite

periods are normally distributed as the number of steps becomes very large; the binomial

distribution approaches a normal distribution. Thus, a binomial tree is a convenient tool for

evaluating option values with finite time intervals. It is also useful for practical real option

decision making models, because it provides a traceable way to evaluate options in a simple

setting and for which early exercise may be optimal, as with an American option.

The two general representations of binomial tree for the process of the stochastic

variables are in Figure 3.3, where the footnote u and d represent moving up and down,

respectively. The corresponding probabilities are the same as in Figure 3.2.

$n=0 \quad n=1 \quad n=2 \quad n=3$

$x(i,n)$	0	1	2	3
0	x	x_u	x_{uu}	x_{uuu}
1		x_d	x_{ud}	x_{uud}
2			x_{dd}	x_{udd}
3				x_{ddd}
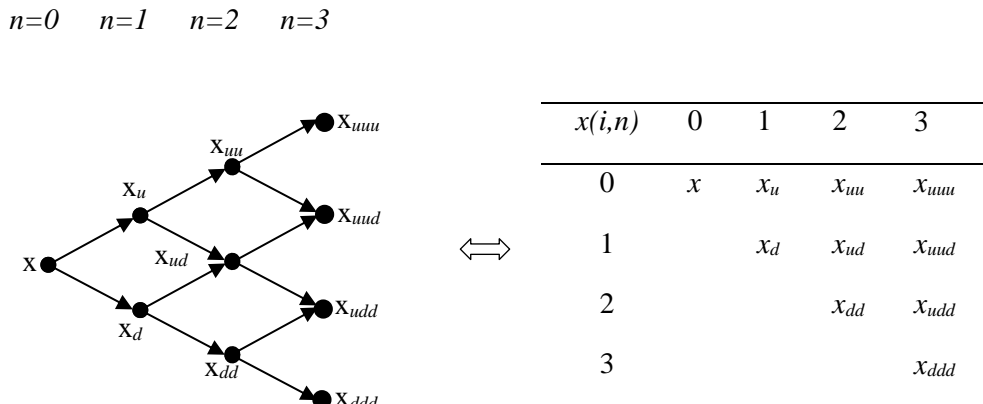
Figure 3.3 Representation of a general Binomial tree

For a financial option, the process of x here could be the movements of stock prices or

any other asset. We can work backward through the binomial tree to price the options. Similarly,

for a real option, the process of x becomes the movement of state variables and we want to generate a cash flow (value) at each node, still working backwards.

The calculation of the original binomial tree in financial options is based on some assumptions and properties. The most important is the assumption about to price options as if the investors are "risk-neutral," that is, there are no arbitrage opportunities. In fact, we are not assuming all investors are actually risk neutral nor are the risky assets expected to earn risk-free rate of return. This is discussed further after the option pricing equations.

In a general binomial process, the call option price at maturity is zero because the option becomes worthless, which follows the terminal condition. Working backwards, the option price (of a call option) is

$$(3.6) \qquad\qquad\qquad C = e^{-rh}[p^*C_u + (1 - p^*)C_d],$$

where C is the value of the option, C_u and C_d represent the value of the option when the stock goas up or down, respectively, r is the continuously compounded annual interest rate, h is the length of a binomial period in years, p^* is the risk neutral probability of an increase in the stock prices, $p^* = \frac{e^{(r-\delta)h}-d}{u-d}$, where $u = e^{(r-\delta)h+\sigma\sqrt{h}}$ and $d = e^{(r-\delta)h-\sigma\sqrt{h}}$ are the up and down movement of stock return, and σ is the annual volatility.

In the real option model, similarly, the replicating portfolio is

$$(3.7) \qquad\qquad\qquad V = \frac{\pi_u{}^*V_u + \pi_d{}^*V_d}{R_f},$$

where

$$(3.8) \qquad\qquad\qquad \pi_u = \frac{Z*R_f - x_d}{x_u - x_d} \text{ and } \pi_d = \frac{x_u - Z*R_f}{x_u - x_d},$$

where π_u and π_d are risk-neutral probabilities, which differ from the actual probabilities, V_u and V_d are the market values of cash flow, $R_f = 1 + r_f$, where r_f denote the one-period risk-free interest rate, Z is the current price of the spanning asset and x_u and x_d are the up and down movements of the state variable.

As described earlier, the Black-Scholes model based on Brownian motion is the limit of a random walk represented by the binomial tree. If it is a European option, which can only be exercised at maturity, there is no problem directly to use equations (3.6) or (3.7), working backwards through the binomial tree to evaluate the option value.

For an American option, which allows early exercises, there should be a comparison between equations (3.6) (and (3.7)) and $Y - S$ at each node when working back through the binomial tree. For example, the financial American option price at a node is $\max(e^{-rh}[p^*C_u + (1-p^*)C_d], Y - S)$ instead of $\max(e^{-rh}[p^*C_u + (1-p^*)C_d], 0)$.

There is another form of option, Bermudan option, which is an exotic option that can only be exercised at specified times during its life (McDonald 2006, Merton 1973). The frameworks are similar to that of the American options. In practice, the manager of a food processing facility may collect insect information every other week or monthly. We need to set the specific exercise times that represent options to treat insects or not. Thus, insect problems are suited for the format of a Bermudan option.

It is important to note that binomial trees are different from a decision tree. The former describes the random process, while the decision tree describes the structure of the problem. There are many different problems, such as options to expand, options to wait and options to stop, with differing decision tree structures. Some complex problems may require more than one kind of binomial trees.

3.4 Monte Carlo valuation

Alternative to binomial pricing approach, Monte Carlo valuation is another common method to evaluating option values, especially when the state variable is path-dependent. In Monte Carlo valuation, specific paths of future state variable are simulated and then be used to compute the discounted expected payoff of the option. The Monte Carlo price is

$$(3.9) \qquad \qquad V = \frac{1}{n} e^{-rT} \sum_{i}^{n} V_{iT},$$

where V_{1T}, …, V_{nT} are the market values of cash flow based n randomly drawn from the simulated state variables.

The binomial tree and Monte Carlo simulation describes the random walk of the state variables of interest. The information about the size of up and down moves and the corresponding probabilities comes from the historic data. The technique for calibrating the data information into a random walk becomes very important. A well-fitted random walk model would provide accurate information for decision-making. In the next section, details for calibrating data information for a random process are described.

3.5 Data calibration

Guthrie (2009) and Dixit and Pindyck (1994) have summarized simple methods to replicate the random process from historic data. Since prices are non-negative and volatility is higher when price is high than when it is low, it is common to use logarithm price changes, which the Black-Scholes model did (equation (3.5)).

However, for many real option problems, the state variable does not have the same properties prices do. Many alternative methods are more suitable to deal with the special data. Here the focus is on methods suitable for insect treatment problem in a food processing facility.

3.5.1 State variable

Insect population is the key uncertainty due to stochastic weather. Flinn et al. (2010) note that insect population is mainly a function of insect growth and insect immigration. Insects grow exponentially under certain weather conditions. Insect immigration depends on weather conditions, facility-specific factors such as integrity of the storage structure and cleanliness of the facility and grounds, and characteristics of the natural habitat surrounding the facility grounds (Campbell et al. 2002).

Those kinds of uncertainty are very hard to model. We can simulate a stochastic binomial process for the potential damage loss as function of the insect population, which is as most of the other real options studies related to pest management have done (Anderson and Weersink 2014, Carlson 1970, Ndeffo-Mbah et al. 2010, Saphores and Shogren 2005).

Suppose the treatment value reflects the avoidance of potential damage, $DL(I_t)$, where DL is a function of insect population, I_t, where the insect population is a function of weather. Then the increment in potential damage DL is

(3.10) $$dDL = A(DL(I_t(W_t)), t)dt + B(DL(I_t(W_t)), t)dz,$$

where dz is the increment of a standard Wiener process, which is the independent increment having an zero mean and instantaneous variance equal to dt (Dixit and Pindyck 1994), and the estimation of $A(DL(I_t(W_t)), t)$ and $B(DL(I_t(W_t)), t)$ should follow information from insect population growth trends.

Then applying Ito's Lemma (Dixit and Pindyck 1994), the differential form of dF for the

process of $DL(I_t)$ is

$$(3.11) \qquad dF = \frac{\partial F}{\partial t} + A(DL(I_t(W_t)), t)\frac{\partial F}{\partial DL} + \frac{1}{2}B^2(DL(I_t(W_t)), t)\frac{\partial^2 F}{\partial DL^2},$$

where $F(DL(I_t(W_t)), t)$ is the functional format of the value of the option from equation (3.2).

The problem is, in practice, the insect population data cannot be collected directly. The

source of insect population information mainly comes from insect monitoring. However, insect

monitoring may provide inaccurate information and it is hard to build a straightforward

relationship between the monitoring data and insect population. Alternatively, using appropriate

weather variables in an insect growth simulation model may provide the best prediction of inset

population, with prediction, that are robust across a range of pre-calibrated scenarios. For this

study, the simulation model developed by Flinn et al. (2010) is used with weather, specifically

temperature, as the random variable determining insect population.

3.5.2 Random walk process

Suppose the movement of weather is follow the process as shown in Figure 3.3. At node

$(0,0)$ the value is W_0, which is based on historical weather data, daily temperature. In each

subsequent period temperature either increases by u or decreases by d. Then the temperature

$W(i, n)$ at node (i, n) would have $n - i$ up moves and i down moves, where $n = 0,1,2,...,T$ and

$i = 0,1,2,...,n$. Moreover, it follows a random walk as the change of temperature is

$$(3.12) \qquad\qquad\qquad dW_t = \alpha W_t dt + \sigma W_t dz_t,$$

where dz is the increment of a standard Wiener process, which iis the independent increment

having an zero mean and instantaneous variance equal to dt, and α and σ are the drift and

volatility.

The information of u and d comes from the empirical data. They could be the percentage of up and down moves, or they could follow some other formats such as adding a value instead of multiplying by a percentage. In some complicate situation, u and d are not constant values. Dixit and Pindyck (1994) and Guthrie (2009) have provided sufficient details about the steps to calibrate the process tree using historic data to estimate the size of up and down moves and the probabilities of those occurrences.

The first step is to gather the information from the data into the estimators of the normalized parameters. As discussed earlier, using changes of the logarithm of the state variable may not be suitable for a temperature process. One obvious reason is that temperature could drop below zero in winter. Thus, we do not take the logarithms and we process temperature change directly.

For the random process, we would like to define the drift and the variance of the change of temperature, where the form of the change is

$$(3.13) \qquad W_{t+1} - W_t = h + \varepsilon_{t+1}, \varepsilon_{t+1} \sim N(0, \varphi^2),$$

where W_t denotes the tth observation of the temperature, h and φ are constant and ε_{t+1} is the stochastic term. This equation describes changes in W as normally distributed with mean h and variance φ^2, from which the parameters h and φ are related to the drift and volatility of the Brownian motion by $h = \alpha \Delta t$ and $\varphi^2 = \sigma^2 \Delta t$ (Guthrie 2009).

Then, historical data is used to determine the parameters of the sample mean $\hat{h}$ and standard deviation $\hat{\varphi}$, then can use then to estimate the population mean $\hat{\alpha}$ and standard deviation $\hat{\sigma}$,

$$(3.14) \qquad \hat{\alpha} = \frac{\hat{h}}{\Delta t_D} \quad \text{and} \quad \hat{\sigma} = \frac{\hat{\varphi}}{\sqrt{\Delta t_D}},$$

where Δt_D is the time step in from the collecting data, where the data have one observation every Δt_D years. Here $\hat{\alpha}$ and $\hat{\sigma}$ are the normalized drift and volatility for the Brownian motion process.

The next step is to determine the u and d to build a binomial tree. Δt_M is used to denote time steps in the model, which may differ from the time steps in the data so that we have to convert the unit for consistency. The increases and decreases in value at each step is $\hat{\sigma}\sqrt{\Delta t_M}$. Thus the total up and down moves are $(n-i)\hat{\sigma}\sqrt{\Delta t_M} + i\left(-\hat{\sigma}\sqrt{\Delta t_M}\right)$ at node (i,n), then the temperature equals

(3.15) $$W(i,n) = W_0 + (n-2i)\hat{\sigma}\sqrt{\Delta t_M},$$

from which we can define $W(i,n+1) = W_0 + ((n+1)-2i)\hat{\sigma}\sqrt{\Delta t_M} = W(i,n) + \hat{\sigma}\sqrt{\Delta t_M}$ and $W(i+1,n+1) = W_0 + ((n+1)-2(i+1))\hat{\sigma}\sqrt{\Delta t_M} = W(i,n) - \hat{\sigma}\sqrt{\Delta t_M}$. Then the additive size of up move is $U = \hat{\sigma}\sqrt{\Delta t_M}$ and the size of down move is $D = -\hat{\sigma}\sqrt{\Delta t_M}$.

The third step is to estimate the probabilities. The method is to set the expected value of changes in temperature over the next period equal to the normalized parameter estimates (Guthrie 2009). The expected change over the next period at node (i,n) is

(3.16) $$\lambda_u(i,n)\hat{\sigma}\sqrt{\Delta t_M} + \left(1-\lambda_u(i,n)\right)\left(-\hat{\sigma}\sqrt{\Delta t_M}\right) = \hat{\alpha}\Delta t_M,,$$

which implies that

(3.17) $$\lambda_u(i,n) = \frac{1}{2} + \frac{\hat{\alpha}\sqrt{\Delta t_M}}{2\hat{\sigma}},$$

where $\lambda_u(i,n)$ is the probability of an up move at node (i,n) and the probability is constant for all the time increments.

3.5.3 Mean-reverting process

At this point, we want to check the properties from this random process to make sure the temperature values make sense. For a random walk as shown in equation (3.13), the temperature is expected to grow by h at each time step with a constant probability. Thus, as time steps increases, temperature value may increase or decrease into extremely high or low temperatures, which makes the temperature wander unrealistically too much. Some adjustment is necessary to make the temperature process more realistic.

Mean reversion, also called the Ornstein-Uhlenbeck process, is a possible process in which the "shock" dies out eventually. In other words, the mean reverting process forces the stochastic variable to not wander too far away from the starting points. The probability of the outcomes is not constant and the extreme values would have very low or even zero probabilities.

The mean reverting process is different from the Brownian motion process by adding a reversion term to replace the drift parameter but the usage to analyze a real option model remains the same. The form of mean-reverting process is $dx = \eta(\bar{x} - x)dt + \sigma dz$, so the change of temperature is

$$(3.18) \qquad\qquad dW_t = \eta(\bar{w} - W_t)dt + \sigma dz_t,$$

where η is the rate of reversion, $\bar{w}$ is the level that W tends to revert to, dz is the in crement of a Wiener process with a drift rate of 0 and a variance rate of 1, and σ is the variance parameter (Dixit and Pindyck 1994). In this case, W_t is expected follow the normal distribution as

$W_t \sim N(\bar{w} + (W_0 - \bar{w})e^{-\eta t}, \frac{\sigma^2}{2\eta}(1 - e^{-2\eta t}))$ and asymptotically, $W_t \sim N(\bar{w}, \frac{\sigma^2}{2\eta})$.

We still follow three steps to calibrate the historic data in to the mean reverting process but there are a few adjustments on the methods (Dixit and Pindyck 1994, Guthrie 2009). For step one, instead of equation (3.13), we regress the temperature process as a first-order autoregressive (AR(1)) process (Guthrie 2009),

(3.19)
$$W_{t+1} - W_t = \beta_0 + \beta_1 W_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0, \varphi^2),$$

where W_t denotes the tth observation of the temperature, β_0, β_1 ($\beta_0 < 0$) and φ are constant and

ε_{t+1} is the stochastic term. This equation describes changes in W as normally distributed with

mean $\beta_0 + \beta_1 W_t$ and variance φ^2, from which the parameters β_0, β_1 and φ are related to the

Ornstein-Uhlenbeck parameters by $\beta_0 = (1 - e^{-\eta \Delta t})\overline{w}$, $\beta_1 = -(1 - e^{-\eta \Delta t})$ and $\varphi^2 =$

$\frac{\sigma^2}{2\eta}(1 - e^{-2\eta \Delta t})$ (Guthrie 2009). Then we get

(3.20)
$$\hat{\eta} = \frac{-\ln(1+\hat{\beta}_1)}{\Delta t_D}, \quad \overline{w} = \frac{-\hat{\beta}_0}{\hat{\beta}_1} \text{ and } \hat{\sigma} = \hat{\varphi}\left(\frac{2\ln(1+\hat{\beta}_1)}{\hat{\beta}_1(2+\hat{\beta}_1)\Delta t_D}\right)^{1/2},$$

where $\hat{\eta}$, $\overline{w}$ and $\hat{\sigma}$ are the normalized estimators for the mean-reverting process.

