Stochastic demand forecast under seasonally cyclical fluctuation and the optimal investments by real options approach

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A b s t r a c t

Title	Stochastic demand forecast under seasonally cyclical fluctuation and the optimal investments by real options approach (季節性周期変動における確率的需要予測とリアル・オプション・アプローチによる最適投資)

(800 words)

Demand forecasting prior to an actual demand is inevitable in supply chain. If there is a gap between them, friction against smoothing should be removed. However, the soft drink industry has been faced with technological and market uncertainties. The technological uncertainties, for example, arise from reasons as strengthen in food sanitation standard, wasteful use of resources short expiration date, and innovation in containers. The market uncertainties are such as daily demand which is known just on the day stating production, sudden cancellation of production contract, and product life cycle. Because of these uncertainties, an improved cooperative supply chain between buyer and supplier is required in order to build out the productive system for commercial production.

The focus of this study is to determine the appropriate demand forecasting in yearly and monthly units, and to respond to them from supplier's (producer's contract with buyer) perspective by using real options approach (ROA). The basic idea of ROA is to enable the investment for improved value of commodity or real assets through flexible decisions in the future. Here, real option is a right, but not an obligation, to exercise. In this study, ROA is applied to the matters, from not only long but also short terms, of concern about supply chain.

This study is mainly divided into three parts: (1) potential capital investment for long term sales, (2) potential capital investment in seasonal high demand for medium term sales, and (3) possible investment in the optimal production for daily sales.

First topic is potential capital investment for long-term sales. Annual demand is forecasted by autoregressive integrated moving average (ARIMA) model which is one of the methods for time series analysis. ROA indicates when, how much sales and how to respond to demand in cases of demand increase and decrease. If sales of soft drink are favored, the supplier can exercise the option to expand (American call option) and is expected to increase the sales. If the sales are unfavorable, the supplier can exercise the option to shrink (American put option) and is expected to shrink down, sparing the cost. These options are evaluated by four-step process in binomial lattice only once. The option value becomes increased when flexible decision for irreversible investment is made under uncertainty.

Second is potential capital investment in seasonal high demand for medium term sales. The demand of soft drink may not be fulfilled in the summer because the supply is too low to meet the demand. Monthly demand is forecasted by seasonal autoregressive integrated moving average (SARIMA) model which depicts seasonal movements. Two alternative options are compared and evaluated, one is Bermudan call options to employ additional workers to increase efficiency in summer and dismiss in winter. This attitude is repeated each year. The other is American call option to replace equipment to improve machine capability throughout the year. These options are evaluated by four-step process in binomial lattice with 10,000 runs of Monte-Carlo simulation. Results show that employing additional workers has an advantage over replacing equipment under uncertainty. But, the highest improvement is gained if the two options happen to be alternatively exercised. It is wiser for the producer to forecast the sales, have the both American and Bermudan options and seek for the opportunity of the American. The decision for investment is usually subject to time lags before it can be made. Under the independent American call option based on SARIMA model forecasting, signal of monthly sales prior to critical optimal investment timing is evaluated. Then it is observed to enable to provide robust signal of decision-making for option exercise.

Third and final is possible investment in optimal production for daily sales. In response to the daily repeated supply chain of soft drink under uncertain demand, ROA is applied to a flexible amount of production. A supplier can exercise call and put options in order to modulate between the demands and the efficiency of her productive capacity. Sensitivity analysis can be used to find critical conditional and decision variables at a decision tree, with call and put options for flexibility of positive and negative daily production. Next, effects of the exercisable duration and quantity in the three-stage cycle are compared with more multi-stages. This study shows that options can yield more their value to options with a longer stage and larger exercisable quantity.

In conclusion, even if the target period is long or short-term, the results reveal that ROA is useful for the supply chain. The flexibility in ROA allows supplier to avoid downside risk and

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Chapter 1 Introduction

1.1 Abstract

Market demands of most products have uncertainty until contract is concluded. They need the methods to forecast and correspond to demand at different time period.

In this study concerning about soft drink production, first problem is to find the demand forecast of seasonal products and to find the best attitude to anticipate the right demand. Next problem is to coordinate daily and seasonal demands with efficiency.

The forecast analysis focuses on the following issues:

(a) To forecast seasonal demand of products using time series analysis method with seasonal autoregressive integrated moving average (SARIMA).

(b) The forecasted demand is converted to free cash flow (FCF) and make a real options analysis whether additional invest is needs or not.

(c) To find the best daily and seasonal production using real options analysis to modify the gap between actual demand and optimal production with high efficiency.

Furthermore, the forecasting model studied in this research can be expected to apply to any sales forecasting with seasonality and is based on real options analysis.

1.2 Study Context

Generally, the matter about the future prediction is based on the supposition and judgment of the person concerned with the available information now, then a known or unknown risk and uncertainty are inherent. According to ISO 9000:2015, a risk is the "effect of uncertainty" on an expected result and the effect is a positive or negative deviation from what is expected, and uncertainty is a state or condition that involves a deficiency of information and leads to inadequate or incomplete knowledge or understanding.

Whenever we try to achieve something, there's always the opportunity that matter will go according to supposition. In fact, sometimes we get positive or negative results. This is just the condition of uncertainty. Therefore, the real achievements to become clear in the future may turn out greatly different by various factors. Because of this, we need to reduce uncertainty as much as possible. It is the mater of the rational supposition and judgment using available information now, and it can greatly find more than enough value to predict even if results may be different. Unlike expectation to guess matter beforehand, it is on a signpost of the future activity to check the matter and add logic beforehand.

Market demands of most products have uncertainty until contract is concluded. In most of today's business environment, seasonality is an important factor. Many products have seasonal effects. It is often found that demand of seasonal products becomes significant only in the specific period in a year. For example, the demands of soft drink are higher during summer and lower during winter, or has yearly cyclic pattern.

Demands of daily delivery products have another uncertainty because of daily repeated contract. As for soft drink, inventory is not effective because of short best-before date and products are produced every day to meet demands. It is often found that demand of daily repetitive produced products becomes clear until just the day before production.

Furthermore, future demand may not follow the historical pattern of the past demand. It needs the methods to forecast and correspond to demand at different time period. Therefore, accurate demand forecasting for seasonal and daily delivered products is considered a vital component for an effective business.

The most known forecasting techniques currently available are based on extrapolation of historical demand data. For accurate forecasting, it is important to estimate the parameters of forecasting models with the most recent demand information and enable forecast then be updated as new demand information becomes available.

In delivery products, as fresh soft drinks, there are always flows of products from producers to business customers every day. Orders are placed prior to the day of production, then products are produced to meet demand. Demand information flow returns back to the production flow. It is important for producers to modify the demand to meet efficient demand among days.

1.3 Problem Statement

In this study, first problem is to find the demand forecast of seasonal products and the best attitude to anticipate the right demand. Next problem is to coordinate daily and seasonal demands with efficiency.