For steps two and three, we use the same concept to estimate the temperature value and

the probabilities for a binomial tree. For the temperature value $W(i, n)$ at node (i, n), equation

(3.15) remains the same format. For the probabilities, the format is more complicated. The

expected change in temperature is now as $(1 - e^{-\hat{\eta}\Delta t_M})(\overline{w} - W(i, n))$. The probabilities vary by

node because they depend on the value of temperature at each node. Similar to the method to get

equation (3.17), the probability of an up move at node (i, n) equals

(3.21)
$$\lambda_u(i, n) = \frac{1}{2} + \frac{(1 - e^{-\hat{\eta}\Delta t_M})(\overline{w} - W(i, n))}{2\hat{\sigma}\sqrt{\Delta t_M}}.$$

Equation (3.21) may not contain complete information because $W(i, n)$ maybe too large

or too small to make $\lambda_u(i, n)$ out of the range of [0,1]. We could reset $\lambda_u(i, n)$ as

$\min\{1, \max[0, \lambda_u(i, n)]\}$. In other words, we want to reset $\lambda_u(i, n)$ to zero if it is negative, which

makes the next move certainly down due to a too large $W(i, n)$ and to one if it is greater than one,

which makes the next move is certain to be up due to a too small $W(i, n)$.

In this case, some of the values in a binomial tree are not reachable when the temperature value moves too high or too low. Then the adjusted binomial tree is shown as in Figure 3.4, and it is called a truncated binomial tree. The single arrow at some nodes indicate that the next move is certain in those situations. The empty circles show that those points are not reachable from node (0,0). The two dash lines are the bounds that are equivalents to the conditions of $\lambda_u(i,n) \in [0,1]$.

$n=0$　$n=1$　$n=2$　$n=3$　$n=4$

$$W(i,n) = \bar{w} + \frac{\hat{\sigma}\sqrt{\Delta t_M}}{1 - e^{-\hat{\eta}\Delta t_M}}$$

$$W(i,n) = \bar{w} - \frac{\hat{\sigma}\sqrt{\Delta t_M}}{1 - e^{-\hat{\eta}\Delta t_M}}$$
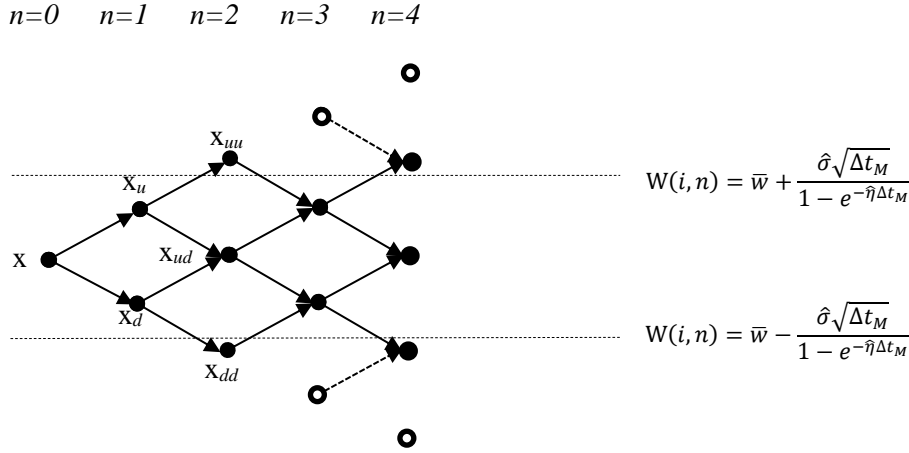
Figure 3.4 Representation of a truncated Binomial tree

The biggest advantage of using the mean-reverting process is that this method avoids those points that the temperature would never be reached. In addition, since the probabilities are specified at each node instead of being constant during the process, it seems more reasonable for a range of temperatures conditions.

Both Dixit and Pindyck (1994) and Guthrie (2009) have discussed the main difference between random walk process and mean-reverting process. In general, the variance of the random walk is continuous and accompanied with further time steps while that of the mean-reverting process tend to be stable.

Mathematically, as shown in equations (3.13) and (3.19), the key difference is the term $\beta_1 W_t$. The choice of method is then based on a significance test of parameter β_1. If β_1 is tested to

be zero, then a regression of random walk process is preferred. From another point of view, we can say that equation (3.13) is a special case of equation (3.19).

Empirical real options models have shown that the state variables are often mean reverting due to complicated situations for a long run (Guthrie 2009). In fact, many studies about weather derivatives have shown details about temperature calibration techniques; almost all have agreed that temperature is a mean reverting process (Bellini 2005, Benth and Šaltytė-Benth 2005, Dornier and Querel 2000, Roustant et al. 2004, Wang et al. 2015). They have argued that temperature processes are even more complex than the original AR(1) process (as equation (3.19)).

Seasonality or trend exist for daily temperature. A certain seasonal pattern such as lower temperature in winter and higher in summer (Benth and Šaltytė-Benth 2005, Dornier and Querel 2000), or temperature trends such as an increase in average temperature (e.g. global warming) (Zapranis and Alexandridis 2006, 2008, 2009), can be modeled such that daily average temperature is an additive time series as

$$(3.22) \qquad\qquad W_t = ss_t + cc_t + \tilde{\sigma}_t,$$

where ss_t is the seasonal component, cc_t is the trend-cycle component, and the $\tilde{\sigma}_t$ is the noise, $t = 0,1,2,\ldots$.

Usually, seasonal patterns can be presented as a cosine function, $ss_t = c_0 + c_1\cos(\frac{2\pi}{T}t + t_p)$, c_0 and c_1 are the average level and amplitude of the mean temperature, respectively, T is the period, which indicates the number of time periods required to complete a single cycle of the cosine function and $1/T$ is the frequency and t_p is the phase displacement.

Using the trigonometric identity $\cos(A + B) = \cos A \cos B - \sin A \sin B$, then $ss_t =$ $c_0 + c_1^c \cos\left(\frac{2\pi t}{T}\right) + c_1^s \sin\left(\frac{2\pi t}{T}\right)$, where c_1^c and c_1^s are the regression parameters where $c_1^c = c_1 \cos(t_p)$ and $c_1^s = -c_1 \sin(t_p)$, respectively.

If more than one kind of cycle exists including regular seasonality and some irregular cycles, the model should include all the possible sine and cosine functions, including random effects in both the phase and the amplitude. Then the mean variation of the temperature with time patterns is

$$(3.23) \qquad \overline{w}_t = \mathcal{B}_0 + \sum_{j=1}^{T/2}[\mathcal{B}_1^c \cos\left(\frac{2\pi jt}{T}\right) + \mathcal{B}_1^s \sin\left(\frac{2\pi jt}{T}\right)] + \mathcal{B}_2 t,$$

where the first term $\mathcal{B}_0$ describes the reverting mean, the second term describes the seasonal and cycle variations, the third term describes the mean trend of increases or decreases over time (sometimes, it could be quadratic or some other forms) and the $\mathcal{B}$s are the coefficients to be estimated.

The spectral analysis decomposes a time series into underlying sine and cosine functions of different frequencies with differing periods (a full cycle) and amplitudes (maximum/minimum value during the cycle) as above. Besides regressions, Fast Fourier Transform (FFT) transforms a signal from the time domain to the frequency domain. FFT is a common method used to fit the data into best set of frequencies, which is available in many computer software.

If adjustment to a mean reverting Ornstein-Uhlenbeck is necessary, the reverted mean and the standard deviation are not constant any more as in equation (3.18),

$$(3.24) \qquad dW_t = d\overline{w}_t + \eta(\overline{w}_t - W_t)dt + \sigma_t dz_t,$$

or let $dW_t = W_{t+1} - W_t$ and $d\overline{w}_t = \overline{w}_{t+1} - \overline{w}_t$, then we get

$$(3.25) \qquad\qquad\qquad d\dot{W}_t = -\eta\dot{W}_t dt + \sigma_t dz_t,$$

where $\dot{W}_t = W_t - \bar{w}_t$, and $\dot{W}_t$ follows a mean-zero Ornstein-Uhlenbeck process, where the

reverted mean term is $\dot{w} = 0$. Then our regression model for the empirical data is,

$$(3.26) \qquad\qquad \dot{W}_{t+1} - \dot{W}_t = \dot{\beta}_0 + \dot{\beta}_1 W_t + \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim N(0, \varphi^2),$$

where $\dot{\beta}_0$ is expected to be 0 and $\dot{\beta}_1$ ($\dot{\beta}_1 < 0$) and φ are that we need to estimate the normalized

estimators, $\hat{\eta}$ and $\hat{\sigma}$, for the mean-reverting process from equation (3.20) and also the

probabilities from equation (3.21). Then after that, we add the time patterns back to the process.

The above information will be sufficient to estimate the stochastic process for

temperature with the assumption that it should normally distributed after removing the time-

related patterns. However, many studies have found that the residuals also contain seasonality

(Benth and Šaltytė-Benth 2005, Zapranis and Alexandridis 2006) and that temperature process

does not follow normal distribution very well (Richards et al. 2004, Zapranis and Alexandridis

2006). Some studies even applied a more complicated process like a jump process (Richards et al.

2004), Levy process (Benth and Šaltytė-Benth 2005) or wavelet analysis (Zapranis and

Alexandridis 2006). They prompted many different forms (higher-order) of ARMA models or

GARCH models as alternatives.

3.5.4 Path-dependent stochastic process

If seasonal patterns or autocorrelations exist in the variance, φ^2 is no longer constant but

follows a more complicated time-dependent format. Weather data – daily temperature for

example, is path-dependent.

One of the important assumptions about binomial trees is that the order of moving up and

down does not matter, which describes the Markov properties that past states do not have

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influence on the future given the present state. Path-dependent weather does not have Markov properties. Therefore, the temperature values at each node cannot recombine in the binomial tree. As shown in Figure 3.5, as time increases from n to $n+1$, the number of outcomes, i, then moves from 2^n to 2^{n+1}.

$$n{=}0 \qquad n{=}1 \qquad n{=}2 \qquad n{=}3$$
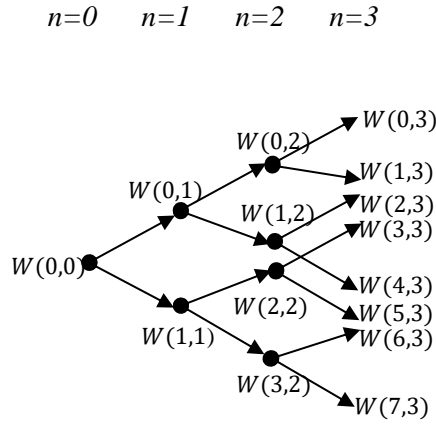
Figure 3.5 Random process with non-constant variance

Monte Carlo simulation is a good method to simulate the path-dependent process of the state variable. Based on the mean reversion property on equation (3.24), we can get the continuous form of the temperature with time patterns as

(3.27) $$W_t = \bar{w}_t + (W_0 - \bar{w}_0)e^{-\eta t} + \int_0^t e^{-\eta(t-\tau)} \sigma_\tau dz_\tau, \text{ or}$$

$$\dot{W}_t = \dot{W}_0 e^{-\eta t} + \int_0^t e^{-\eta(t-\tau)} \sigma_\tau dz_\tau,$$

where $0 \leq \tau \leq t$, and a time-discrete version of the temperature as

(3.28) $$\Delta W_t = \Delta \bar{w}_t + \eta(\bar{w}_{t-1} - W_{t-1})\Delta t + \sigma_{t-1}\Delta z_t,$$

where $\Delta W_t = W_t - W_{t-1}$, $\Delta \bar{w}_t = \bar{w}_t - \bar{w}_{t-1}$ and $\Delta t = 1$. Since an insect treatment decision is a discrete problem, equation (3.28) will be used for Monte Carlo simulations of temperature paths.

3.6 Risk-neutral probabilities

In real option models, there is a very important term, risk neutral probabilities. It is closely related to how to estimate the "current price of the spanning asset", which is Z in equation (3.8) or in a more general case,

$$(3.29) \qquad \pi_u(i,n) = \frac{Z(i,n)*R_f - x(i+1,n+1)}{x(i,n+1) - x(i+1,n+1)},$$

$$\pi_d(i,n) = 1 - \pi_u(i,n).$$

In finance, investors are usually considered as risk averse. Their behaviors require a premium to bear risk when expected values are riskier to achieve than the other alternatives, which results in greater difficulty in evaluating pricing. Imagine a risk neutral world in which an investor cares only about the expected return, and not risk. Then the risk premium can be averted with the expected return equal to risk-free rate.

Many references such as McDonald (2006) and Guthrie (2009) have explained that pricing an option using real probabilities with standard discounted cash flow calculation is equivalent to option pricing. Rendleman (1999) even derived the relationship between the risk-neutral and true probabilities. This approach does not require assumptions about investors' risk aversion. Option pricing using risk-neutral probabilities is preferred to avoid having to make those assumptions.

There are many methods to determine the risk-neutral probabilities. The methods involve forward or futures prices. One of the common methods is using Capital Asset Pricing Model (CAPM) to adjust for risk by subtracting true probabilities and risk premium (Guthrie 2009, Luenberger 2002, Rendleman 1999).

Define Z in equation (3.8) as a hypothetical portfolio, which is composed of a holding of "one-period risk-free bonds and a stake in the market portfolio of risky assets",

$$(3.30) \qquad Z = \frac{E[\tilde{x}] - (E[\tilde{R}_m] - R_f)(\frac{Cov[\tilde{x},\tilde{R}_m]}{Var[\tilde{R}_m]})}{R_f},$$

where $\tilde{x}$ is the random state variable after one period, from which the expected market value of the cash flow, $E[\tilde{x}] = \lambda_u(i,n)x(i,n+1) + (1 - \lambda_u(i,n))x(i+1,n+1)$ is estimated using the true probabilities, $\tilde{R}_m$ is the random total return on the marked portfolio, $E[\tilde{R}_m] - R_f$ represents the market risk premium, and $\frac{Cov[\tilde{x},\tilde{R}_m]}{Var[\tilde{R}_m]}$ is the coefficient that measures the quantity of risk.

Then the probability of moving up is

$$(3.31) \qquad \pi_u(i,n) = \lambda_u(i,n) - (\frac{E[\tilde{R}_m] - R_f}{x(i,n+1) - x(i+1,n+1)})(\frac{Cov[\tilde{x},\tilde{R}_m]}{Var[\tilde{R}_m]}),$$

where the second term is the adjustment from the true probabilities and the risk-neutral probabilities. There is much available information about the market risk premium $E[\tilde{R}_m] - R_f$ that can be directly adopted. Then we need to get the information for the coefficient term, $\left(\frac{Cov[\tilde{x},\tilde{R}_m]}{Var[\tilde{R}_m]}\right)$, which has the terminology called price beta in Finance literature.

As suggested by Guthrie (2009), we can regress the residual from the regression (equations (3.13) or (3.19)) that estimates the binomial process on a proxy for the market portfolio, as

$$(3.32) \qquad \hat{\varepsilon}_t = \omega_0 + \omega_1 r_{m,t} + v_t,$$

where $r_{m,t}$ is the return on the market portfolio proxy. The estimated parameter $\hat{\omega}_1$ is the useful estimate of beta, which is equal to $\hat{\omega}_1 \sqrt{\frac{\Delta t_D}{\Delta t_M} * \frac{1 - e^{-2\hat{\eta}\Delta t_M}}{1 - e^{-2\hat{\eta}\Delta t_D}}}$ (Guthrie 2009).

The market portfolio proxy can be some broadly based stock index such as S&P500 index (Guthrie 2009). Richards et al. (2004) pointed out that the basis risk should refer to the difference between a weather index for a particular location and the actual value of the same weather that applies to the specific firm. They also suggested a measure of aggregated economic activities, which reflects any contingent claim on weather. For example, they used county-based personal consumption expenditures.

However, such a proxy is not available for options such as the real option to treat insects. Chicago Mercantile Exchange (CME) began to trade weather options for some major U.S. cities since 1999 but such options have lack of liquidity. Thus, it is hard to find a market portfolio for this incomplete market. In this situation, we can assume a scalar of the physical probabilities. This scalar reflects the manager risk aversion.

In practice, one of the reasons that IPM program might not completely substitute for a calendar-based insect treatment because some managers are more concerned about incurring potential damage than incurring unnecessary treatment cost. That behavior of some managers shows risk aversion about insects growing in the food processing facility. As a result, in our problem we assume the manager is risk averse, so that the scalar is set to be a value that is greater than 1.

3.7 Timing options model

The next step is to establish the optimal decision model. Our problem is a timing problem. Real option models can be used for timing decisions as well as for measuring the value of the option. Time plays an important role for option decisions because the option model involves timing and values timing. Thus, timing option model becomes a common tool for

decision-making. In this section we describe the structure of timing option models and their use in making decisions using dynamic programming.

The structure of the optimal timing problem is as shown in Figure 3.6. At each node, either the decision maker can exercise the obligation or she can wait. If she exercises the option, the decision tree terminates, which is a solid round in Figure 3.6. If she does not exercise the option and wait, she moves to the next period on the decision tree (shown as arrows). Then she faces the choice of the same two actions, at which this situation repeats itself until the end.
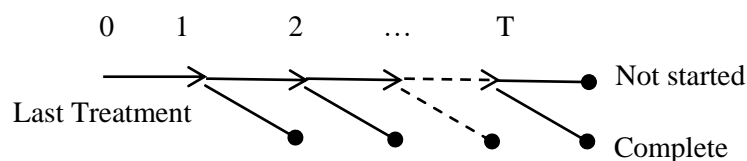
Figure 3.6 Decision tree for the optimal timing problem

When the decision is to exercise the option, the payoff involves the grain from the exercises and the cost of exercise. While if the decision is to wait at time n, usually the manger bears a cost of waiting immediately. At time $n + 1$, the problem will be worth $V_{u,n+1}$ if an up move occurs and $V_{d,n+1}$ if a down move occurs. The option is an American type option, evaluated by comparing min{the cost of treating , the cost of not treating} at each node.