The demand of the seasonal products increases as the main demand season approaches. Demand forecasting of daily delivered but seasonal volume variated products always occur in two stages: first stage is to forecast the demand for a monthly range, and second stage is to modify the demand for daily ranges. In the forecasting process at first stage, the demand data is collected from the historical data. Next, after demand is observed, the detailed forecast processing is performed. Production plans are also drawn so that demand can be satisfied all over the year. In detail, while actual demand is revealed, products is produced. As there are some gap between daily demand and optimal production, producers struggle for minimizing the gap at second stage.

1.4 Research Goals

This study has two goals. First is to forecast demand of products with seasonality using time series analysis method and to adopt the best forecasting method to result in meeting adequately to the demand. Second is to modify the gap between actual demand and optimal production resulting in high efficiency.

1.5 Research Objectives

This study is to create models to predict future demand of products with seasonality using time series analysis method so that capability to produce can be prepared as precisely as possible. The forecast analysis focuses on the following issues:

(a) To forecast seasonal demand of products using time series analysis method with seasonal autoregressive integrated moving average (SARIMA).

(b) To convert the forecasted demand into free cash flow (FCF) and make a real options analysis whether additional invest is needs or not.

(c) To find the best daily and seasonal production using real options analysis to modify the gap between actual demand and the optimal production with high efficiency.

1.6 Solution Approach

This study is carried out by using mainly IHS global EViews (Version 8), Oracle Crystal Ball (Fusion Edition) and Microsoft Excel (Version 2010). Some software is available to determine the uncertainty and sensitivity of random variable from simulation (de Neufville et al. 2006; Bhat and Kumar 2008; Chan 2011). Commercial Crystal Ball is one of the software for Monte-Carlo simulation (Bhat and Kumar 2008; Chan 2011; EPM information development team 2012). The Crystal Ball is an analytical tool in spreadsheet form and forecasts that the result from Monte-Carlo simulation helps quantify the uncertainty so that user can facilitate better decision-making.

Demand is forecasted using historical data and SARIMA models. Forecasted models are verified by stationary states and tested by the results of a forecast measuring indicators such as tracking signals. Once the demand forecast is completed, real options analysis is performed through the calculation of FCF, making event tree and decision tree by determining the option value of investment for the targeted demand. Sensitivity analyses are also used to find whether additional invest is needs or not. After that, using real options approach (ROA), the best daily production is embarked for modifying the gap between daily demand and the optimal production with high efficiency.

1.7 Scope and Opportunities

Accurate measures of demand risk can be important in some applications. The forecasting model studied in this research can be applied to any sales forecasts with seasonality and becomes the base for ROA. The model is especially applicable to forecast sales of beverage and food products such as soft drink, drinking milk, and vegetables. Products with daily delivery systems in supply chain are widespread in food industries. The model can also be applied to forecast the demand of products of that inventory is not effective such as seasonal influenza vaccine, goods for poll enosis, and tourist industry.

1.8 Actual Time Series Data

The dataset presented in the study is collected from a soft drink producer located in Toyohashi city unless otherwise specified. Although this company has several business domains in food industries, the study is focused on only soft drink segment. Soft drink project to be evaluated has a large potential production by historical sales. The dataset represents the partial demand of soft drinks, for central region area of Japan ordered from one of a leading soft drink group in Japan during a time period from January 2008 to December 2014.

1.9 Organization of the Dissertation

Apart from the introduction, the study is organized as follows. Chapter 2 provides a description of the relevant literature of demand forecasting model and ROA methods.

First of two research goals previously mentioned is to forecast the demand of products with seasonality using time series analysis and to adopt the best forecast to result in adequately meeting the demand. Chapter 3 demonstrates binomial lattice models for solving two simple options such as an American call option (the option to expand) and an American put option (the option to shrink) in case of annual demand using ARIMA model. Chapter 4 gives a simulation of Bermudan and American call options as the option to expand in case of seasonal high demand using SARIMA model. The performance of SARIMA forecasting model is also presented. After that, in Chapter 5, the signals for decision-making prior to the optimal investment timing are studied to exercise call option using SARIMA model.

Second research goal is to modify the gap between actual demand and the optimal production to result in high efficiency with meeting the demand. In Chapter 6, the daily gap between demand and the optimal production is obtained and the ROA effectiveness in daily delivery products is determined by sensitivity analyses. Using ROA method, the best daily production is established for modifying the daily gap between demand and the optimal production with high efficiency. Chapter 7 simulates the ROA effectiveness using actual data for multi-stage. Finally, Chapter 8 summarizes the observations and conclusions of this research and the possible future research.

Chapter 2 Literature Review

2.1 Abstract

Soft drink industry is one of the industries which have seasonal patterns in sales. So, the sales may be forecasted by time series analysis in consideration of seasonal components. Seasonal Autoregressive Integrated Moving Average (SARIMA) is one of the time series forecasting methods and estimates future sales using historical data. According to forecasted sales, supply chain should be prepared to optimize possibly the material and product flows and the supportive information flows to meet requests from the downstream. The request by soft drink industry includes efficient and effective flows to minimize total costs. Under supply chain, an investment project is a series of cash inflows and outflows, typically starting with a cash outflow followed by cash inflows and/or outflows in later periods. Investment projects may require different investment appraisal methods to appropriately assess their impact, value and profitability. Real options approach is innovative methods to assess the investment.

2.2 Soft Drink Industry in Japan

2.2.1 Production Structure of Soft Drink

To enhance the understanding of the packaged drink, here is a brief explanation of the products and the market. Ready-to-drink or personal-packaged drink is a beverage that one can drink directly out of the container. Such drinks are mainly made by procuring and formulating raw materials and filling containers with them.

Useful soft drinks market in Japan are surveyed and summarized by Japan Soft Drink Association (Japan Soft Drink Association 2005). Production of soft drink in Japan is reviewed by the association if no additional references. The growth rate has been recently worried due to the Japanese market saturation of soft drinks. Sports drinks, mineral water and teas are expected to increase in growth. Thus, profitability in the soft drink industry will remain high, but market saturation may make a deceleration of growth. In order to continue to grow in profits, soft drink industry needs to fit into diverse supply chains.

Through Showa era (1945-1988) after World War II, soft drinks demand in Japan was started by mainly carbonated drinks and fruit drinks. Since the beginning in Heisei era (1989-2005 present), in addition to the above two drinks new categories have created further demands. Figure 2-1 shows the production structure of main categories based on production volume of soft drinks for ready to drink in Japan from 2008 to 2014 (Japan Soft Drink Association 2005; 2011; 2015). Soft drinks for ready to drink include the tea, carbonated, coffee, mineral water, sports, fruits, lactic vegetable and soybean drinks, and except for alcohol drinks, drinking milk which contains of milk solid over three percentage and condensed drinks for dilution. Tea drinks include mainly black tea, green tea and oolong tea.

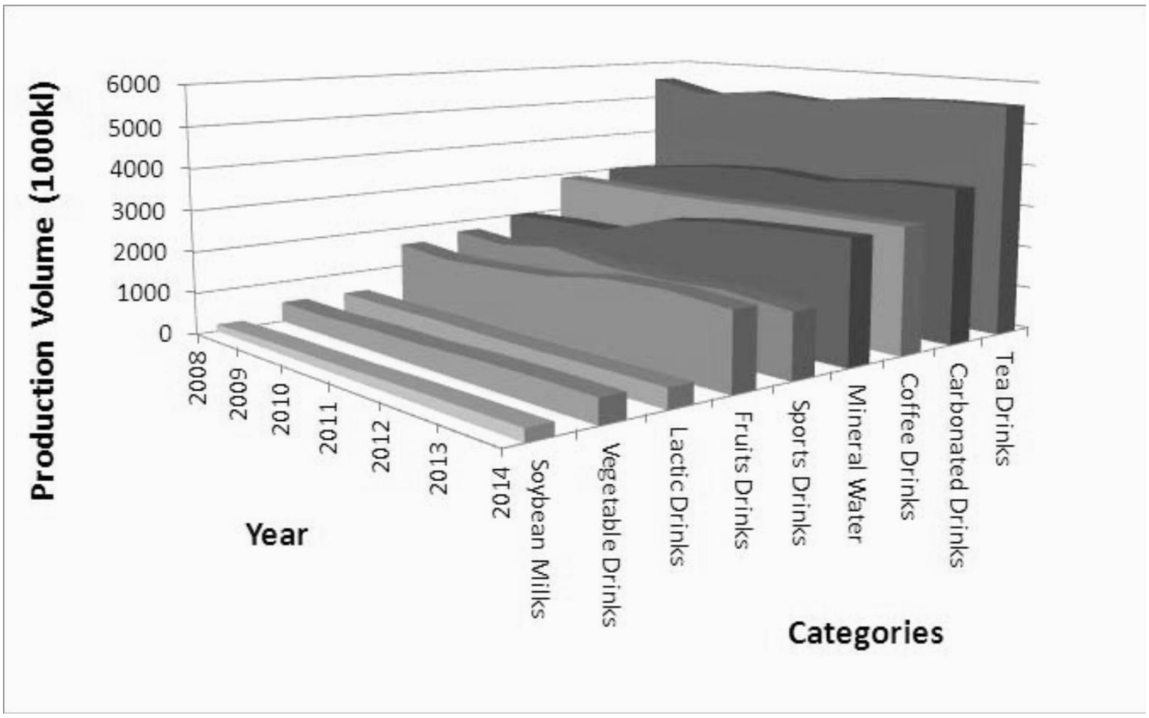


Fig. 2-1 Production structure of main categories in Japan from 2008 to 2014 (Sourced by Japan Soft Drink Association 2011,2014,2015)

2.2.2 Configuration of Containers

Oolong tea and green tea grew explosively from 1981 and 2000, respectively. These trends are prevailing today as shown in Figure 2-1. There are mainly two reasons for these trends; one is that the extraction technique in the production is improved to get good taste, the other is that innovations in containers such as polyethylene terephthalate (PET) and carton container promote convenience without affecting the taste just like heavy fragile glass bottle. Compared with the PET, bottle or can, the expiration date of the soft drink filled in the carton is usually very short, but there is conspicuous advantage for carton containers to avoid excessive heat sterilization and keep good taste in order to facilitate microbial control by cold storage. Our common carton case is that the effective shelf life in refrigerator is about two weeks after production. Another merit for carton as container is cheap initial investment cost of filling machine.

Container of soft drink started from glass bottle, another container as can and carton appeared in the 1960s and 1970s, respectively. After that, PET container has increased rapidly and become the majority of container by now. It shows the configuration of containers from 2008 to 2014 in the figure 2-2 (Japan Soft Drink Association 2005; 2011; 2015). PET container is the most dominant, following can, carton and glass bottle.

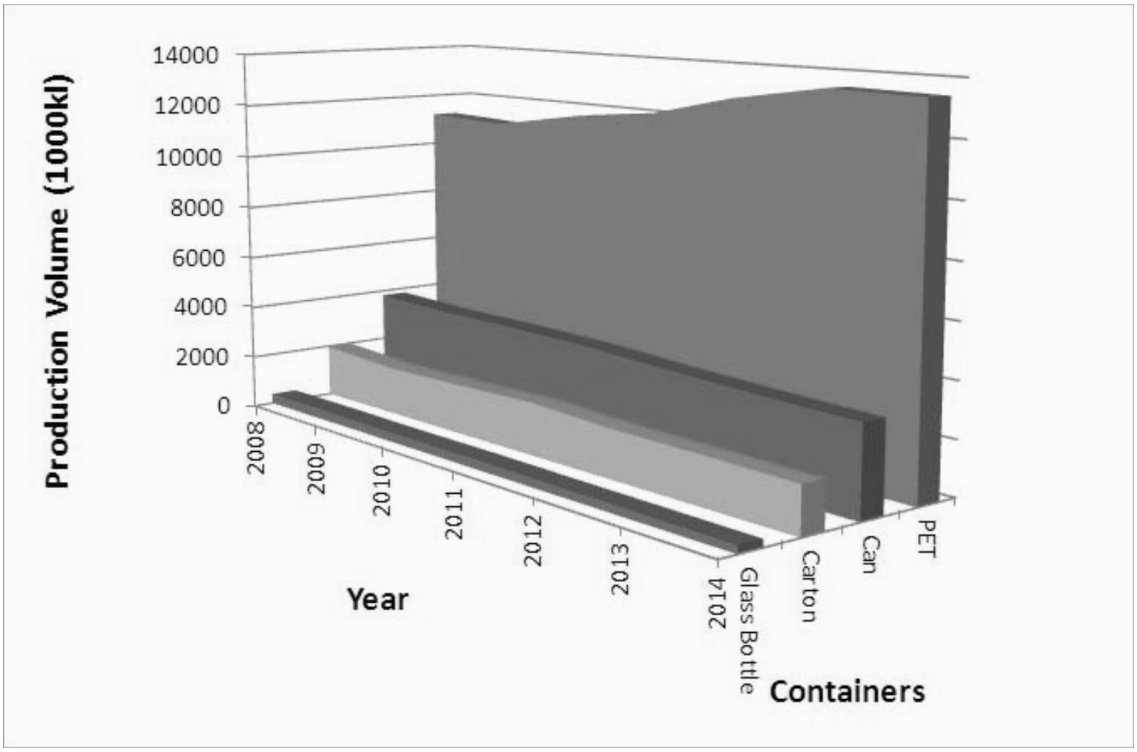


Fig. 2-2 Configuration of containers in from 2008 to 2014 (Sourced by Japan Soft Drink Association 2011,2014,2015)

The development and diversification of distribution systems also caused a soft drink demand. Super markets and convenience stores in addition to traditional vending machine have been rapidly expanding after 1989. Soft drinks have been handled in the new business category, such as drugstores and discount stores.