For example, we set a discrete time problem with the maturity as T, we use binomial trees to estimate the random walk of the variables (as in Figure 3.5). As discussed earlier, the insect problem is like an option to abandon. The motive to abandon is to reduce loss by eliminating the insect damage.

Particularly, if the decision is to treat insects, it incurs treatment cost TC at time 0 and the decision tree terminates. If the choice is to wait at time 0, it bears the potential economic loss from insect, D_0. Then the problem moves to time 1 in the decision tree.

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At time 1, there are the same two choices: treat insects or wait. If the decision is to treat

insects, it incurs treatment cost TC at time 1 and the decision tree terminates. If the decision is to

wait at time 1, it bears the potential economic loss from insect, D_1. Then the problem moves to

time two in the decision tree and so on until time $T - 1$, the last opportunity to choose.

If the decision is to treat insects, it incurs treatment cost TC at time n and the decision

tree terminates. If the decision is to wait, no treatment occurs and insects keep growing

indefinitely. Then the project bears a huge potential damage D_n for all $n \leq T - 1$. At time T, the

option is worthless but the project bears a potential damage loss. Thus the terminal condition

$(n = T)$ here is

$$(3.33) \qquad\qquad\qquad\qquad V(i, T) = \frac{D(i,T)}{Rf^T},$$

from which we calculate backward. According to equation (3.2), the option value for each node is

$$(3.34) \qquad V(i, n) = \min\{TC, D(i, n) - B^{TC}(., n) + \frac{\pi_u(i,n)^* V(i,n+1) + \pi_d^* V(i+1,n+1)}{R_f}\},$$

for all $n = T - 1, \dots, 2,1,0$, where TC is the treatment cost, $D(i, n)$ is the cost of potential damage,

$B^{TC}(., n)$ is the benefit from postponing the treatment, which is saving a long run treatment by

reduced frequency. The two terms in equation (3.34) are the cost of treating and the cost of

waiting.

Valuing the option at each node is the process of making decisions. A lower cost of

waiting means that there is a premium for waiting (the time value). In contrast, a lower cost of

treating triggers optimal timing. By calculating backwards, the value of this option to treat insect

from binomial pricing method is $V(0,0)$.

In the Monte Carlo simulation, there are no up and down movements for specific

simulated temperature path. Equation (3.34) is adjusted for each simulated temperature path as

$$(3.35) \qquad V(i,t) = \min\{TC, D(i,t) - B^{TC}(i,t) + \frac{V(i,t+1)}{R_f}\},$$

where $i = 1, \dots, n$ represents the ith simulated temperature path. By calculating backwards, the ith value of the option to treat insect is $V_i = V(i, t_i^*)$, where t_i^* is the trigger denoting optimal timing when cost of treating becomes lower than the cost of waiting. Then the ith option value is substituted into equation (3.9) to obtain the value of the option to treat insects from Monte Carlo valuation.

3.8 Optimal stopping model

Another important thing about timing is the maturity T. As we list in Table 3.1, the decision to exercise or to wait is based on two factors: the option state and the time value. The time value equals the value of the option minus the intrinsic value. Intrinsic value is the value of exercising the option (minimum of zero).

The decision maker would prefer to wait until the time value becomes zero to exercise an option that is "in-the-money". Thus, the conclusion must be one of the three situations: 1) exercise at any point before maturity and the problem ends then, 2) exercise at maturity, and 3) never exercise during the period.

It is possible that the third situation would occur if the maturity is incorrectly set earlier than the optimal treatment date. If the maturity is extended until a long time later, even approaching infinity (as in Figure 3.7), it could be valuable to hold the option until the time value reaches zero at some point. On the other hand, if the optimal treatment date has been reached, the extended maturity will not change the decision.
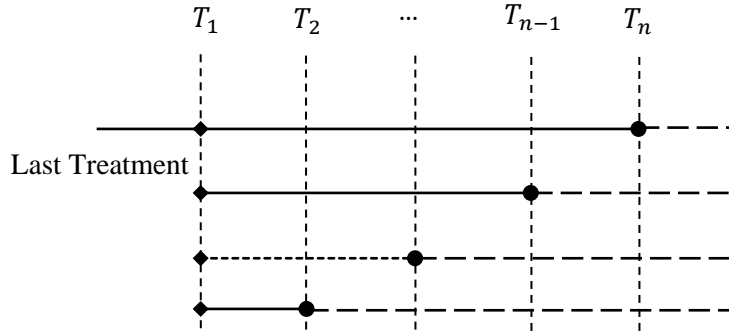
Figure 3.7 Diagram for the optimal timing problem

With an infinite time period, we can use the decision tree above to solve an empirical

timing option for a decision making. By setting a range of different levels of operating flexibility,

the option value, $V^{T_n}(0,0)$ for each T_n varies. Since this option is to save a cost, we are looking

for the break-even threshold where it reaches the maximum of the option value,

$$(3.36) \qquad\qquad V^* = \max_n E(\min(TC^Y, D_{T_n}) * e^{-rt}),$$

where V^* is the optimal solution, the maximum option value and the conducted T_{n^*} may be the

optimal time to wait. The optimal stopping time (maturity) is the point at which extending the

maturity will not change any result.

Most previous real options studies related to pest management follow Dixit and Pindyck

(1994)'s, using Ito's lemma to complete this accomplishment (Anderson and Weersink 2014,

Carlson 1970, Ndeffo-Mbah et al. 2010, Saphores and Shogren 2005). Assuming the starting date

is when the last fumigation occurs, back to equation (3.36), the value of the option to treat insect

is gives the differential form of dF by applying Ito's Lemma to solve the following free boundary

values (Dixit and Pindyck 1994, Mun 2002, Ndeffo-Mbah et al. 2010),

$$(3.37) \qquad \frac{\partial V}{\partial T_n} + A(D(I_t), t)\frac{\partial F}{\partial D} + \frac{1}{2}B^2(D(I_t), t)\frac{\partial^2 F}{\partial D^2} - \rho F = 0,$$

where ρ is an exogenous instantaneous rate of return from the Bellman equation $\rho F dt = E(dF)$. The solution is expected to show the trigger value for which maturity is optimal, V^*, and the optimal maturity (stopping time), T_{n^*}.

Since an insect treatment decision is a time-discrete problem, the equivalent problem turns to using dynamic programming to solve equation (3.36) by setting $i = 1, \dots, n$ where $i = n$ means to set up the maturity as n times from last treatment. Then the optimal solution is $V^* = \max(V^{T_1}, \dots, V^{T_n})$ and the optimal timing to treat, T_{n^*}, is from which the V^{T_n} is maximum.

The timing option concept can be adopted to solve the insect treatment optimal timing problem. The discrete binomial process can be used to simulate an empirical problem. An option to abandon provides a theoretical framework to evaluate the value of option and the time option. The concept of geometric Brownian motion process provides a guideline to build a general model for insect treatment timing. Based on the above theories, we construct several real option models of insect treatment problem, from a straightforward single-decision framework to a more difficult sequential decision framework.

CHAPTER IV

PROCEDURES AND METHODOLOGY

4.1 Data

Daily temperature data (ºF) from 1999 October to 2017 in Alva, Oklahoma is used. Alva,

Oklahoma was selected because its variable weather is likely to reflect a larger range of insect

growth condition than locations that are consistently cool or consistently warm. The data is

downloaded from the Oklahoma Mesonet website *mesonet.org*, which is a world-class network of

environmental monitoring stations in Oklahoma. The descriptive statistics of the temperature (in

Fahrenheit) data are shown in Table 4.1.

Table 4.1 Descriptive Statistics of Daily Temperature (ºF) in Alva, Oklahoma from 1999 to 2017

Temperature (F)	N	Mean	Std Dev	Minimum	Maximum
Daily Maximum	6,935	71.99	20.15	9.01	113.52
Daily Minimum	6,935	46.18	19.00	-15.45	84.29
Daily Average	6,935	58.79	19.13	4.17	97.74

In practice, the managers usually collect insect information and make the decision about

insect management biweekly or monthly. Therefore, the data is reorganized from daily into

biweekly to show the biweekly temperature trend and the changes of the temperature trend in a

one-year period (Figure 4.1 and Figure 4.2, respectively). In the figures, the starting point is

selected to be October for each calendar year from 1999 to 2017. Since the insect population

model by Flinn et al. (2010)used temperatures as Celsius (ºC) instead of Fahrenheit (ºF), the units

of the data values are converted from °F to °C for empirical estimation.
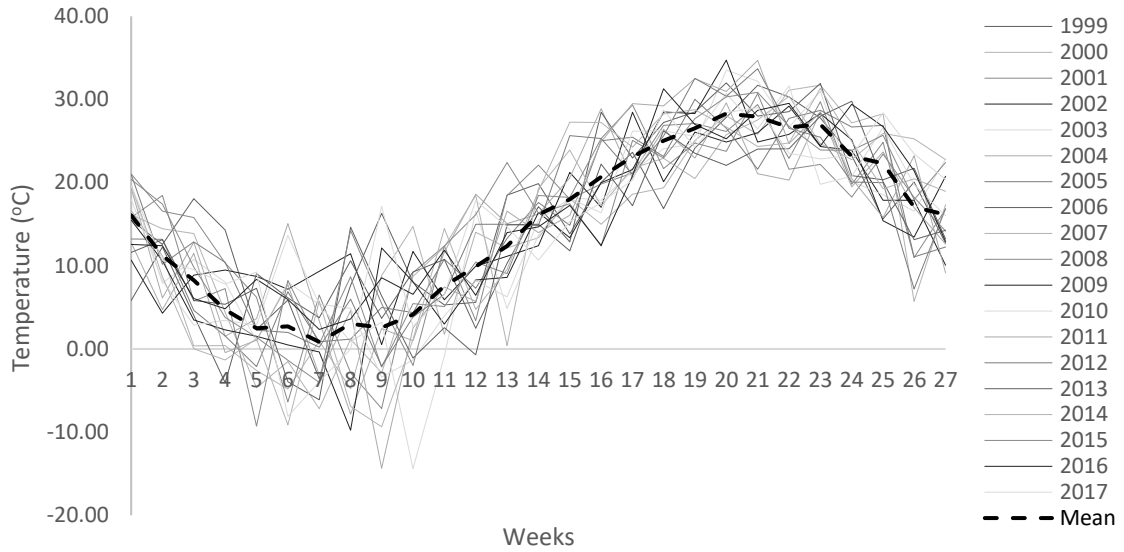
Figure 4.1 Biweekly temperature (ºC) from October 1999 to 2017 in Alva, Oklahoma
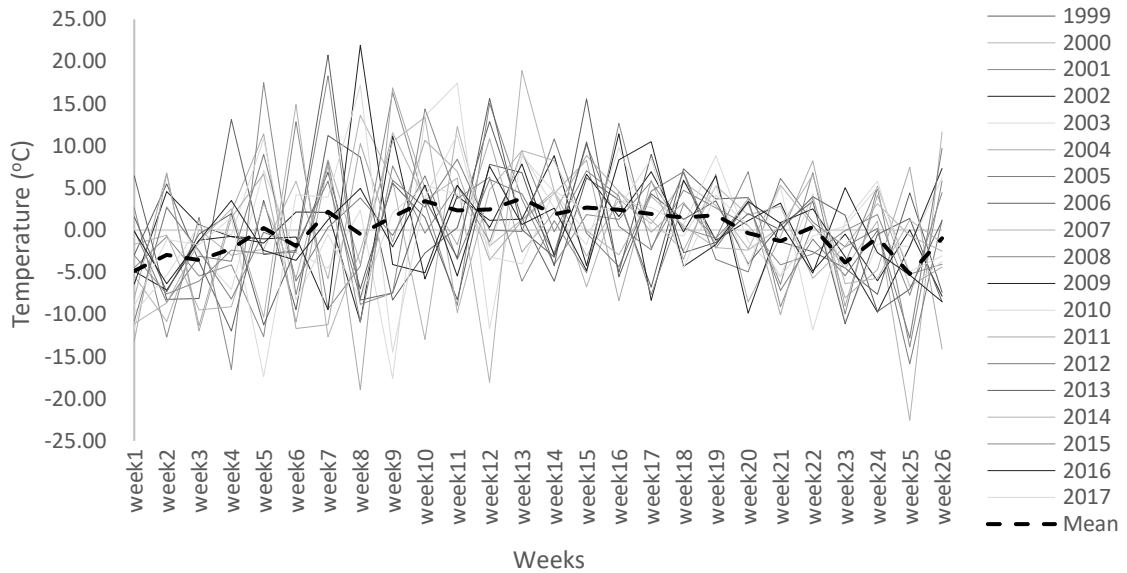
Figure 4.2 Biweekly temperature (ºC) changes from October 1999 to 2017 in Alva, Oklahoma

Daily average temperatures are still used to estimate the parameters when calibrating the data to fit a stochastic process because a large number of smaller steps provides more information. Prior to estimating the stochastic process, normality, seasonality and trend for daily average temperature in Alva, Oklahoma was tested. February 29 was removed from the sample in each leap year to make years with equal size.

Table 4.2 Data Analysis of Daily Temperature (ºC) in Alva, Oklahoma from 1999 to 2017

	Statistic Values	P-value
Normality test		
Pearson chi-square χ^2	946.46	0.00***
Jarque-Bera	297.44	0.00***
Anderson-Darling	57.23	0.00***
skewness	-0.22	
kurtosis	2.08	
Time patterns test		
Trend	1.74	0.08
Quadratic Trend	2.18	0.11
Seasonality (dummies)	6,847	0.00***

In Table 4.2, the values of the χ^2-statistics of Pearson's criteria of goodness-of-fit with the corresponding *P*-value indicates non-normality of the empirical distributions. The *P*-value of χ^2-statistics is significant at the 1%. The negative skewness and kurtosis values also show asymmetry of the empirical distributions. The Jarque-Bera test also shows evidence of non-normality, significant at the 1% level. The histogram shows the non-normality (Figure 4.3).
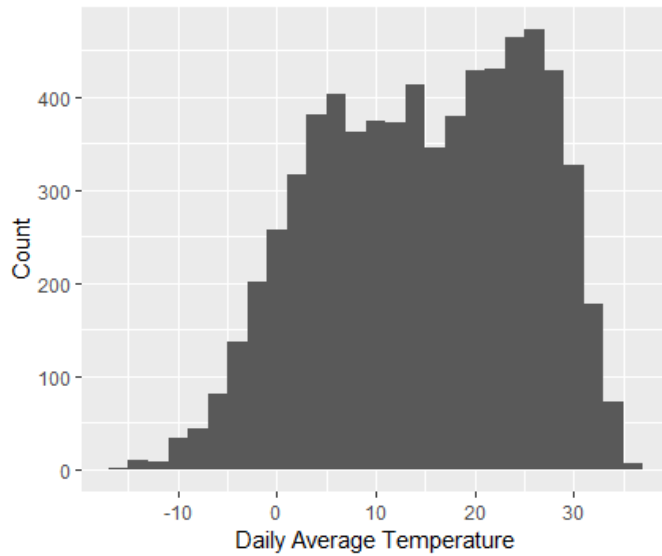
Figure 4.3 Histogram of daily average temperature from 1999 to 2017 in Alva, Oklahoma

Figure 4.4 displays a seasonal-trend decomposition of daily temperatures based on Loess regression (Cleveland et al. 1990), which is a nonparametric technique that uses local weighted regression to fit a smooth curve through points in a scatter plot. The seasonal and trend lines show strong seasonality within a period of year, as well as some strong cyclical behavior over a period of about 3-8 years. There is no apparent trend for a long run increase or decrease in the data over this period.
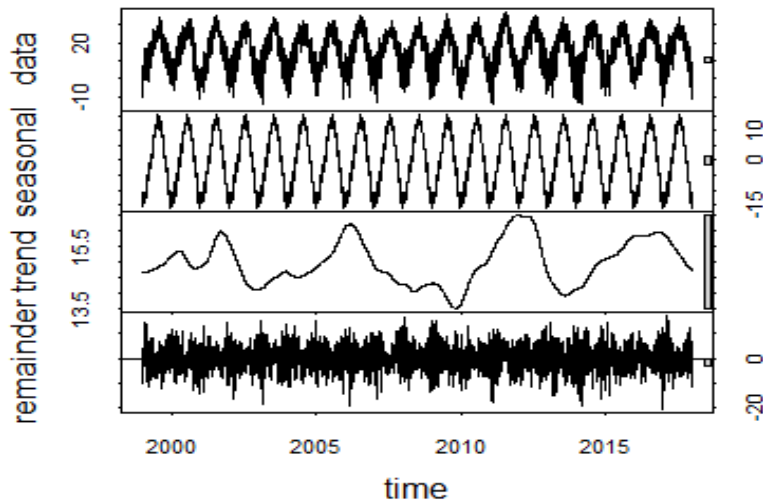
Figure 4.4 Daily average temperature with time series patterns from 1999 to 2017 in Alva, Oklahoma
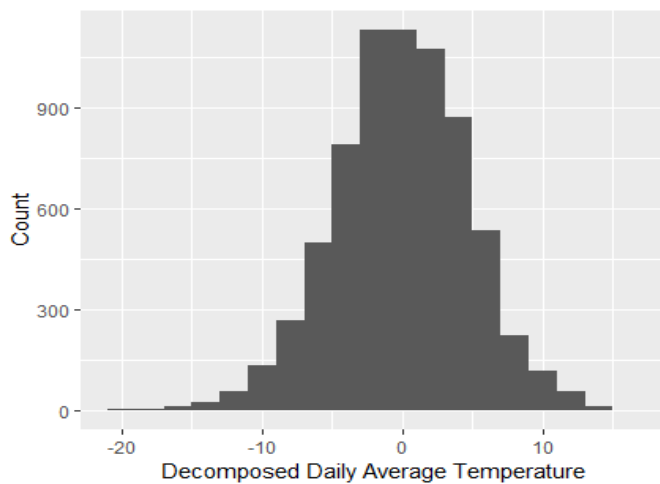
Figure 4.5 Histogram of seasonal-trend decomposed daily average temperature from 1999 to 2017 in Alva, Oklahoma

The graph in Figure 4.5 presents a histogram of the data adjusted by removing seasonality from seasonal-trend decomposition. Compared to the histogram of daily average temperature in Figure 4.3, the shape looks closer to a normal distribution. However, it shows

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some asymmetry in the form of skewness. In the next section, more details about testing

normality, seasonality and cyclicity are discussed in the procedure for weather process.