2.2.3 Rates of Consignment Production

Manufacturers change the supply chain management of products along with R&D of that captures the consumer needs by marketing and establishes a production system that sets up production from retail information to meet demand with a short delivery time. Major manufacturers are promoting in-house production to eliminate the contract manufacturing plants in the various local area of Japan. On the other hand, small and medium-sized enterprises, in order to arrange a new supply chain management, are utilizing a method of contract manufacturing in cooperation with other manufacturers.

The figure 2-3 shows rates of consignment or contract production of main categories of soft drink in Japan from 2008 to 2014 (Japan Soft Drink Association 2005; 2011; 2015).

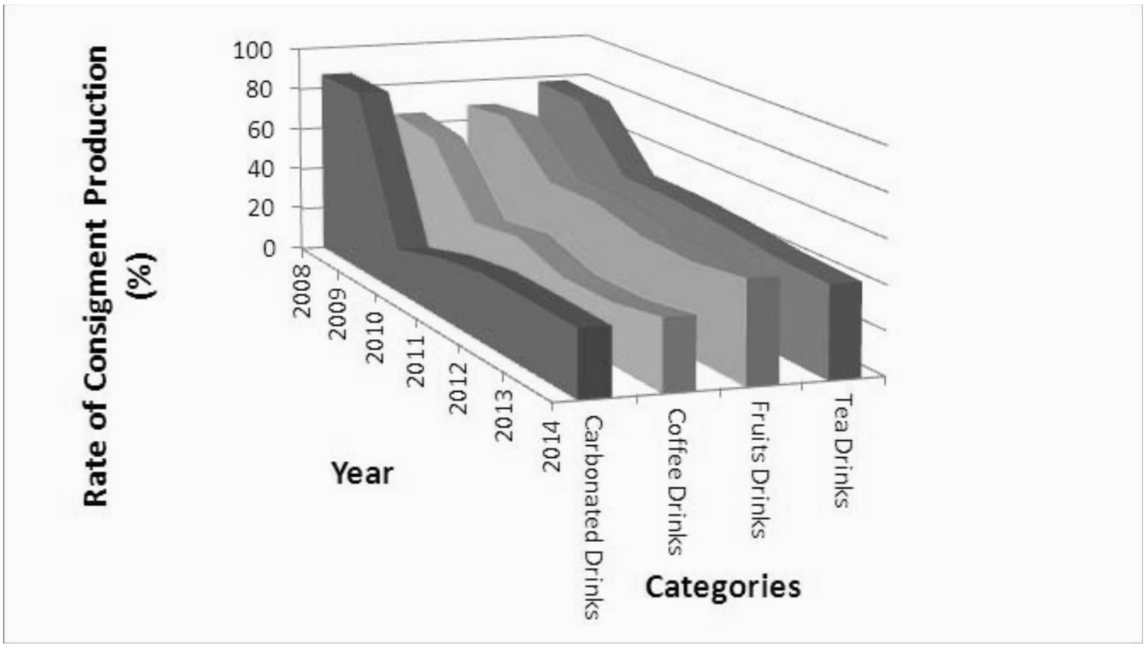


Fig. 2-3 Rates of consignment production of main categories of soft drink in Japan from 2008 to 2014 (Sourced by Japan Soft Drink Association 2011,2014,2015)

The rates of consignment production in the major categories have been coming down, but have still maintained a 30 to 40%. Sales information of products such as point－of－sale (POS) can be gathered within a short period of time at good accuracy, manufacturers can respond to the request of the retail store, and supply chain management has been enhanced to lower an appropriate inventory and a short delivery time.

2.2.4 Monthly Expenditure on Soft Drink

The figure 2-4 shows monthly expenditure on soft drink by modifying data from Japanese government (Japanese Ministry of Internal Affairs and Communications Statistics Bureau of the Japanese government 2016). The data are survey results of monthly expenditures for two-or-more person households in Japan. Note that the results contain not only ready-to drink but also semi-finished products such as tea leafs, cocoa, coffee and the condensed. Strictly speaking, the results are not suitable for monthly production. There is no available data about monthly soft drink production in Japan. The movements for expenditure are similar to that for production that author knows. That is, soft drink has a seasonal movement with higher demand in summer and lower in winter.

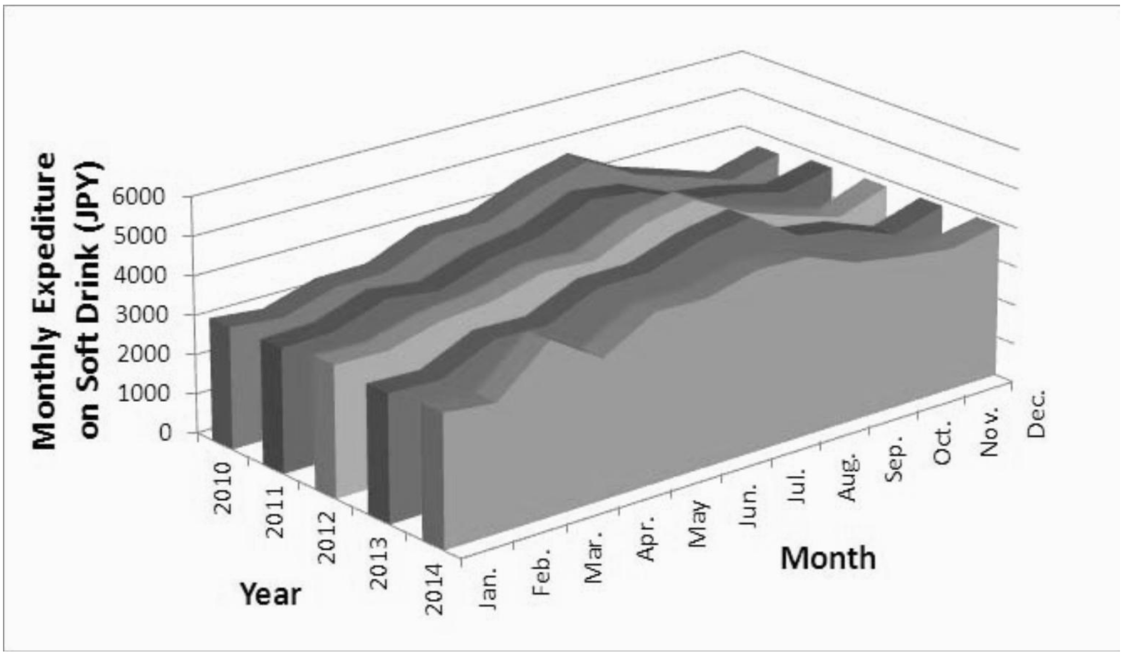


Fig. 2-4 Monthly expenditure on soft drink in Japan from 2010 to 2014 (Sourced by Japanese government 2016)

2.3 Time Series Analysis

2.3.1 Definition of Time Series Analysis

A time series is a sequence of observations taken sequentially in time. Time series analysis is concerned with investment appraisal and techniques on what is depend, and required to get meaningful statistics. Most important time series forecasting is to predict stochastic models to get future value based on historical data. Time series analysis has mainly two types; linear and nonlinear time series analysis. The main characteristics of soft drink sales are seasonal patterns in the long term and have a possibility to capture the movement by nonlinear time series analysis. When time series analysis faces the seasonal movement, two procedures are considered; one is to remove seasonal movement from time series as seasonal adjustment, the other is to handle the data accordingly as time series forecasting. The latter is my perspective in this study. Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) are dominant tools to handle time series forecasting. Time series analysis can be applied to forecasting future sales.

2.4 Supply Chain

2.4.1 Definition of Supply Chain

Developing concise definitions of term “supply chain” can be very painful since there are typically many people with divergent opinions ready to defend their perspectives on the subject in question

(Ullrich 2014). Here is a fair and wide spread definition of the term "supply chain (Chopra and Meindl 2012):"

> "*A supply chain consists of all parties involved, directly or indirectly, in fulfilling a customer request. The supply chain includes not only the manufacturer and suppliers, but also transporters, warehouses, retailers, and even customers themselves. Within each organization, such as a manufacturer, the supply chain includes all functions involved in receiving and filling a customer request. These functions include, but are not limited to, new product development, marketing, operations, distribution, finance and customer service.*"

This definition encompasses two perspectives; one is inter-organizational perspective, the other is intra-organizational perspective. The inter-organizational perspective addresses a network of companies that is referred to as a supply chain. The intra- organizational perspective deals with the supply chain within a company. Supply chain should be achieved to get material and products flows, and supportive information flows to receiving and filling a down steam's request. The customers' requests include efficient and effective flows to minimize total costs.

2.4.2 Flexibility of Supply Chain

It is important for supply chain to recognize flexibility as a key strategy for efficiently and effectively improving, especially in facing demand uncertainty. The flexibility of supply chain has already been studied (Bertrand 2003). Definition of flexibility in this study is the ability to improve the condition to cope with the variety of environmental needs in reversible manner. The flexibility requires investments and should be justified on the basis of the potential benefits. Most manufacturing flexibility has dealt with each internal company level, not the supply chain coordination level (Bertrand 2003). Furthermore, the manufacturing flexibility mainly stems from three sources: variety of the manufacturing technologies employed, amount of capacity available for production, and timing and frequency of production (Bertrand 2003). The variety of flexibility is depends on what is required over what needs to change or be adapted. As flexibility at the plant level is illustrated as constraints on the volume and arrival timing of the products, the volume flexibility is one of the manufacturing flexibilities. Manufacturing flexibility is, however, difficult to measure (Beskese et al. 2004; Giachetti 2003; Mishra et al. 2014).

The soft drink industry should be informed daily regarding production from buyer at latest just one day before the manufacturing start. The industry has daily multi-orders with a very short interval. Even with such daily reorder production, a supplier can have some flexibility for manufacturing. The manufacturing flexibility is widely recognized as a critical component to achieving the optimal advantage for the manufacturer, that is, supplier. Volume is one of the major dimensions in flexibility (Koste et al. 1999; Beach et al. 2000; Vokurka et al. 2000; Zhang et al. 2003; Raturi et al. 2004; Ali and Ahmad 2014; Singh and Acharya 2013; Kundi and Sharma 2015). The key problem in developing a response to volume flexibility is making balance between the order demand from buyer and the production supply from supplier at the same time.

As manufacturing processes are organized in the middle of the supply chain, it is not enough to request the burden of flexibility only on the side of supplier. Instead, if the supplier can know the buyers' inventory and modify the buyers' order for original demand even slightly, it will be a chance to improve productivity. Then information availability of the demand and inventory is valuable for the supplier, who can use to improve productivity. In a supply chain consisting of a supplier and a customer, if the supplier manages inventories, he can coordinate batch size so as to minimize his own costs (Van Nyen et al. 2009).

Company could implement the optimal actions but often lacks the incentive to do so (Cachon 2003). Thus, a company might adjust their trade to create the incentives via a contract. Private information that the other companies do not possess is very important to implement one's own optimal actions in the supply chain coordination. Due to the high uncertainty in manufacturing process, a method to increase the flexibility needs to be used (Kleinert and Stich 2010). Real options approach (ROA) is one of the methods used for increasing suppliers' flexibility in recent years (Lander and Pinches 1998).

2.4.3 Waste Reduction of Supply Chain

In Japan, supplier has been required reduction in the waste of food by domestic law (Japanese Government 2001; Japanese Ministry of Agriculture, Forestry and Fisheries 2013). In other regions, the reduction in the waste of food is also paid attention to food and agriculture organization of the United Nations (FAO 2011), European Commission (EC 2011), European Union (EU 2011), and United States of America (EPA 2016; USDA 2016). To make supply chain capable to bear simultaneously regular and risk condition, supplier requires proactive planning and flexibility in the decisions making (Mangla et al. 2014). If the waste is produced, priority gives the reduction in the waste than the profit. But, the priority for supplier is to evaluate productivity, adhering to Japanese environmental laws and regulations. Supplier should make a decision to obtain economic benefits while keeping environmentally friendliness.

In the business practice of the food supply chain in Japan, the days between production and expiration dates are divided by 3 (Japanese Government 2001). This is called as rule of one thirds in food supply chain. The first one thirds after production is for the deadline of the delivery. The next two thirds after production is for the deadline for sale in retails. Buyer is afraid of occurrence of surplus dead inventory and return of products from retailers, so repeats demand-order daily to modulate inventory in detail.

Author hears the existence of prolonged deadline of delivery abroad. For example, three fourths or a half is common in U.K. and in the United States, respectively. Then a one-third is too short even if it is common in Japan. And it is said that rule of one third in part hinders reduction in food waste.

2.5 Traditional Investment Appraisal Methods

2.5.1 Definition of Investment

Investment is to allocate cash in the expectation of some advantage in the future and expect to higher return in comparison with its own risk. Therefore an investment project is a series of cash inflows and outflows, typically starting with a cash outflow followed by cash inflows and/or outflows in later periods. Investment projects can be categorized in many different ways because of substantially different characteristics and may require different investment appraisal methods to appropriately assess their impact, value and profitability. Here are some methods to assess the investment.