4.2 Procedures

4.2.1 Weather process

<u>Seasonality and cyclicity</u>

Since seasonality may exist, appropriate adjustments are made before calibrating the data.

We model the daily average data using spectral analysis with a period of 365, a frequency of

1/365. This seasonality indicates that the best predictor of the temperature on a particular date is

the temperature one year earlier. Thus the annual cycle of temperature is a simple cosine as $T =$

365.

In addition, some irregular cycles may exist. As shown in Figure 4.4, there might be

some cycles lasting longer than one year. Zapranis and Alexandridis (2006) suggested an

unusually warm or cold year might occur every few years. They also noted that there is a long run

cycle of about 20 years, but that range is beyond our data availabilities.

The Fast Fourier Transform (FFT) procedure provides some basic information about the

seasonal components. Figure 4.6 shows that the 20th and 39th positions along the frequency array

may have significantly high values. Those positions represent cycle periods of 1 year and 0.5

year, respectively. There are some other potential cycles such as 4.75 or 6.33 years. This study

will mainly focus on the high frequency patterns.
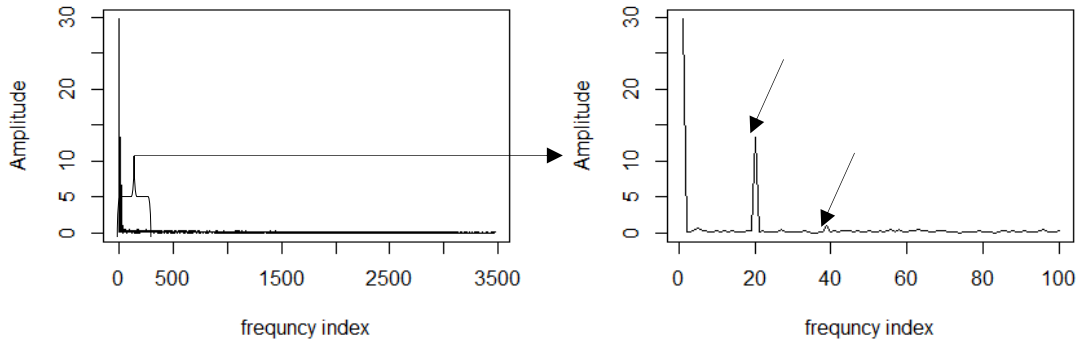
Figure 4.6 Fourier transforms for daily average temperature from 1999 to 2017 in Alva, Oklahoma

Then the seasonal mean is estimated as

(4.1)
$$\bar{w}_t = \hat{b}_0 + \hat{b}_1 \cos\left(\frac{2\pi}{365}t + \hat{t}_{p1}\right) + \hat{b}_2 \cos\left(\frac{2\pi}{(0.5)*365}t + \hat{t}_{p2}\right).$$

where 1/365 indicates daily frequency per year. Since the step of the binomial tree in this study is for two weeks, it necessary to convert the frequency from daily data to the biweekly data as 1/26. Table 4.3 displays the results of the coefficient of cyclicity and seasonality for the daily average temperature in Alva, Oklahoma for equation (4.1). The first two columns are the coefficients from the identity cosine and sine regression model. The last two columns are the estimated amplitude and phases from the coefficients. The numbers match the Fast Fourier Transform procedures.

Table 4.3 Spectral Model for Daily Average Temperature (ºC) in Alva, Oklahoma from 1999 to 2017

Cycles	Coefficient of cosine term	Coefficient of sine term	Amplitude	Angle phase
Mean	14.96			
One year	-3.77	-12.78	13.32	2.85
Half of a year	0.44	0.81	1.06	-2.27

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After removing the seasonal and cyclical components from the daily average temperature in Alva, Oklahoma, the AR(1) process following equation (3.26) is estimated. Table 4.4 displays the results of the coefficient of the AR(1) model for the deseasonalized and detrended weather data. The constant $\dot{\beta}_0$ is close to zero, as expected. $\dot{\beta}_1$ describes the rate of change for the deseasonalized and detrended weather.

Table 4.4 AR(1) Model for The Deseasonalized and Detrended Daily Average Temperature in Alva, Oklahoma from 1999 to 2017

Variable	Coefficient	Std. Error	t-statistic	P-value
$\dot{\beta}_0$	-0.08	0.12	0.65	0.52
$(1 + \dot{\beta}_1)$	0.66	0.01	73.65	0.00***
Normality test for residual				
Pearson chi-square χ^2			280.23	0.00***
Jarque-Bera			425.18	0.00***
skewness	-0.33			
kurtosis	4.02			

With the estimated coefficients, the normality of the residuals is tested. The values of the χ^2-statistics of Pearson's criteria indicates non-normality of the residuals. The *P*-value of χ^2-statistics is significant at the 1%. The skewness is negative and kurtosis value is greater than three, which show asymmetrical empirical distributions. The Jarque-Bera test also shows evidence of non-normality at the 1% level of significance.

Autocorrelation functions (ACF) and the partial autocorrelation functions (PACF) of both the residual and the square of residual are used to determine the existence of any significant lag correlations or seasonality exist (Benth and Šaltytė-Benth 2005, Zapranis and Alexandridis 2006). In Figure 4.7, the autocorrelation of the residual is significant for the first several lags. The

autocorrelation of the squared residuals shows a time dependency in the variance of the residuals, where it can observe a seasonal variation.
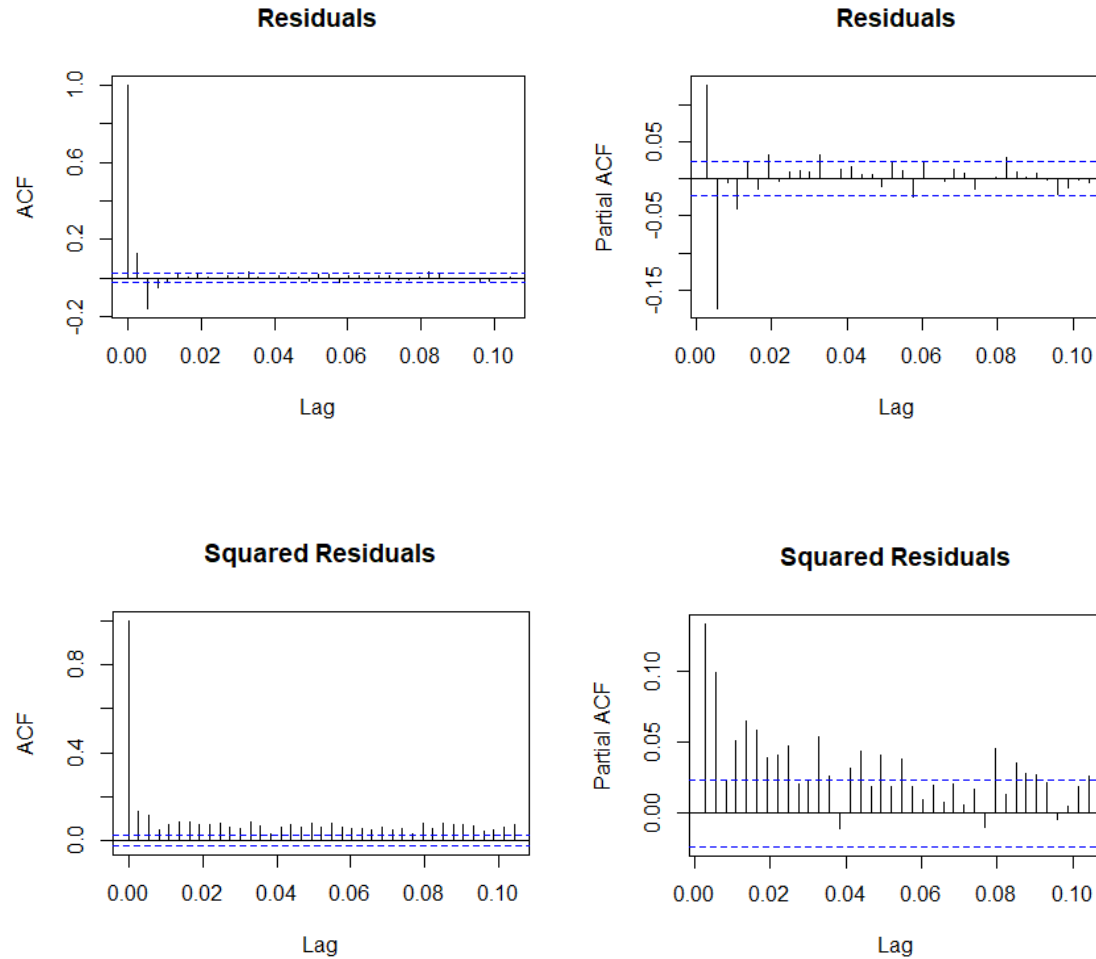
Figure 4.7 ACF and PACF for the residual and the squared residual of the AR(1) model of the deseasonalized and detrended daily average temperature

Since seasonality exists, Generalized Autogressive Conditional Heteroskedastic (GARCH) model is considered to deal with the non-normality in the variance. The *GARCH(m,n)* model describes the variance at time *t* is conditional on observations at the previous *m* times and *n* past variances, as well as some external form such as seasonal patterns.

Fast Fourier transform is used to estimate the significant cycle periods. There are potentially cycles within squared residual, the 0.2 year, half year, one year and 2.7 years. From the linear regression on the squared residuals and those cycles, only the one year cycle is significant. The Amplitude and the Angel phase are displayed in Table 4.5.

Table 4.5 Spectral Model for Daily Average Temperature (°C) in Alva, Oklahoma from 1999 to 2017

Cycles	Coefficient of cosine term	Coefficient of sine term	Amplitude	Angle phase
Mean	11.71			
One year	2.70	6.03	6.60	-0.42

Then to identify the GARCH model, the ARCH test has been done. The statistics tests for changes in variance across time by using lag windows that range from 1 through 12, the p-values for the test statistics strongly indicate Heteroscedasticity with $p < 0.0001$ for the first two lag windows. Since the kurtosis value shows an asymmetric, the model also includes a dummy for a negative value in the error term. Then the full AR(1)-GARCH(2,1) model that we estimate is:

(4.2)
$$\dot{W}_t = \dot{\beta}_0 + (1 + \dot{\beta}_1)\dot{W}_{t-1} + \dot{\varepsilon}_t,$$

$$\dot{\varepsilon}_t | \Theta_{t-1} \sim N(0, \, h_t),$$

$$h_t = \alpha_0 + \alpha_1 \dot{\varepsilon}_{t-1}^2 + \alpha_2 \dot{\varepsilon}_{t-2}^2 + \alpha_3 J_{t-1} \dot{\varepsilon}_{t-1}^2 + \alpha_4 J_{t-2} \dot{\varepsilon}_{t-2}^2 + \beta_1 \, h_{t-1} +$$

$$\gamma_{1,q}^c \cos\left(\frac{2\pi q t}{365}\right) + \gamma_{1,q}^s \sin\left(\frac{2\pi t}{365}\right),$$

$$J_{t-1} = \begin{cases} 0 & \text{if } \dot{\varepsilon}_t \geq 0 \\ 1 & \text{if } \dot{\varepsilon}_t < 0 \end{cases},$$

where Θ_{t-1} is information available in time t-1, the term $\alpha_2 J_{t-1} \dot{\varepsilon}_{t-1}^2$ show the reaction from a negative impact is stronger than a positive impact, and the conditional variance contains GARCH(2,1) and seasonal patterns and $\alpha_1 \geq 0, \beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$.

Binomial tree

The problem starts after last insect treatment, when insect population was eliminated and starts to rebound since then. The managers estimate the insect population based on weather information every other week since last treatment. Two starting dates are picked: April 21 and October 21, which respectively represented warm and cool weather environments for insect growth.

Three steps to simulate the binomial process and the corresponding probabilities of the weather are as following:

1. *Estimate the AR(1) model and estimate the normalized Ornstein-Uhlenbeck (OU) parameters for the detrended and deseasonalized weather.*

   The rate of mean reversion per annum is $\hat{\eta} = \frac{-\ln(1+\hat{\beta}_1)}{\Delta t_D}$ and the variance is $\hat{\sigma}_t = \hat{h}_t \left(\frac{2\ln(1+\hat{\beta}_1)}{\hat{\beta}_1(2+\hat{\beta}_1)\Delta t_D} \right)^{\frac{1}{2}}$. Since this is daily data, then $\Delta t_D = \frac{1}{365}$. Since the volatility is not constant through all time, the $\hat{\sigma}_t$ is a series of numbers. At each time t, the temperature value is conditionally normally distributed based on the information of previous temperature. For each time, steps 2 and 3 are used to estimate the up and down movements and the corresponding probabilities. The structure of the binomial tree will be like in Figure 3.5

2. *Fill in the binomial tree for the for the detrended and deseasonalized weather using the normalized estimation and add the time patterns back to the estimation;*

   The detrended and deseasonalized weather at node (i, n) is $\dot{W}(i, n) = \dot{W}_0 + (n - 2i)\hat{\sigma}_t\sqrt{\Delta t_M}$, the estimated weather is then $W(i, n) = \dot{W}(i, n) + \overline{w}(., n)$, where $\overline{w}(., n)$ is the time pattern that vary by time but will be constant for all the up and down movement during time n. The up movement is $W(i, n + 1) = W(i, n) + \hat{\sigma}_t\sqrt{\Delta t_M} + \overline{w}(., n + 1)$ and the down movement is $W(i + 1, n + 1) = W(i, n) - \hat{\sigma}_t\sqrt{\Delta t_M} + \overline{w}(., n + 1)$. The time steps in the

binomial tree is two weeks, $\Delta t_M = 1/26$. The starting values are the true weather on April 21, 2018 and October 21, 2018.

3. *Estimate the probability and risk-neutral probability of an up move at each node for the OU process.*

The probability of an up move at each node for weather is the same as the probability of an up move at each node for detrended and deseasonalized weather, the probability is $\lambda_u(i, n) =$ $\frac{1}{2} + \frac{(1-e^{-\hat{\eta}\Delta t_M})(-\dot{W}(i,n))}{2\hat{\sigma}_t\sqrt{\Delta t_M}} = \frac{1}{2} + \frac{(1-e^{-\hat{\eta}\Delta t_M})(\bar{w}-W(i,n))}{2\hat{\sigma}_t\sqrt{\Delta t_M}}$. As mentioned earlier, this study assumes the manager is risk aversion that he will strengthen the problem of an increasing possible of the potential damage. The risk-neutral probability of moving up is $\pi_u(i, n) = z\,\lambda_u(i, n)$, where z is a scalar that is greater than 1, for example, 1.05.

Monte Carlo simulation

Besides just up and down movements along the binomial tree, Monte Carlo simulation is also considered to sample the temperature process. Based on equation (3.28), the sample path simulation equation for W_t is using the discrete-time expression as

(4.3)
$$W_t = W_{t-1}e^{-\hat{\eta}\Delta t} + \bar{w}_t(1 - e^{-\hat{\eta}\Delta t}) + \hat{\sigma}_t\sqrt{\frac{1-e^{-\hat{\eta}\Delta t}}{2\hat{\eta}}}\,N(0,1),$$

where $\hat{\sigma}_t$ is vary by time from the GARCH model on equation (4.2) and $N(0,1)$ is a random number that follows a normal distribution with mean zero and variance of one (Dixit and Pindyck 1994).

Since the historic data is daily temperature while the decision-making time interval is every two weeks, the time intervals for the mean return rate and the volatility where adjusted. According to equation (3.20), the mean return rate is annualized. Thus, the Δt in equation (4.3) is

set as the value of $\Delta t_m = 1/26$, which is the biweekly rate. However, since the variance is not a constant, we cannot use the same method to scale the volatility.