2.5.2 Economic Investment Appraisal Methods

Traditional economic theory of investment project has derived the marginal decision rule that investment should be exercised in a quantity at which the marginal profit is equal to the marginal cost, and developed mainly two approaches: one is based on per-period value, and the other is based on Tobin's q (Dixit and Pindyck 1994). The per-period value is compared with the difference between an incremental unit of capital as a factor of production and an equivalent per-period rental cost or user cost that can be computed from the purchase price, the interest and depreciation rates, and applicable taxes (Jorgenson1963; Dixit and Pindyck 1994). The user cost expands to account for the facts that the machine might wear out, the price of the machine might change, and the government imposes taxes. The Tobin's q is compared with the capitalized value of the marginal investment to its purchase cost (Tobin 1969; Dixit and Pindyck 1994). The Tobin's q decides on investment if q is bigger than 1. These theories are used for static investment appraisal methods.

2.5.3 Financial Investment Appraisal Methods

Nowadays, following three financial methods are developed and dominant in practice.

First is a payback period method. The targeted measure used for this method is the time it takes to recover the asset invested in the project. It can be calculated based on average figures or on total figures. Average figures are used here.

The payback period of an investment project is the period until which the asset invested is regained from the surplus cash flow generated by the project.

The payback period can be determined by dividing the investment expenses by annual cash flow:

$$\text{Payback period} = \frac{Investment\ expenses}{Annual\ cash\ flow} \qquad (2-1)$$

It is easy to understand and apply the payback period, but note that it does not consider the time value of money, opportunity cost and uncertainty.

Second is net present value (NPV) method focuses on selecting projects that maximize the NPV generated for the investors. The NPV is the net monetary gain or loss from a project, compared by discounting all present and future cash flows and expenses related to the project. Basic equation of NPV is expressed as following;

$$\text{NPV} = -\text{ Investment expenses } + \text{Future annual cash flows} \qquad (2-2)$$

All future cash flows related to an investment project are discounted back to time (t=0)., taken to represent the start of the investment project. The NPV represents a specific kind of PV. Equation 2-2 can be converted into Equation 2-3 with discount rate;

$$\text{NPV} = -\text{ Investment expenses } + \sum_{n=0}^{N} \frac{Annual\ cash\ flow}{(1 + Discount\ rate)^n} \qquad (2-3)$$

Where, n is a period index usually based on unit of year, N is maturity, and discount rate is considered as time value factor of money such as interests of national bonds or weighted average cost of capital. This method is reflecting the time value of money. In the case when NPV is positive, the investment project is profitable. If NPV is negative, the investment will not be done to prevent from resulting in loss. Based on NPV's rule, only investment is conducted with positive NPV value. This method considers time value, but note that it does not consider opportunity cost to wait and uncertainty.

Third and final is internal rate of return (IRR) method. The targeted measure used for this method is the rate of return to recover the asset invested in the project.

$$\text{IRR} = \frac{\text{Return}}{\text{Investment expenses}} \times 100 \qquad (2-4)$$

IRR can be determined by breaking point of NPV when discount rate is unknown in Equation 2-4. In other word, IRR is calculated by the discount rate that leads to a NPV of zero. IRR is used to compare the profitability of projects. This method does not account for time to get return.

Apparently, managers find it easier to compare investments of different sizes in terms of percentage rates of return than by monetary volume of NPV. IRR, as a measure of investment efficiency may give better insights in investment conditions. However, when comparing mutually exclusive projects, NPV is the appropriate measure.

2.5.4 Difference between Economic and Financial Methods

There are two principal methods for economic and financial appraisal of different investment project. Economic methods are more static than financial one, and useful for a comparison with the results of dynamic financial procedures, for approximate and quick appraisal or when the time intervals between output and input are short enough or can be neglected. On the other hand, the financial methods are more dynamic than the economic one, and useful for the beginning of the project when the time intervals between output and input are long or cannot be neglected. Because financial methods are based on the project risk that future values of variables are not known with certainty at present. In contrast to the financial methods, the economic methods are based on assumption that all project risk is incorporated into its constant output.

2.5.5 Survey that Describes Current Practice of Corporate Finance

Here is a comprehensive survey that describes the current practice of corporate finance offered by Graham and Harvey with modification in Figure 2-5 (Graham and Harvey 2001). In total, 392 Chief Financial Officers (CFOs) throughout the U.S. and Canada responded to the survey, for a response rate of 9%. Forty percent of the companies are manufacturers. They survey the question how frequently your company uses the techniques when deciding which projects or acquisitions to pursue and evaluate the percentage of “yes” with always or almost always. According to their results, companies are likely to use NPV (75.61%) and IRR (74.93%), following to payback period (56.74%). These three traditional methods are mainly static. They found that companies that value financial flexibility and dynamic character are more likely to value real options (26.59%) in project evaluation. Real options are more dynamic than traditional method because of taking into consideration of flexibility, uncertainty and irreversibility (Dixit and Pindyck 1994).

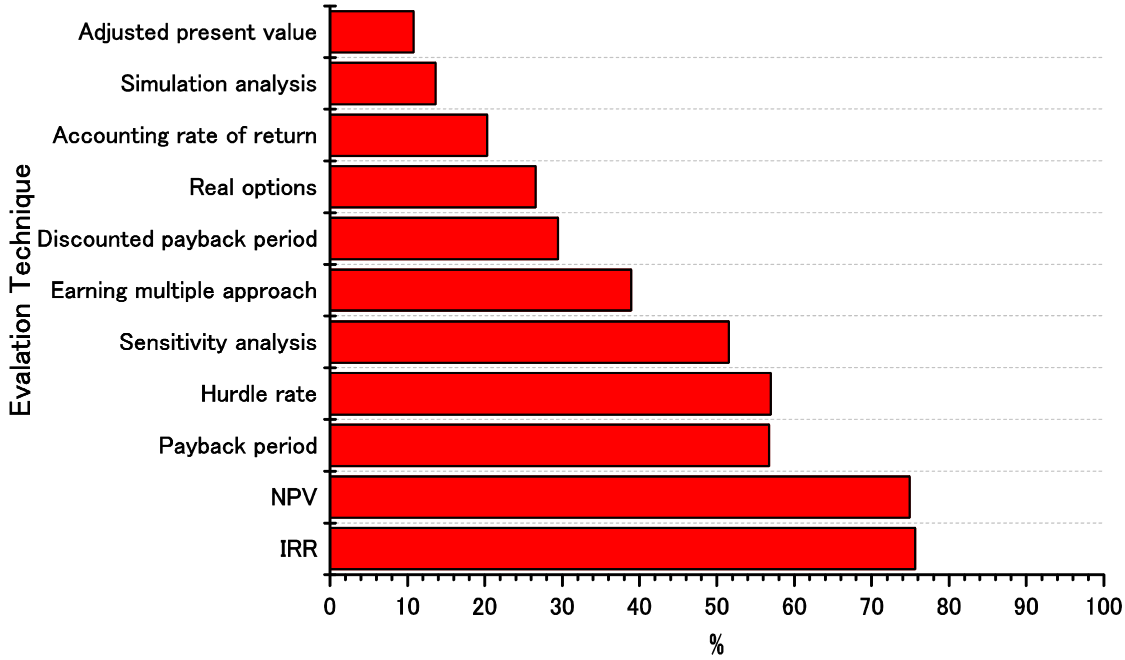


Fig. 2-5 Results of survey the question how frequently your firm uses the techniques when deciding which projects or acquisitions to pursue and evaluate the percentage of "yes" with always or almost always (Source by Graham and Harvey 2001)

2.6 Innovative Investment Appraisal Method by ROA

2.6.1 Call and Put Options

ROA is an approach to evaluate investment opportunities to acquire real assets that are called as real options (Dixit and Pindyck 1994). ROA is the most acceptable dynamic solution for investment, which is derived from a conceptual extension of financial option theory (Black and Scholes 1973; Merton 1973; Dixit and Pindyck 1994).

First of all, here is a description of call and put options. The call and put options have the same exercise price and the same time to maturity. In a contract, buyer has the call, and seller has the put. Especially one who has options is called as holder instead of either buyer or seller. And one who receive obligation when option is exercised is acceptor.

Summary of the call and put options are shown in Table 2-1. It will briefly describe the important concept of options. The call and put options are a contractual agreement that give a holder the right but not the obligation to buy or sell an asset in pre-determined amount of money on or before a specified date. An asset has two types; one is financial assets for financial options, the other is real assets for real options.

Table. 2-1 Summary of the call and put options

Options	Exercise timing	Exercise date	Acceptor	Holder	Exercise frequency
Call option	European	Just on maturity	Obligation to SELL asset if option is exercised	Right to BUY asset	Only one time
	American	On or before maturity			
Put option	European	Just on maturity	Obligation to BUY asset if option is exercised	Right to SELL asset	
	American	On or before maturity			

For example, seller's perspective is obligated to buying-right-holder's decision-making. The buying-right-holder is one who bought the option. If seller sells a call option to the holder, the seller owes to the holder the obligation of the call option, which is a right to buy an asset at a pre-determined exercise price on or before the exercise date. The exercise price is the price that seller and holder have agreed. The exercise date is the date on which the seller and buyer have agreed. If the call option is European type, exercise date is just on maturity and exercise frequency is only one time. If American type, exercise date is on or before maturity and exercise frequency is only one time. If, next, seller sells a put option to holder, the seller owes to the holder the obligation of the put option, which is a right to sell an asset at a pre-determined exercise price on or before the exercise date. If the put option is European type, exercise date is just on maturity and exercise frequency is only one time. If American type, exercise date is on or before maturity and exercise frequency is only one time. That is, exercise date and frequency are same as the case of call.

2.6.2 Representative Basic Options

Representative basic options, effectiveness and option type (call or put) are summarized in Table 2-2 (Copeland and Antikarov 2003; Brach 2003).

Table 2-2 Basic options, effectiveness and option type

Options	Effectiveness	Call or Put
The option to defer (The option to wait)	Wait until further information reduces uncertainties.	Put option
The option to abandon (Abandonment option)	Dispose of an unprofitable project.	Put option
The option to switch (Switching option)	Change input/output parameters	Call option
The option to expand (Expanding option)	Expand capacity depending on market conditions	Call option
The option to shrink (The option to contract)	Downsize capacity depending on market conditions	Put option
Growth option (Learning option)	Create future related opportunities.	Call option
Compound option	Option on another option to take the project to next level	Call option

2.6.3 ROA Rule

ROA is fundamentally different from NPV, and the NPV is a special case of ROA that assumes no flexibility in decision making. (Copeland and Antikarov 2003). NPV is constrained to pre-committing today to a go or no go decision. Mathematically, NPV is equivalent to taking the maximum of a set of possible mutually exclusive alternatives:

$$NPV\ rule\text{: MAX}(at\ t = 0)[0,\quad E_0 V_T - X] \qquad (2-5)$$

where, E_0 is expected value at $t = 0$, V_T is underlying asset at $t = T$, T is maturity, and X is investment expenses. NPV is to compare all possible mutually exclusive routes to determine their value, $E_0[V_T - X]$ for call option, then to choose the best among them. ROA takes a different perspective. Mathematically, ROA for call option is an expectation of maximums, not a maximum of expectations:

$$ROA\text{ for call option }rule\text{: }E_0\text{MAX}(at\ t = T)[0,\quad V_T - X] \qquad (2-6)$$

Conversely, ROA for put option is an expectation of minimums, not a minimum of expectations:

$$ROA\text{ for put option }rule\text{: }E_0\text{MAX}(at\ t = T)[0,\quad X - V_T] \qquad (2-7)$$

2.6.4 Three Conditions for Option Value

Decisions are made when information about the state of investment project is revealed. NPV rule do not have uncertainty, but ROA rule has. The basic idea of ROA is proposed to state that investment in improved value of commodity or real assets is possible through flexible decisions in the future (Myers 1977). Especially, if ROA is satisfied with following three conditions, investment can be delayed to yield option value (Dixit and Pindyck 1994).

Condition1. There is an irreversible sunk cost.

Condition2. There is an uncertainty about managerial circumstances over the future.

Condition3. Investment opportunity is not just in a present one, but in the future.

If there is little uncertainty and the results can be ignored, ROA cannot use any options at all. Otherwise, it is an opportunity to use ROA. If ROA applies to flexible decision making of investment with irreversibility to be equated with the sunk costs under uncertainties, the focus is on the value of information (Pindyck 2008).

The main difference between financial option and ROA lies in underlying asset. Whereas financial option is written on financial asset with income generated by real asset, ROA is written on real asset with income generated by productive ability. Therefore, financial option regulates the distribution of the income. On the other hand, ROA can regulate real asset generating managerial value. In other word, the underlying asset for a financial option is a security such as a share of common stock or a bond, while the underlying for a ROA is a tangible asset such as a business unit or a project. According to Gamba and Tesser, ROA have another three important reasons (Gamba and Tesser; 2009). Firstly, the available data in real options are affected by endogeneity, and the estimation must be done under the hypothesis that the data set is a replication of a controlled stochastic process. Second, a company's objective function is not completely known, and not all factors affecting the decision can be observed. For example, unobservable factors may be related to productivity or to cost parameters affecting companies' payoffs. Third, different companies, although in the same industry, may have different parameters for the same objective function. In consideration of these things, ROA is based on the idea that a continuous distribution of company with unobserved parameters can be well approximated by a discrete scalar distribution, which can be estimated.