One of the methods is to simulate the daily data using daily volatilities. Then we pick up weather information from the dates of interest. For a binomial process, the variance is conditionally normally distributed along the path-dependent process tree. Thus, we can just pick up the simulated variance for the interested day and scale that into biweekly volatility using equation (3.20). The estimated variance describes the volatility for the following two weeks based on what has happened so far. Moving forward in time step by step, we repeat the estimation process until the end of the data. In addition, one of the advantages of this method is that we have full information about weather so that we can pick any date as a starting day of the problem.

50,000 samples of weather paths were drawn. Then insect populations were simulated and the associated potential damages were calculated based on each weather information. Under each individual temperature path, the results of the option value are calculated using equation (3.9). Each individual weather path represents different possible outcomes of potential damage loss. The expected option value is the mean value from the large sample size of individual estimations for different scenarios. The expected option value describes general information about the insect pattern and potential damages. Some individual paths from the sample size were also used for some empirical analysis.

4.2.2 Insect population

The insect population is the growth from a previous population, $I_t = f(I_{t-1}, W_t)$, from Flinn et al's (2010) insect model, which means different previuos insect population results in different insect growth with the same weather. Therefore, a general insect population function is used that has a growth pattern similar as the path-dependent insect growth model

$$(4.4) \qquad I_t = \begin{cases} I_0 * \left(1 + \alpha e^{\Delta t_M t \beta W_t}\right)^t * (1 - \delta), & \text{if } W_t < 20 \\ I_0 * \left(1 + \alpha e^{\Delta t_M t \beta W_t}\right)^t, & \text{if } W_t \geq 20 \end{cases},$$

where I_t is the insect population at time t, W_t is the weather value at time t, α and β are

parameters for insect growth model, Δt_M is the discrete time interval in terms of one year. δ is the

insect death rate due to a low temperature when the weather value W_t goes below the criteria 20

°C, if $W_t \geq 20$, $\delta = 0$, otherwise, δ is set to be 0.8. Then insect population only bases on the

initial insect population, time steps and the weather information at time t, and it is deterministic

function of weather.

4.2.3 Insect damage cost

The insect damage cost is the monetary loss from potential live insect infestation onto the

food product. While insect damage in grain storage can be measured with insect damaged kernels

and other grade and non-grade characteristics, it is hard to develop a direct equation to estimate

economic damage based on insect population in processed food products because there are few, if

any, market-determined discounts. In addition, it is difficult to determine the true insect

infestation level.

Rather, the economic damage is likely a function of consumer perceptions, the breadth of

insect infestation (e.g., one package or an entire lot), and the intensity of insect infestation (e.g.,

many insects, one insect, or insect fragments). Sometimes, insect-infested products may still be

acceptable with a discounted price. More often, an entire lot is rejected, or products already

distributed may be recalled. Moreover, it is highly speculative to put a dollar value on indirect

losses due to insect infestation, such as loss of goodwill. Little information is available to help

model this loss, so a damage loss function with somewhat arbitrary, though subjectively

reasonable, parameters is specified, and a range of alternative specifications is tested to determine

the effect of these assumptions on the results.

There might be a very high cost associated with a live insect in the final product, but perhaps a low probability of it occurring. However, that probability would be a function of the total insect population, as well as other factors that might influence how likely an insect would enter the product. The following insect damage loss function is specified:

$$(4.5) \qquad\qquad D(S_t) = L * \vartheta(I_t),$$

where L is the cost of a recall, or public relations damage or both and $\vartheta(I_t)$ is the probability of loss, which is a function of insect population at time t, I_t.

We propose that the probability of loss increases with time, since individual insects will be more likely to infest the product if they stay in the facility longer. As a result, the probability of economic loss increases nonlinearly with time.

To simplify, this model assumes $\vartheta(I_t) = t * (\theta I_t)^2$, where θ is the probability of one insect entrance into the product during unit of time. Here, θ is set equal to 0.008 and 0.00008 to determine how the result is sensitive to the insect damage.

For most recalls, the direct recall cost can be calculated by multiplying the number of units of the recalled batch that are in distribution channels by the wholesale price of the product as reported in the appropriate year (Jarrell and Peltzman 1985). In addition, there are some indirect recall costs, such as the loss of goodwill and the loss of processing profit for a period in the event that an insect infestation forces the facility be shut down.

To keep it simple, the direct recall cost is considered. The recall cost should be a fixed number as,

$$(4.6) \qquad\qquad L = p * Q,$$

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where p is the price of the product ($/lb) and Q is the amount of the recalled products (lb).

Usually, the number of recalled batches is large and the economic loss is significant.

For example, on May 31, 2016, General Mills Inc. initiated a nationwide recall of three brands of flour, totaling about 10 million pounds, in response to a 20-state E. coli outbreak that sickened 38 people. This would cause about $9 million loss. Moreover, on July 8, General Mills Inc. tripled the size of its flour recall at 30 million pounds. As a benchmark, suppose the price of a 2 lb. bag of Gold Medal All Purpose Flour is $1.84. If the recall size is 10 million pounds, the recall loss would be $9.2 million.

4.2.4 Treatment cost

An economic-engineering model developed by Adam et al. (2010a) is adopted for estimating costs of insect control treatments with sulfuryl fluoride (ProFume®) for fumigating food processing facilities to calculate the treatment cost, TC, including fumigation cost, C_F, and opportunity cost of shutting down, C_{Sh},

(4.7) $$TC = C_F + C_{Sh},$$

where C_F includes fumigant, labor, training, electricity and equipment cost, and C_{Sh} is due to loss of productivity.

Table 4.6 illustrates the possible types of treatment costs that may be incurred. The magnitude of each possible cost depends on the specific approach. Variable costs include labor, chemical and material costs, and value of product loss, since those costs depend on the amount of grain treated or the number of treatments. Fixed costs, those not varying with frequency of treatment, include equipment costs, liability insurance, and training costs.

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Table 4.6 Insect Treatment Cost Components

Possible costs	Formula
Fumigation cost	
Labor cost (various kinds)	Wage ($/hr)*hours*number of workers
Costs paid to vendors (e.g. training workshop fees)	(Training hours per worker*hourly labor cost + registration fee)*number of workers
Electricity cost	Electricity cost ($/kwh)*operation time (hr)*power (kw)
Equipment cost	Amortized equipment cost ($/yr) + maintenance cost (% of equipment cost, $/yr)
Chemical cost	Chemical price ($/unit)*units used
Shut-down opportunity cost	
Value of product loss	Shutting down time (hr)*productivity ($/hr)

According to Adam et al. (2010a), the treatment cost is $ 21,711 for fumigating with sulfuryl fluoride (ProFume®), following the Dow Agroscience average field test dose of 40 g/m^3 at price of 15.34 $/Kg, in a 28,317 m^3 food processing facility (Table 4.7).

Table 4.7 Cost of Fumigations in a 28,317 m^3 Food Processing Facility for Profume

Item	Cost per Job ($)
Equipment	58
Labor	4,134
Training	19
Fumigant	17,500
Total Cost	21,711

Source: Adam et al. (2010a)

As emphasized in previous chapters, postponing treatment can reduce the frequency of treatment, and thus the total number of treatments over time. To calculate the potential savings from reducing frequency of treatments, a frequency scalar is used to adjust the value of TC:

(4.8)
$$TC_t^\gamma = TC/\gamma^t,$$

where $\gamma = 1 + \Delta t_M$ is a scalar used to adjust the value of TC, Δt_M is the discrete time interval between potential treatment dates. If insect treatment is postponed t times, treatment cost savings are $B_t^{TC} = TC - TC_t^{\gamma}$. In the option model, this is a benefit of waiting to treat. For example, if the treatment occurs 14 weeks after the previous treatment, that treatment cost is divided by $(1+1/26)^7$ to get a treatment cost per year, since there are 26 two-week intervals in a 52-week year, and 7 two-week intervals in 14 weeks.

4.2.5 Economic threshold

The economic threshold ET can be defined as the insect population at which the economic loss caused by this population exceeds the cost of control: treatment cost, TC, is compared to expected economic loss from insect infestation, $E[D(ET)]$. If $TC \leq E[D(ET)]$, treatment is conducted. If $TC > E[D(ET)]$, treatment is not conducted. Hence

(4.9) $$TC = E[D(ET)] = L * \vartheta(ET) = p * Q * \theta t E[ET^2],$$

$$ET = \sqrt{\frac{TC}{\theta t p Q}}.$$

To find the static economic optimal treatment time, the ET is compared with estimated daily insect population. The date at which insect number $E(I_t)$ exceeds the threshold ET is the optimal treating date.

4.2.6 Real option models

Several scenarios with alternative specifications of real option models are described below in order to meet the following objectives:

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Objective 1). Determine the value of deferring insect treatment using a real option approach instead of making an immediate decision by economic threshold criteria.

Option to defer insect treatment

In this scenario, insects grow from the last treatment until the time at which it reaches the economic threshold. The economic threshold treatment date is the selected at current time that conventionally managers make an instant decision about insect treatment. The result of the decision includes treat or not to treat by economic threshold.

Nevertheless, instead of making that instant decision, the option model uses a single step binomial tree to forecast the possible outcomes two weeks later. With this option, the results then include treating insect at current time, treating insect later or not to treat at all. This option is an opportunity but not an obligation for an insect treatment. Holding this option allows us to keep the opportunity to treat, waiting until a later time when we can make a better decision based on the information available then about possible later outcomes.

Last treatment t_0 t_1

April 21

October 21
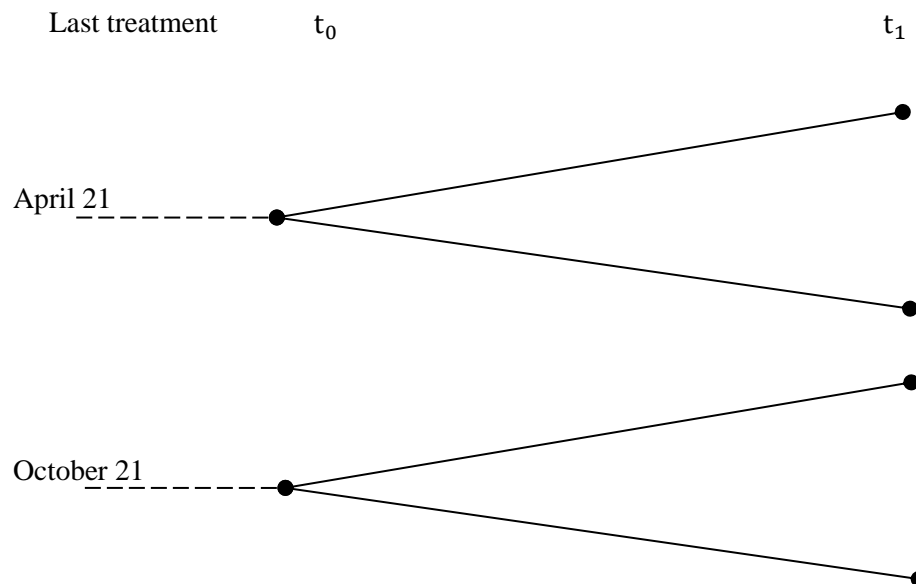
Figure 4.8 Binomial model for a single-step option model of the insect treatment problem

Binomial trees (Figure 4.8) will be mainly used to accomplish this objective because a binomial tree displays alternative possible outcomes. The trees can provide sufficient information because the weather path before the selected starting point is objective, and the potential up and down moves to the next time is conditionally normally distributed. Assuming the last treatment occurs on April 21 or on October 21. Individual temperature paths from the Monte Carlo simulations, where each individual path represents one particular possible weather movement, are randomly chosen.

Objective 2). Determine the value and optimal time to treat insects.

<u>Optimal timing to treat insects</u>

In this scenario, we collect information about weather and insect population as early as immediately after the last treatment until an appropriate ending time. We hold an option to treat insects, which can be exercised at any step during this given time interval. Once we exercise the option, the option is no longer available and the problem ends. If we do not exercise the option and hold it, this option become useless at maturity. This is a multi-time American (Bermudan) option with which the decision to treat or not can occur at any of the discrete time steps. The decision is made by comparing the cost of waiting and the cost of treating of each time step (as in Figure 3.5). The value of the option is defined by equation (3.33) and equation (3.34).

The maturity is set up as two weeks after the treatment date from the economic threshold model, which allows it to exercise insect treatment at any time from last treatments to the economic threshold treatment date. In addition, the maturity is set up as one year from last treatment, which allows it to make a decision about treatment during a whole year.

In this procedure, both binomial tree and Monte Carlo simulations are used. Binomial

process allows it to trace all the possible outcomes along the tree. Monte Carlo simulations

simulate a large sample size of weather paths. The methods as described above are used to value

the option by comparing the cost of waiting and the cost of treating at each time step. The mean

result from all the individual estimations is the expected option value among all possible

outcomes (equation (3.9)).

Objective 3). Determine the effect of timing flexibility on the value of an option for insect treatment.

Optimal stopping model (for expiration date)

This scenario relaxes the assumption about the fixed maturity time to determine the effect

of timing flexibility on the value of option for insect treatment. Imagine managers can choose the

optimal expiration date of an option to treat insects that they own. This optimal expiration date is

the date when the option has the highest value based on equation (3.36). From the time this

expiration date is chosen, the manager evaluates every two weeks whether to exercise the option

or not, using equations (3.33) through (3.35). This represents the optimal time to treat.

Figure 3.7 shows several possible points of maturity. For each maturity T_n, insect

treatment decision must be completed by T_n or the opportunity is lost forever. Thus, for each

maturity, the option is an American option in which the manager can treat insects by comparing

the cost of waiting and the cost of treating at each time step from the last treatment until the end.

T_{n^*} is the optimal expiration date, this date is chosen by comparing the cost of treatment

and the cost of waiting, which are calculated using equations (3.33) and (3.34). Among the

different maturities, dynamic programming is used to determine the maximum value among the

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option values, as in equation (3.36) that determines T_{n^*}. Once T_{n^*} is chosen, the method described under objective 2, "optimal timing to treat insects", is used to determine the optimal exercise, or treatment date.

The difference between the optimal stopping model and the timing option model is that the optimal stopping model determines the optimal maturity, while the timing option model determines the optimal time to treat insects before maturity. For a European option, the optimal stopping model and the timing option may be the same. However, since the option to treat insects is an American option and it allows early exercise, the optimal stopping model and the timing option model are different and both models can work together to make a decision. After the optimal maturity date from optimal stopping model is chosen, the optimal time to treat insects can be estimated using the timing option model from time zero up the optimal maturity date.

In order to test the sensitivity of these results to initial damage cost specification, the same procedures are conducted for probabilities of damage equal to 1/100 of the initial probability, and for probabilities 100 times the initial probability.

4.2.7 Total costs for the optimal decisions

Based on the treatment decisions from optimal timing real option models and the economic threshold model, total costs, including treatment cost and damage loss, are evaluated from equation (3.1). The cost from real option models and the cost from the economic threshold model are compared to determine which model results in lowest cost decisions.

This study focuses on the timing decision of only one treatment. There will be zero or one treatment during the time period, based on an optimal timing option model. Since reducing frequency of treatments can reduce total treatment costs over a period of time, this savings is calculated by adjusting the treatment cost according to how soon after the previous treatment a

new treatment is required. This is done by multiplying the treatment cost times a scalar that normalizes the treatment frequency, as in equation (4.8).

The potential damage is measured four different ways. First, damage is based on insect population at the optimal expiration date from the optimal stopping model. This insect population reflects growth after the optimal treatment and before expiration. The damage cost is calculated using the damage loss equation, equation (4.5), and annualized using equation (4.8). A second way is to estimate the potential damage immediately after treatment. In this situation, the potential damage should be zero because insect treatment can kill almost all the adult insects. A third way is to estimate the maximum damage that has occurred during the time from the last treatment to the optimal expiration date. A fourth way is to estimate the maximum damage that has occurred during the time from the last treatment to the optimal treatment. The damage costs and treatment costs under each method are annualized by multiplying the costs by $26/t$, where t is the number of two-week time intervals between the last treatment and the optimal treatment.

CHAPTER V

RESULTS

5.1 Weather process

Table 5.1 displays the results of the coefficient estimation from the AR(1)-

gjrGARCH(2,1) model for the deseasonalized and detrended daily average temperature in Alva,

Oklahoma. The deseasonalized and detrended weather is assumed to be a zero-mean Ornstein-

Uhlenbeck (OU) process, and the intercept is zero as expected. The coefficient of the AR(1) term

is 0.7 and is statistically significant. The heteroscedasticity and ARCH terms in the variance are

significant. The variance is significantly autocorrelated in first and second lags.

Table 5.1 AR(1)-GARCH(2,1) Model for The Deseasonalized and Detrended Daily Average Temperature in Alva, Oklahoma from 1999 to 2017

Variable	Coefficient	Std. Error	t-statistic	P-value
Mean				
Interception	-0.00	0.13	-0.01	0.99
AR(1)	0.70	0.01	76.07	0.00***
Variance				
Constant	4.66	1.11	4.20	0.00***
ARCH(1)	0.17	0.03	6.37	0.00***
ARCH(2)	0.16	0.05	3.37	0.00***
GARCH(1)	0.46	0.11	4.41	0.00***
Asymmetry term (1)	-0.14	0.03	-4.61	0.00***
Asymmetry term (2)	-0.16	0.04	-3.65	0.00***
Sine of one year cycle	0.85	0.14	3.19	0.00***
Cosine of one year cycle	2.61	0.63	4.13	0.00***

Figure 5.1 to Figure 5.3, shows the simulated temperature paths, the resulting simulated insect numbers and potential damage costs. The left graphs are from April 21 and the right graphs are from October 21. The dotted line is the mean of all the simulations. The temperature values (Figure 5.1) vary around the seasonal mean, especially so at the coldest temperatures.
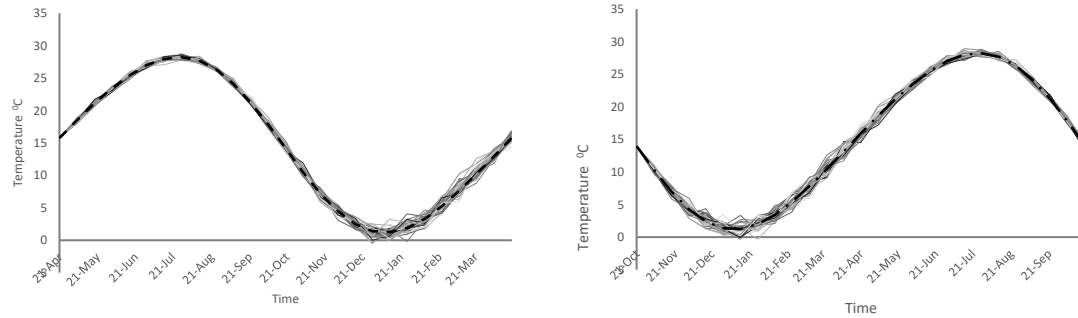
Figure 5.1 Simulated mean reverting biweekly temperature from April 21 and October 21
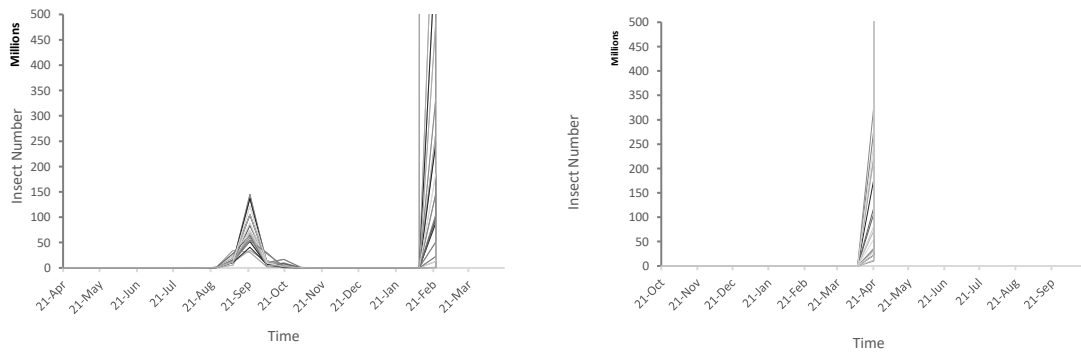
Figure 5.2 Simulated insect population based on simulated mean reverting biweekly temperature
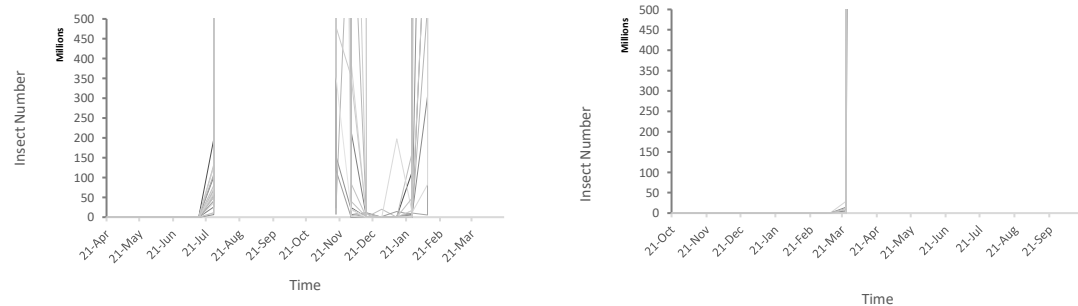
Figure 5.3 Simulated potential damage based on simulated mean reverting biweekly temperature

After a treatment on April 21, simulated insect population (Figure 5.2) expands rapidly around the middle of July. If no treatment is conducted, the rapidly expanding population results in large potential damage (Figure 5.3). Insect population starts to decline when temperatures become cool in October. However, the population declines only to about 40 insects/floor. Thus, potential damage stays high until it starts to drop around December. Then when temperatures start warming, insect population again expands rapidly.

After a treatment on October 21, insect population begins to expand rapidly around the end of March, which is a more delayed expansion compared to the period after treatment on April 21 due to the cooler weather. Accordingly, potential damage expands around the same time. Since the temperature stays high for the rest of the year, insect population expands to very high values and does not decrease. Therefore, potential damage keeps increasing without any treatment.

Treating insects at the time of rapid population expansion is likely too late to avoid substantial economic damage. Given the model parameters assumed here, insect population above 10 insects/floor may potentially cause significant loss. Typically, managers would have treated before that, avoiding substantial damage loss.

5.2 Economic threshold

Following an economic threshold model, the treatment date is where the expected damage first exceeds the treatment cost. From equation (4.9), the economic threshold (ET) varies with time. Figure 5.4 presents the relationship between time and the economic threshold insect number. The graph is the simulated ET without considering the benefit from decreasing treatment frequency.
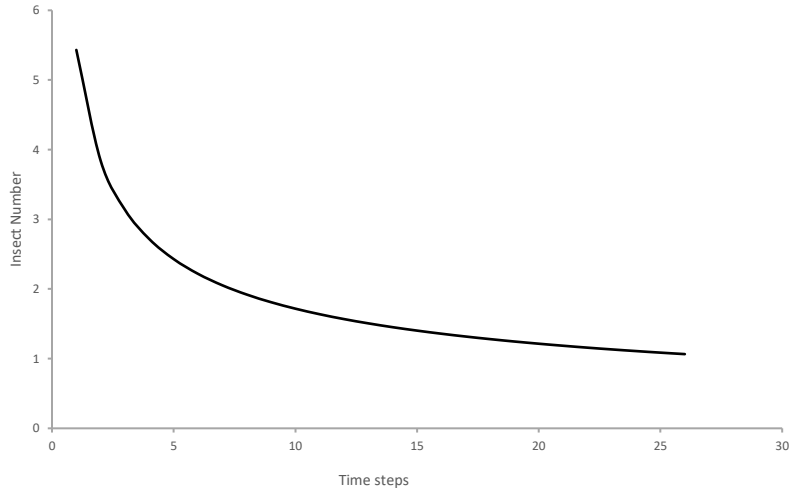
Figure 5.4 Economic threshold (ET) insect number with and without considering benefit from decreasing treatment frequency

The value of ET decreases with time as expected. Since the time interval considered here is two weeks, depending on the rate of growth of insect population, the gap between insect population from one observation until two weeks later can be large, so the economic threshold condition $TC \leq E[D(ET)]$ holds but it may not lay in the trigger where $TC \approx E[D(ET)]$ empirically.

Table 5.2, shows the average optimal result using empirical historic temperatures in the economic threshold model. After the last treatment on April 21, the temperatures are potentially high during the summer. As a result, the next treatment is necessary on July 28, which is 14 weeks after the last treatment. The weather reaches 27.87^0C on July 28 and the insect population is 90 insects/floor, averaging over the time period 1999-2017. The calculated ET is 2.34 insects/floor, which indicates that damage just exceeds the treatment cost on July 28.

Table 5.2 Results from Economic Threshold Model

Categories	Values	
	April 21	Oct 21
Last treatment		
Treatment date	July 28	March 23
Weeks after last treatment	14	22
Weather (°C)	27.87	10.16
Insect population (insects/floor)	90	10
ET (insects/floor)	2.34	2.01

If the last treatment occurred on October 21, temperatures fall through the winter, staying low until late spring the following year. As a result, the next treatment is not required until 22 weeks after last treatment, on March 23. The temperature reaches 10.16°C and the insect population is 10 insects/floor, averaged over the time period. The calculated ET is 2.01 insects/floor, which indicates that damage just exceeds the treatment cost on March 23.

The temperature and insect population at the time of treatment when the last treatment occurred on October 21 is lower than the values of temperature and insect population at the time of treatment when the last treatment occurred on April 21, as expected. Treatment is required even though both values are low because the longer insects stay in the facility the higher the probability that damage will occur. As a result, although insect population is low, it causes a large potential loss due to its duration.

Figure 5.5 summarizes the results of identifying each year's optimal date of insect treatment based on the economic threshold using historical data. The arrows point out the week of the of treatment date averaged over the 19 years.
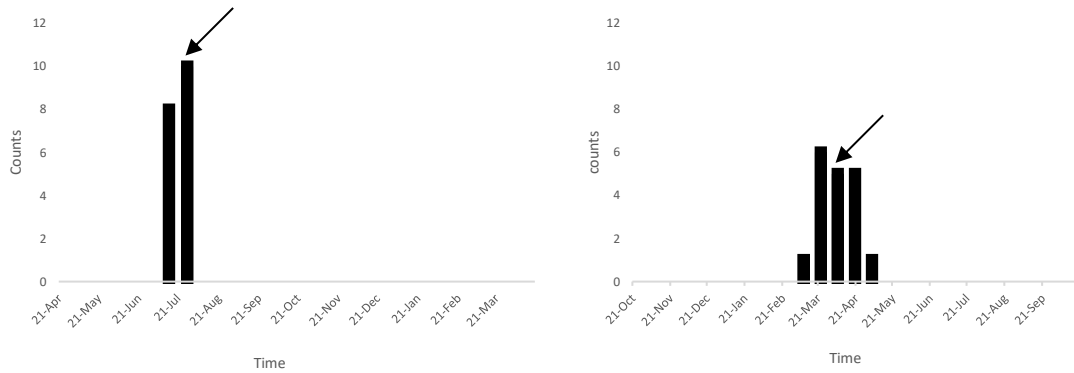
Figure 5.5 Empirical counts for the treatment dates based on economic threshold

When the last treatment occurred on April 21, the date of insect treatment varies across years, with a range from July 14 to July 28. The average over all years was July 28, although, less than half of the years had a treatment date before July 28. When the last treatment occurred on October 21, the date range is even wider, from February 24 to April 20, with an average date of March 23. This shows the possibility that in any given year the economic threshold treatment date might differ from the average. This suggests the possibility that a real option approach might be valuable because it takes into account probabilities of differences in temperature and insect population outcomes.

Objective 1). Determine the value of deferring insect treatment using a real option approach instead of making an immediate decision by economic threshold criteria.

5.3 Option to defer insect treatment

The starting points, t_0, as shown in Figure 4.8, are selected based on the information on the optimal treatment date from the conventional economic threshold models. When the last

treatment occurred on April 21, the starting points of interest are July 14 and 28, while when the

last treatment occurred on October 21, the starting points of interest are March 9 and March 23. t_1

is one step (two weeks) later. The comparison of the results from the economic threshold model

and a single period real option model can answer the following questions:

1) *If insect population in a particular year does not reach the economic threshold*
   criterion (ET) at the historical average economic threshold treatment date, instead of
   making a decision to not treat insects, is there any incentive to hold this opportunity as
   an option to wait until later to make the decision?

At the economic threshold treatment date, if insect number does not reach the ET, the

economic threshold approach does not signal treatment. A real option model, however, gives other

possibilities. Figure 5.6 displays a temperature path under which the insect population does not

reach to the ET.

Weather	7.20
Rn Prob.	8.93%
Insect	0.45
Damage	1608.46

Weather	Insect Number	Damage
25.37	$2.54*10^{13}$	**$5.69*10^{30}$**
-5.49	0.00	0.00
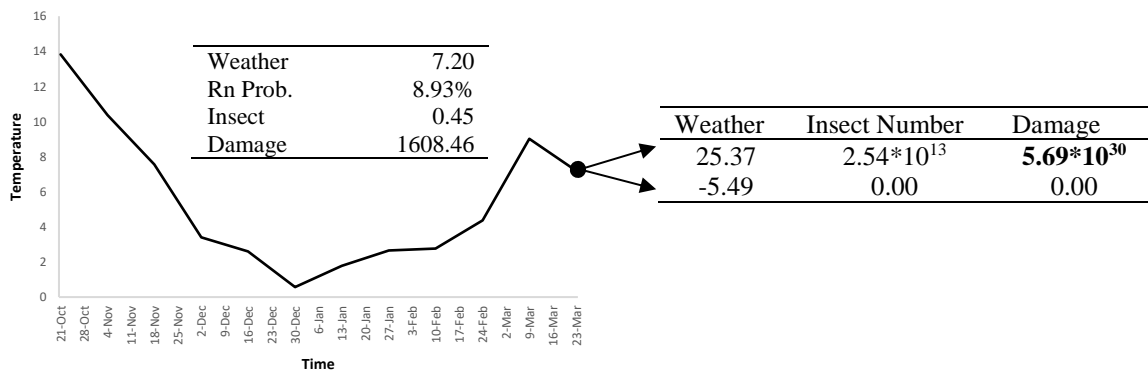
Figure 5.6 Weather path in which insect population does not reach the ET (10 insects/floor) on
March 23 from last treatment on October 21

Under this particular temperature path starting from the last treatment on October 21,

insect population grows to 1.41 insects/floor on March 23. The potential damage is $1,608.46.

Compared to the treatment cost on March 23, which is $ 21,711, the economic threshold approach

indicates that no treatment should occur. If the problem were to end here, the cost would be a

damage cost of $1,608.46. However, if the problem continues, by not treating, potential damage

cost might increase if insect population grows before the next decision point two weeks later, on April 6.

With a real option approach, though, the manager can be thought of as holding an option to treat at a future time, say two weeks later on April 6, instead of the problem ending on March 23. In the example presented in Figure 5.6, the temperature increases to 25.37°C with a risk-neutral probability 8.93% and decreases to -5.49°C with a probability 91.07%. If temperature increases, the result would be significant potential damage that exceeds the treatment cost on April 6, so the decision indicated is to treat with a cost of $21,711. If temperature decreases, the potential damage does not exceed the treatment cost, and the decision concludes with a decision to not treat, with a cost of zero.

Thus, an option to treat later results in an expected cost of $\frac{21711}{Rf} * 8.93\% + \frac{0}{Rf} *$ $(1 - 8.93\%) = \$1,762.54$, taking into account the potential damage cost two weeks later. In contrast, the expected cost without an option to treat insects on April 6 is $\frac{5.69*10^{30}}{Rf} * 8.93\% + \frac{0}{Rf} *$ $(1 - 8.93\%) + 1,608.46 = \$4.61 * 10^{29}$, a very large loss. Thinking of the decision in this way – holding an option to treat later, compared to making a decision on March 26 and not considering later treatments – helps to illustrate the value of holding an option to treat later. If insect population does not reach the ET at a particular evaluation date, the economic threshold model may underestimate the cost of not treating, whereas a real option model may suggest treating at that time because the probabilities of future damage loss are evaluated. Therefore, a real option approach may help to protect from a huge potential loss.

2) *If insect population exceeds the ET earlier than the historical average economic threshold treatment date, should insect treatment occur immediately based on the economic threshold concept, or is there any incentive to wait until later to make the decision?*

When insect population reaches to ET, it indicates that insect treatment should occur. However, the real option model may provide other possibilities if the temperature drops in the following days and the insect population is thus reduced significantly by nature. Figure 5.7 displays a temperature path under which insect population reaches the ET earlier than the economic threshold treatment date.

Upper graph data table:

Weather	Insect Number	Damage
38.47	$3.38*10^4$	$5.88*10^{12}$
20.17	1.69	14,656.80

Weather	29.06
Rn Prob.	0.49%
Insect	2.49
Damage	27,273.94

Lower graph data tables:

Weather	10.96
Rn Prob.	11.32%
Insect	2.09
Damage	32,140.94

Weather	Insect Number	Damage
29.20	$6.96*10^{12}$	$3.92*10^{29}$
-2.04	0.00	0.00
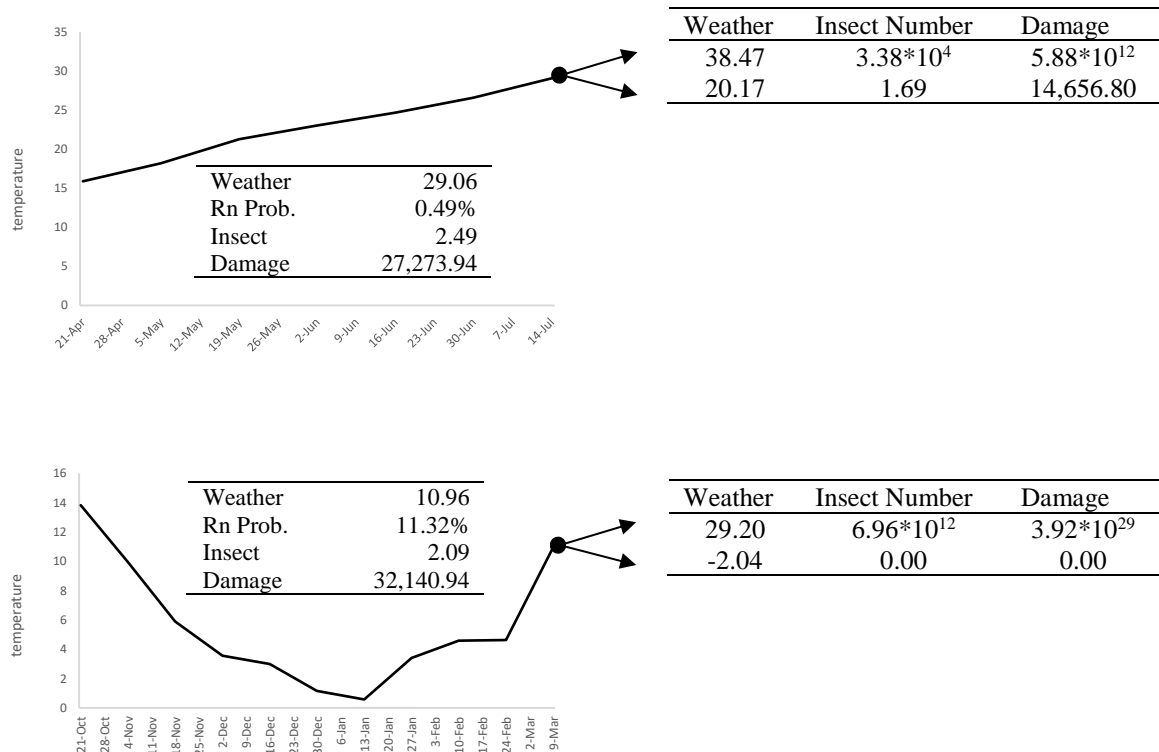
Figure 5.7 Weather paths under which insect population reaches the ET (10 insects/floor) earlier than the economic threshold treatment date

The upper graph in Figure 5.7 shows a temperature path from last treatment on April 21. Temperature increases continually so that insect population grows to 2.49 insects/floor on July 14. The potential damage is $27,273.94. Compare to the treatment cost on July 14, which is $ 21,711, the economic threshold model indicates that treatment should occur, and the problem ends with a total cost of $21,711, the treatment cost.

With a real option approach, the manager can consider treating two weeks after July 14 instead of on July 14. In effect, the manager can be modeled as having an option to treat on July 28. The temperature may increase to 38.47^{o}C with a very low risk-neutral probability 0.49% and it may decrease to 20.17^{o}C with the probability 99.51%. If temperature increases, it may result in significant potential damage that exceeds the treatment cost on July 28. The manager chooses to treat with a cost of $21,711. If temperature decreases, the potential damage is lower than the treatment cost on July 28, so the manager chooses to not treat insects, incurring a damage cost of $14,565.80 on July 28.

The cost of waiting to treat later (holding an option to treat later) results in an expected cost of $\frac{\$21,711}{Rf} * 0.49\% + \frac{\$14,565.80}{Rf} * (1 - 0.49\%) = \$32,295.42$. This is a higher cost than treating the insects on March 28 ($21,711), so holding the option to treat later is not worthwhile.

The lower graph in Figure 5.7 shows a weather path from last treatment on October 21. Insect population grows to 2.09 insects/floor by March 9. The potential damage is $32,140.94. Compared to the treatment cost on March 9, which is $21,711, the economic threshold model indicates that insects should be treated, with a total cost of $21,711.

If there is an option to treat two weeks later on March 23, the temperature increases to 29.20^{o}C with a risk-neutral probability 11.32% and it decreases to -2.04^{o}C with a probability 78.68%. If temperature increases, it causes significant potential damage that exceeds the treatment cost on March 23. The problem concludes with a decision to treat at a cost of $21,711. If temperature drops, the potential damage does not exceed the treatment cost, so the problem concludes with a decision to not treat insects, with a cost of zero.

The expected cost of waiting to treat later (holding an option to treat later) is $\frac{\$21,711}{Rf} *$ $11.32\% + \frac{0}{Rf} * (1 - 11.32\%) = \$2,234.26$. Compared to treating on March 28 at a cost of

$21,711, holding the option to treat later saves some cost because there is a chance that treatment will not be required.

From the results, we conclude that an option to defer insect treatment may be worthwhile because it might save treatment cost. If the optimal timing is located in a season when temperatures are increasing, the occurrence of potential damage is more certain. Deferring insect treatment increases the total cost due to likely future damage. If the optimal timing is located in a season with decreasing temperatures, there are chances that potential damage may not occur and that treatment will not be required. Therefore, total expected cost may be reduced.

Objective 2). Determine the value and optimal time to treat insects.

5.4 Optimal timing to treat insect

The timing option is an American option model which allows the early exercise at each node between the starting time and maturity. The problem is assumed to start from the last treatment, either April 21 or October 21, through multiple steps along time to the end. The steps are biweekly. Based on the result from the economical threshold, the maturity, T_n is set to be $T_n = 8$ steps (16 weeks) from the last treatment on April 21, to be $T_n = 12$ steps (24 weeks) from the last treatment on October 21, and to be $T_n = 26$ steps (52 weeks), one year from either treatment date.

Table 5.3 summarizes the result of the option values based on different maturity settings, with the methods of both binomial pricing model (BP) and Monte Carlo valuation (MC). The option values are $11,798.84 for binomial pricing and $21,711 for Monte Carlo valuation from last treatment on April 21. The maturity time August 11 allows any treatment after April 21 until July

90

28. The option values are -$4,140 for binomial pricing and $20,194.53 for Monte Carlo valuation

from last treatment on October 21. The negative number means there is some benefit of postponing

treatment. The maturity time on April 6 the next year allows any treatment after October 21 until

March 28.

Table 5.3 Option Values Based on Different Maturities

No.	Option Value	Last treatment	t	Maturity date	Decision	Estimation method[c]
1	$11,798.84	April 21	8	August 11	June 30 to end	BP
2	$21,711.00	April 21	8	August 11	b	MC
3	-$4,410.00	October 21	12	April 6[a]	December 16 to end	BP
4	$20,194.53	October 21	12	April 6[a]	b	MC
5	$21,711.00	April 21	26	April 19[a]	b	MC
6	$21,711.00	October 21	26	October 19[a]	b	MC

a. It goes to the next year. b. These are the mean results, results from individual paths vary. c. BP is binomial pricing model and MC is Monte Carlo
   valuation

Extension of the maturity means that the opportunity to treat insects lasts longer. When the

maturity time is extended until one year later, the option values are $21,711 for both cases

(compare No. 2 and No. 5 in Table 5.3). Compared with the results when the maturity dates are set

to the date selected by the economic threshold model for last treatment on April 21, the option

value does not change. This result indicates that the decision about insect treatment would likely

have already been made before the economic threshold selected date. Therefore, no matter how

long the maturity is extended, the results are the same. In contrast, when the last treatment date is

October 21, and maturity is extended to one year, the option value increases from $20,194.53 to

$21,711 (compare No. 4 and No. 6 in Table 5.3). This indicates that holding the option until up to

one year is more valuable than holding the option until up to 12 weeks.

Comparing the option values between the two starting points, the value of holding insect

treatment starting from April 21 is higher than when starting from October 21, as expected. The

weather from April to September is warmer than from October to March, and is more likely to

result in damage. Holding an option after April 21 can potentially save more damage cost than holding the option after October 21.

Figure 5.8 shows intrinsic value, timing value and the option value on the timing options for those given time ranges based on the mean from the simulated weather paths. Since the values vary over a wide range, the lines are plotted on a logarithmic scale. The dotted lines are the intrinsic values, which indicate the cost of exercising the option. The solid lines are the option values. The arrows between the two lines show the time values. As both intrinsic and the option value increases, time value decreases. When time value becomes zero, there is no difference between the intrinsic and the option value. Therefore, it is time to treat insects.
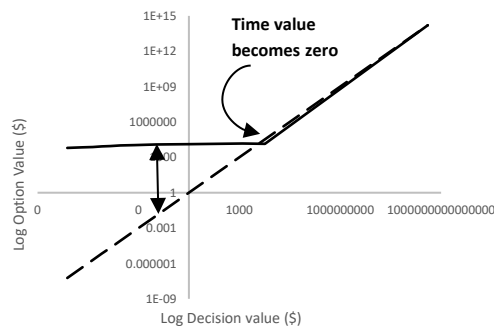
a. April 21 – August 11
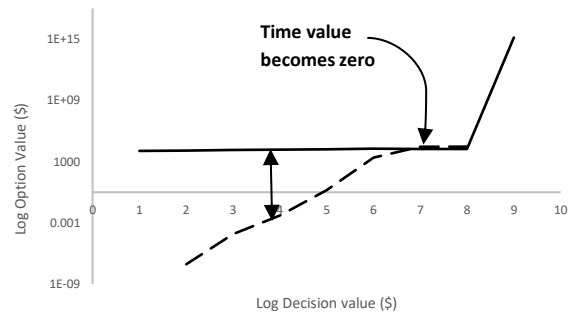
b. October 21 – April 6 next year
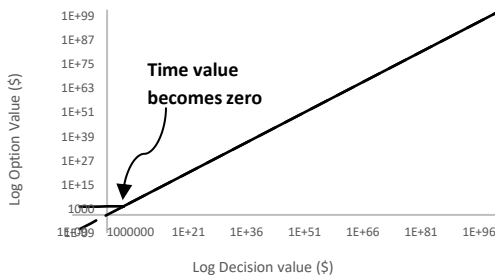
c. April 21 – April 19 next year
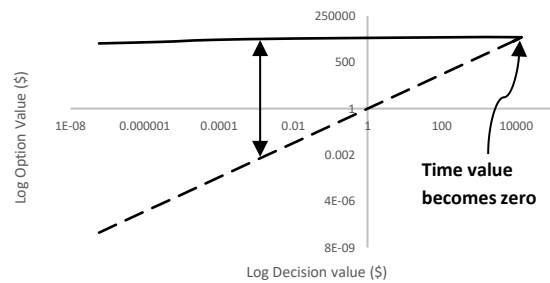
d. October 21 – October 19 next year

Figure 5.8 Intrinsic and time value for timing options for different given time ranges.

If we compare the left two graphs (a and c), time value goes to zero at the same market value; the difference between them is that the option value and intrinsic value are the same for a longer time period in a one year range. This corresponds with the option values from Table 5.3, in which No. 2 and No. 5 have the same values, but No. 5 has a maturity date several months later, April 19 of the following year. Comparing the right two graphs (b and d), time value is retained longer in d because there may be economic reason to treat insects later than with the economic threshold treatment date. If we compare the left graphs with the right graphs, the option retains time value longer when the last treatment was on October 21 than when the last treatment was on April 21. The time value of the option to treat insects may last longer from October 21 than from April 21, because temperatures stay lower after October 21, giving more possibility that no treatment is needed.

Table 5.4 and Table 5.5 show the parts of the results from binomial pricing model from the mean reverting binomial process of temperature. The horizontal separation line in each column indicates that above the lines are the upward moves from values in the previous column (the column to the left) and below the lines are the downward movements. The cells with shades and light color are the outcomes that will not be reached by the properties of mean reversion. The cells in bold font show that there is no time value remaining, indicating the optimal time to treat insects.

Table 5.4 Binomial Process of the Option Value from Last Treatment on April 21

21-Apr 0	5-May 1	19-May 2	2-Jun 3	16-Jun 4	30-Jun 5	14-Jul 6	28-Jul 7	11-Aug 8
11798.84	11811.91	13195.57	16046.74	21711.00	21711.00	21711.00	21711.00	2.81E+58
	11781.04	12585.15	13800.40	19187.25	21711.00	21711.00	21711.00	1.79E+47
		12500.03	13458.88	18873.22	21711.00	21711.00	21711.00	2.33E+45
		13306.05	14884.49	17208.58	21711.00	21711.00	21711.00	7.24E+33
			14774.01	20075.59	21711.00	21711.00	21711.00	1.73E+49
			14473.74	16797.83	21711.00	21711.00	21711.00	1.14E+37
			15658.26	17982.35	21711.00	21711.00	21711.00	6.88E+33
			12611.27	14935.36	17977.49	21711.00	21711.00	6.00E+20
				18369.30	21711.00	21711.00	21711.00	3.91E+44
				16124.40	21711.00	21711.00	21711.00	2.61E+33
				15239.42	20548.78	21711.00	21711.00	3.45E+31
				14935.35	17977.47	21711.00	21711.00	1.50E+20
				17097.95	21711.00	21711.00	21711.00	2.49E+35
				14935.56	17977.68	21711.00	21711.00	2.03E+23
				14935.35	17977.47	21711.00	21711.00	1.43E+20
				10535.92	13578.05	17311.61	21711.00	3.05E+06
					21711.00	21711.00	21711.00	5.01E+45
					21711.00	21711.00	21711.00	3.32E+34
					21711.00	21711.00	21711.00	4.38E+32
					17977.51	21711.00	21711.00	1.80E+21
					21711.00	21711.00	21711.00	3.17E+36
					17977.94	21711.00	21711.00	2.50E+24
					17977.51	21711.00	21711.00	1.71E+21
					13578.05	17311.62	21711.00	9.01E+08
					21271.28	21711.00	21711.00	7.41E+31
					17345.10	21711.00	21711.00	6.64E+20
					13663.13	17396.67	21711.00	9.83E+18
					13578.05	17311.61	21711.00	7.81E+06
					17977.61	21711.00	21711.00	5.78E+22
					13578.10	17311.67	21711.00	1.63E+11
					13578.05	17311.61	21711.00	7.48E+06
					-13173.51	-9439.95	-5040.55	1.53E-02
						21711.00	21711.00	3.42E+46
						21711.00	21711.00	2.25E+35
						21711.00	21711.00	2.96E+33
						21711.00	21711.00	1.17E+22
						21711.00	21711.00	2.15E+37
						21711.00	21711.00	1.66E+25
						21711.00	21711.00	1.12E+22
						17311.62	21711.00	4.69E+09
						21711.00	21711.00	5.01E+32
						21711.00	21711.00	4.32E+21
						21711.00	21711.00	6.30E+19
						17311.62	21711.00	1.38E+09
						21711.00	21711.00	3.80E+23
						17311.72	21711.00	9.17E+11

continued…

Table 5.5 Binomial Process of the Option Value from Last Treatment on October 21

21-Oct	4-Nov	18-Nov	2-Dec	16-Dec	30-Dec	13-Jan	27-Jan	10-Feb	24-Feb	9-Mar	23-Mar	6-Apr
0	1	2	3	4	5	6	7	8	9	10	11	12
-4140.38	-4327.49	935.50	2921.38	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.02E+289
	-3890.93	-3339.27	-3102.75	3312.40	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.47E+262
		-4625.57	-2290.29	645.88	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.35E+243
		-930.12	648.32	3590.89	3967.18	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.33E+208
			2513.94	-29.43	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.40E+231
			-841.49	1734.60	5166.93	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	5.01E+198
			-4779.35	-2455.26	-65.93	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	3.93E+183
			9023.16	11347.25	14389.38	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	4.49E+153
				5245.06	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.09E+225
				-778.68	1284.32	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	5.81E+197
				-137.41	4584.12	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.93E+187
				-128.49	2913.63	5936.17	21711.00	21711.00	21711.00	21711.00	21711.00	1.57E+161
				6643.70	12528.83	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.34E+192
				-499.78	2542.35	5384.32	21711.00	21711.00	21711.00	21711.00	21711.00	7.15E+166
				-7153.51	-4111.38	-377.82	5043.18	21711.00	21711.00	21711.00	21711.00	8.60E+155
				1730.70	4772.83	8506.39	12905.79	21711.00	21711.00	21711.00	21711.00	4.77E+120
					21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.30E+232
					6318.21	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.76E+198
					3685.61	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	6.08E+181
					8031.10	13080.58	21711.00	21711.00	21711.00	21711.00	21711.00	2.88E+150
					3009.98	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.51E+177
					4528.63	8262.20	21711.00	21711.00	21711.00	21711.00	21711.00	5.56E+148
					1977.08	5710.65	11608.23	21711.00	21711.00	21711.00	21711.00	2.56E+137
					-3280.58	452.98	4852.38	10437.87	21711.00	21711.00	21711.00	5.12E+110
					8254.58	21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	8.77E+184
					2839.35	6288.38	21711.00	21711.00	21711.00	21711.00	21711.00	1.71E+159
					-1957.31	1776.25	6841.08	21711.00	21711.00	21711.00	21711.00	8.69E+149
					1926.88	5660.44	10059.84	16819.36	21711.00	21711.00	21711.00	6.29E+122
					-134.41	3599.16	8600.30	21711.00	21711.00	21711.00	21711.00	2.67E+144
					6780.75	10514.32	14913.71	21711.00	21711.00	21711.00	21711.00	4.61E+109
					-6222.92	-2489.35	1910.04	6950.61	21711.00	21711.00	21711.00	1.03E+92
					-5236.94	-1503.37	2896.02	7936.59	13594.58	21711.00	21711.00	2.27E+59
						21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.27E+222
						21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	1.46E+192
						21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	5.34E+179
						7439.49	21711.00	21711.00	21711.00	21711.00	21711.00	1.48E+152
						21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.27E+182
						7944.18	21711.00	21711.00	21711.00	21711.00	21711.00	1.84E+156
						1094.24	6168.41	21711.00	21711.00	21711.00	21711.00	5.97E+146
						1442.71	5842.10	11649.54	21711.00	21711.00	21711.00	1.82E+121
						21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	2.79E+194
						2538.79	21711.00	21711.00	21711.00	21711.00	21711.00	1.55E+159
						5563.81	11612.66	21711.00	21711.00	21711.00	21711.00	4.43E+140
						10294.01	14693.41	21711.00	21711.00	21711.00	21711.00	5.97E+106
						14479.08	21711.00	21711.00	21711.00	21711.00	21711.00	9.52E+130
						12271.11	16670.50	21711.00	21711.00	21711.00	21711.00	4.51E+99
						4291.31	8690.70	13731.27	21711.00	21711.00	21711.00	8.58E+85
						-1540.78	2858.62	7899.18	13557.17	21711.00	21711.00	2.02E+57
						21711.00	21711.00	21711.00	21711.00	21711.00	21711.00	8.30E+175
						9946.27	21711.00	21711.00	21711.00	21711.00	21711.00	1.66E+149
						3452.16	8779.21	21711.00	21711.00	21711.00	21711.00	2.24E+139

continued…

One of the advantages of the binomial process is the ability to trace all the outcomes over time. Starting from the last treatment on April 21 (Table 5.4), the first treatment time is June 30 if temperatures continually increase, indicated by the bold cost of treatment, $21,711. Starting from the last treatment on October 21, the first treatment time is December 30 if temperatures continually increase, again indicated by the bold cost of treatment, $21,711. If temperatures remain very low, no treatment is necessary until the option is expired. If temperatures are between the two possible, some nodes show a possible treatment and some do not.

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Objective 3). Determine the effect of timing flexibility on the value of an option for insect treatment.

5.5 Optimal stopping model

Figure 5.9 shows the effect of timing flexibility on the value of an option for insect treatment. The dotted line represents option values with different maturities from last treatment on April 21. The solid line represents option values with different maturities from last treatment on October 21.
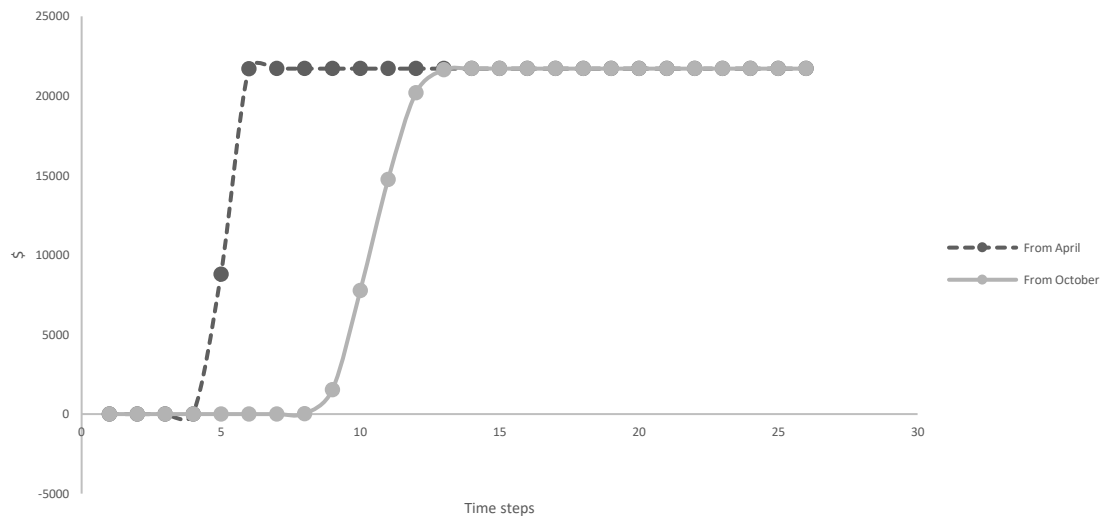
Figure 5.9 The effect of timing flexibility on the value of option for insect treatment

The results show that the optimal length of time to hold an option to treat insects is until July 28 when starting from the last treatment on April 21, which is the same as the optimal treatment date from the economical threshold model. The results from the binomial pricing model shown in Table 5.4 suggest that insect treatments could start June 30, depending on the weather path. Holding the option until July 28 permits June 30 as a possible exercise date. It does not allow

exercise on July 28, which is the last possible treatment date shown in the binomial model in Table 5.4.

Starting from the last treatment on October 21, the results show that the optimal length of time to hold an option to treat insects is until May 18, which is two months later than the economic threshold treatment date. This result, as part of the procedure for choosing optimal maturity date, means that on average, treatments that need to occur will happen before May 18. Thus, there is no need to hold this option later than May 18.

Comparing these results to the economic threshold treatment date, when the last treatment occurred on April 21, the optimal stopping model indicates holding the option to treat insects for a shorter time, to an earlier date than the economic threshold treatment date, July 28. This drives the treatment earlier, primarily because of the very high cost of the potential damage. When the last treatment was on October 21, though, the optimal stopping model indicates holding the option for a longer time, to a later date than the economic threshold treatment date, March 23. The lower temperatures may result in lower potential damage, increasing the value of holding the option longer.

When starting from the last treatment on October 21, the optimal stopping model indicates holding the option to treat insect to a later date than the economic threshold optimal treatment time. Treatments may be necessary after March 23 (the economic threshold treatment date), up until May 4. As a result, the economic threshold model may indicate to treat too early, which unnecessarily increases treatment cost.

Figure 5.10 shows the effect of timing flexibility on the value of an option for insect treatment with different potential damage values. The upper graph shows the case in which potential damage is increased by increasing the probability of the occurrence from 0.008 to 0.8 and

the lower graph is the case in which the potential damage is decreased by decreasing the

probability of the occurrence from 0.008 to 0.00008.
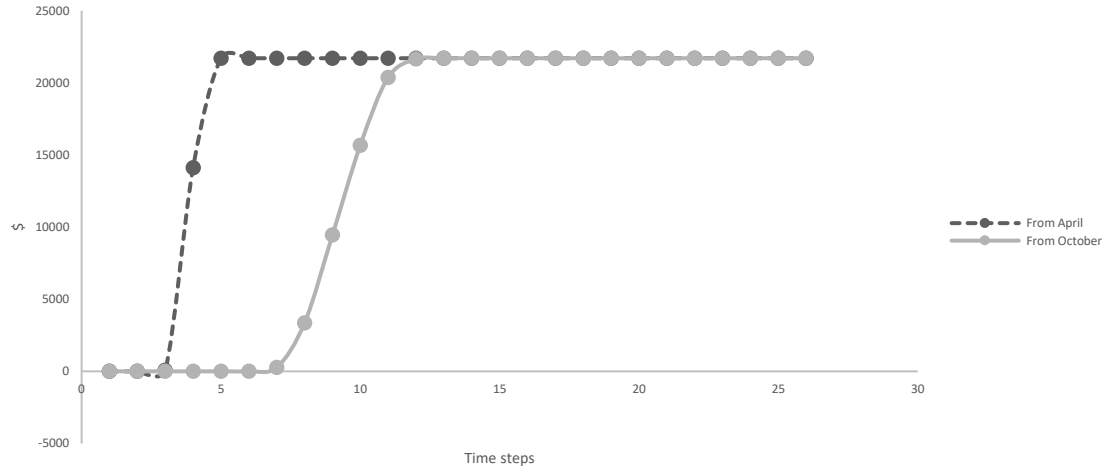
a. Increase the potential damage by increasing the probability of the occurrence
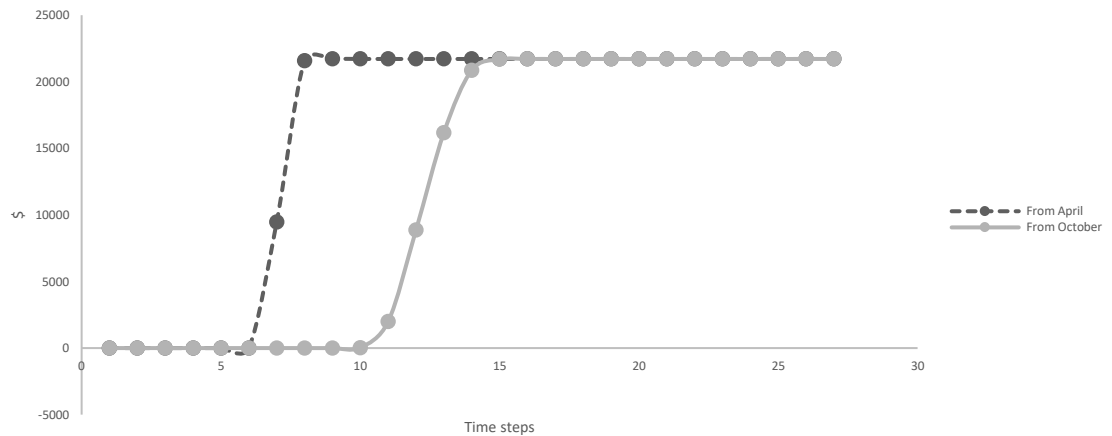
b. Decrease the potential damage by decreasing the probability of the occurrence

Figure 5.10 The effect of timing flexibility on the value of option for insect treatment with different potential damage values

Increasing the potential damage cost pushes the opportunity of insect treatment expired

earlier by two weeks, for both the April 21 and October 21 starting dates. Conversely, decreasing

the potential damage cost results in a later optimal expiration date. However, the magnitudes of the date shifts are different. During a high temperature range, the optimal time to hold the opportunity extends until six weeks if the potential damage decreases, since a treatment is more likely to be needed if it has not already occurred, while during a low temperature range, the optimal time to hold this opportunity extends only two weeks because a treatment is less likely to be needed.

5.6 Total costs for the optimal decisions

Table 5.6 displays the annualized total cost for the insect treatment decisions from optimal timing option models and the economic threshold model. The costs of treatment decisions from optimal timing option models are lower than or equal to the costs of treatment decisions from the economic threshold model, under both warm and cool temperature trends, under several alternative ways of measuring damage cost.

Table 5.6 Annualized Total Cost for the Insect Treatment Decisions from Optimal Timing Option Models and the Economic Threshold Model

Damage	Last treatment	Economic threshold model	Real option model	Insect rebound ending time
Rebound damage	April 21	66,033	66,033	14 weeks from last treatment
	October 21	18,105	15,371	30 weeks from last treatment
Zero damage	April 21	66,033	66,033	Immediately after treatment
	October 21	24,689	19,071	Immediately after treatment
Maximum damage	April 21	776,515	732,967	14 weeks from last treatment
	October 21	155,407,674,210	590,242,575	30 weeks from last treatment
	April 21	776,515	732,967	Immediately after treatment
	October 21	211,919,555,741	657,125,668	Immediately after treatment

The "Rebound damage" way calculates insect damage cost based on insect population after it rebounds from the optimal treatment up until the date specified by the optimal stopping model, which is 14 weeks from the last treatment on April 21 and 30 weeks from the last treatment on October 21. From last treatment on April 21, the costs of threatment decisions from real option

models and the economic threshold model are the same, which indicates that both models lead to similar decisions about the treatment dates. From last treatment on October 21, the costs of treatment decisions from the real option models are lower by $2,734 ($18,105 minus $15,371).

The "Zero damage" way calculates insect damage cost based on insect population immediately after the optimally-timed treatment. Since the treatment has just occurred, there should be no measurable economic damage loss from the remaining insect population. Using this calculation, from the last treatment on April 21, the costs of treatment decisions from real option models and the economic threshold model are the same. From the last treatment on October 21, however, the costs of treatment decisions from the real option models are lower by $5,618 ($24,689 minus $19,071).

For both of these ways of calculating insect damage loss, the calculated damage loss is relatively low, and the difference in cost between the economic threshold model and option models results from a savings in treatment costs using the option models. Option models make better decisions in that some treatments may be later than those indicated by the economic threshold model, without risking much damage loss.

A third way of calculating damage loss is to base it upon the maximum insect population that occurs during the entire time of the decision, from a starting date of April 21 or October 21 until the problem stops, whether this maximum population occurs before the optimal treatment or after.

Concerning about the maximum damage that has reached during the given time, the cost increases due to the damages, especially under the cool weather. The maximum damage could be whichever is greater from the potential damage before conducted treatment, which indicates too late to treat insects or could be the rebound damage after the treatment at the ending point, which indicates early treatments.

The damage information in the costs of real option decisions may be mainly from an insect rebound because real options may conduct early treatments than the economic threshold decisions. The increasing value of the total cost according the insect rebound ending time changes from on 30 weeks to immediately after treatment confirms this result because the increasing annualized scalar results in a higher total cost.

The damage information in the costs of economic threshold decisions may contain both the insect rebound and the too late to treat. In some years (temperature paths), early treatments allow insect rebound afterwards until the ending points while in some other years, too late treatments foregoes a significant damage loss. Therefore, the costs are so high compare to the costs from real option decisions.

CHAPTER VI

CONCLUSIONS AND DISCUSSION

6.1 Conclusions

This study evaluated the value of an option for insect treatment to help managers make decisions about the optimal timing to treat insects. Daily temperature, which is the main source of uncertainty about insect population and the corresponding potential damage loss, was used as the stochastic variable.

A real option model measures the value of an opportunity but not the obligation to treat insects, and can help in several ways. First, an option to defer insect treatment can protect from the cost of failing to control insects. When the static decision indicates to not treat according to the economic threshold concept, results show that a high potential damage loss may occur later. An option to defer treatment (treat later) measures the value of having the opportunity to treat later, which protects from this potential loss.

Second, an option to defer insect treatment can help make a better decision and reduce treatment cost. When the static decision indicates that it is necessary to treat insects according to the economic threshold concept, options measure the value of other possibilities. If temperature drops at a later time, insects may die and the potential damage will decrease, and no treatment is needed because insects are controlled by nature.

This conclusion reflects one of the benefits of adopting a real options framework for decision making. The option models consider future states and these future states may influence the current decision. Since it contains more information, the decision from the option model may be better and give different or even contrasting decisions than a static model.

Third, for decisions about optimal timing, a real option model to treat insects suggests that the best treatment time may be earlier or later than the economic threshold treatment date. If temperature tends to increase after the last treatment, the option model suggests that it is best to hold the option for to treat insects until the same week as the economic threshold treatment date. Within that time period, the optimal treatment date may be 2 weeks earlier than the date indicated by the economic threshold model.

If temperature remains low after the last treatment, the option model suggests that it is best to hold the option to treat insects to a later date than the economic threshold treatment date. Within that longer time period, the optimal treatment time may be 2 weeks earlier or 4 weeks later than the economic threshold date. The total cost of the decisions based on real option models are less than or equal to the cost of the decisions based on economic threshold models.

In the models used here, the hypothetical potential damage loss is very high even though the probability of the occurrence is low. Since a real option model values the opportunity to treat insects later, future high potential damage cost increases the current value of the option.

High potential damage cost is a major factor that drives the optimal treatment date earlier than the economic threshold results. With lower potential damage costs, the optimal date moves later especially under warm weather. With higher potential damage cost, the optimal date moves earlier

Binomial trees list many possible paths when temperature goes up or down. Results from the binomial pricing models and the results from the Monte Carlo valuations are similar but not

completely the same. Monte Carlo integration simulates a large number of samples, so that average results are based on many probability-adjusted possible outcomes. Therefore, Monte Carlo integration may be a more appropriate method to evaluate the value of options for insect treatment. However, it is hard to trace the information about the decisions on insect treatment at each time step when using Monte Carlo integration. In contrast, binomial trees display the possible early exercise dates, although it simplistically considers only two possible movements, up or down for each node. Therefore, although it might give different option valuations, the binomial process may be more appropriate for decision making about timing of insect treatment.

In addition, we found a real option model may provide better decisions about insect treatment than an economic threshold model under conditions including risk. To the extent that possible outcomes are more certain, the advantage option models may be smaller. The cost advantage of a real option decisions over an economic threshold decision is larger under cooler temperature trends, and smaller under warmer temperature trends.

6.2 Discussion

This study used temperature as the stochastic variable and assumed a deterministic relationship between temperature and insect population and as well as between insect population and damage cost. However, in practice the situation may be more complicated. A future extension of this study can relax the deterministic relationships for a more complex structural model. One way to do this is to add a stochastic relationship between temperature and insect population. Thus, even if temperature is constant, insect population could vary, conditional on some distribution. Similarly, immigration rate could vary, or there could be a stochastic relationship between insect population and the probability of the occurrence of potential damage.

This study used a published computer simulation model (Flinn et al. 2010) to estimate the insect population. The advantage of this method is that the primary data input to the model is temperature, data for which can be easily obtained, and the growth model has been calibrated to empirical data. However, there may be other ways, including empirical data from insect monitoring, to model insect population and its relationship to measures of insect cost.

In addition, this study mainly focused on one insect treatment decision after the previous treatment. However, additional insect treatments may be necessary because of insect rebound. Thus, further studies could build a sequential timing option model, where the decision about first insect treatment timing will consider the possibility of subsequent treatments. Then, with a sequential timing option model, the decision about the frequency of insect treatment may be more reliable.

A difficulty with building a sequential timing option model is that the potential damage rebound from treatment may not be linearly related to time. Option values are calculated backwards using dynamic programming. However, the rebound damage for the later treatment decision will determined by the optimal timing from the last treatment. Few studies have considered this kind of application using a real option model. Successfully completing that will be provide a more useful tool for decision making in insect control problems, and would contribute to the literature.

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