2.6.5 Three Methods for Option Value Calculations

There are three main methods of option value calculations for determining more practical ways of computing ROA depending upon the nature of the change problem: (1) Black-Scholes model: (2) Binominal lattice model: and (3) Monte Carlo simulation. First two methods are based on the concept of risk free arbitrage in the financial market place. The Monte-Carlo simulation approach is often used for valuation of options when assumptions of simpler analytical models are violated. One type of option valuation model stand out in terms of practical implementation for a given transition problem.

2.7 Black-Scholes Model for European Call Option

2.7.1 Procedure of Black-Scholes Model

The beginning of financial options is the Black-Scholes model which has empirically tested predictions for a European call option. This model is dealt with in continuous time. The opportunity to invest means to have the call option, which gives the right to acquire the underlying asset. Option holder pays a specified cost within a given period to acquire the underlying asset. The Black-Scholes model is based on the assumption that the underlying asset follows the dynamics given by the following stochastic differential equation:

$$\mathrm{dV}_t = \mu V_t \mathrm{d}t + \sigma V_t \mathrm{d}Z_t \qquad (2-8)$$

where: $\mathrm{V}_t =$ The price of the underlying at t period

$\mathrm{dZ}_t =$ The standard Wiener process whose increments are uncorrelated

$\mu =$ The annualized drift

$\sigma^2 =$ The variance rate of the underlying stock

Risk-neutral valuation justifies the annualized drift is equal to the risk-free rate.

The general solution of this differential equation is given by Ito's equation, which yield a lognormal distributed random variable

$$\mathrm{V}_t = \mathrm{V}_0 e^{[(r_f - \sigma^2/2)t + \sigma N\sqrt{t}]} \qquad (2-9)$$

where: $\mathrm{V}_0 =$ The price of the underlying at the initial time

$\mathrm{N} =$ The cumulative stndard normal probability of unit normal variable with mean 0 and standard deviation $1(N \sim \mathrm{Normal}(0,1))$

Although it is usually impossible to find an analytical solution to the Black-Scholes equation, it is possible to find such a solution for a European call option.

The Black-Scholes model is following:

$$C_t = V_0 N(d_1) - X e^{-r_f(T-t)} N(d_2) \qquad (2-10)$$

where: $C_t =$ The price of the call option at t period

$\mathrm{N}(d_1) =$ The cumulative standard normal probability of unit normal variable d_1

$\mathrm{N}(d_2) =$ The cumulative standard normal probability of unit normal variable d_2

$\mathrm{X} =$ The exercise price

$\mathrm{T} =$ The time to maturity

$r_f =$ The risk free rate

$e =$ The base of normal logarithms

$$d_1 = \left[\ln\left(\frac{V}{x}\right) + (r_f + \frac{\sigma^2}{2})(T-t)\right] / \left[\sigma(T-t)^{1/2}\right]$$

$$\mathrm{d}_2 = \frac{\left[\ln\left(\frac{V}{N}\right) + \left(r_f - \frac{\sigma^2}{2}\right)(T-t)\right]}{\left[\sigma(T-t)^{\frac{1}{2}}\right]} = \mathrm{d}_1 - \sigma(T-t)^{1/2}$$

Especially, if $\mathrm{t} = 0$, the Black-Scholes model is following:

$$C_0 = V_0 N(d_1) - \mathrm{X} e^{-r_f T} N(d_2) \qquad (2-11)$$

where: $C_0 =$ The price of the call option at initial time point zero

$d_1 = \frac{ln(V/_X)+r_f T}{\sigma\sqrt{T}} + \frac{1}{2\sigma\sqrt{T}}$

$d_2 = d_1 - \sigma\sqrt{T}$

2.7.2 Put-Call Parity

There is a mathematical relationship between European call and put options if requirements for C_t, P_t, X, V_0, and r_f are fulfilled. The relationship is based on put-call parity (Luenberger 2009; Hull 2015). The put-call parity relationship is algebraically represented as;

$$C_t - P_t + Xe^{-r_f T} = V_0 \qquad (2-12)$$

where: $P_t =$ The price of the put option at t period

The relationship is found by noting that a combination of P_t, C_t, and r_f has a payoff identical to that of V_0.

2.7.3 Black-Scholes Model for European Call Option

By using the put-call parity relationship, P_t can be gained as follows;

$$P_t = Xe^{-r_f(T-t)}N(-d_2) - V_0 N(-d_1) \qquad (2-13)$$

The opportunity to abandon means to have a put option. The put-call parity allows call and put for exchanges against each other.

2.7.4 Seven Assumptions Embedded in the Black-Scholes Model

It is important to note the seven assumptions embedded in the Black-Scholes model to understand its limitations for use in ROA (Copeland and Antikarov 2001). The seven are:

Assumption 1. The option may be exercised only at maturity. It is a European option. A European option can only be exercised on the expiration date, whereas an American option can be exercised at any time before and including the expiration date.

Assumption 2. There is only one source of uncertainty. Rainbow options which have multiple uncertainties are ruled out.

Assumption 3. The option is contingent on a single underlying risky asset. Compound options which have multiple assets are ruled out.

Assumption 4. The underlying asset pays no dividends.

Assumption 5. The current market price and the stochastic process followed by the underlying asset are known.

Assumption 6. The variance of return on the underlying is constant through time.

Assumption 7. The exercise price is known and constant.

2.7.5 Expanded NPV for Call Option

Financial option enables to protect from the downward risk of the underlying asset, while benefiting from the upward potential. This asymmetry between upside and downside payoffs is shown as Expand NPV (ENPV) structure of a call option in Figure 2-6 (Smit and Trigeorgis 2004). Note that this figure is a case without dividend. If the value of exercise price of call option is equal to the value of underlying asset price, the call is said to be at the money (V=I). The call option is in the money when the value of underlying asset price is above the value of exercise price (V>I). Conversely, the call option is out of the money if the value of underlying asset price is below the value of exercise price (V<I).

The dotted line represents the timing value of call option before maturity, which is always higher than the solid line as intrinsic value of call option. This value is the dynamic real options value. At maturity, if the value of underlying asset is lower than the value of exercise price, a call option is not exercised and do not yield expanded NPV which means payoff with exercised option. Otherwise, the call option is exercised. It is called as time value in option theory, which is the difference between intrinsic value of call option and timing value of call option before maturity. This value is the static NPV. If there are no opportunity costs of waiting or dividend-like benefits to holding the asset, the holder will postpone the decision to exercise until the maturity. If, during the later stage, the underlying asset such as market demand develops favorably and be higher than static NPV, the holder can invest and obtain the ENPV, which means the flexibility value added to static NPV. The price of the call option at that period is flexibility value and calculated by subtracting static NPV from expanded NPV. If, however, the underlying asset turns out to be lower than static NPV, the holder can decide not to invest and loses what it has spent to obtain the option. Like financial option, ROA also enables to protect from the downward risk of the underlying asset, while benefiting from the upward opportunity.

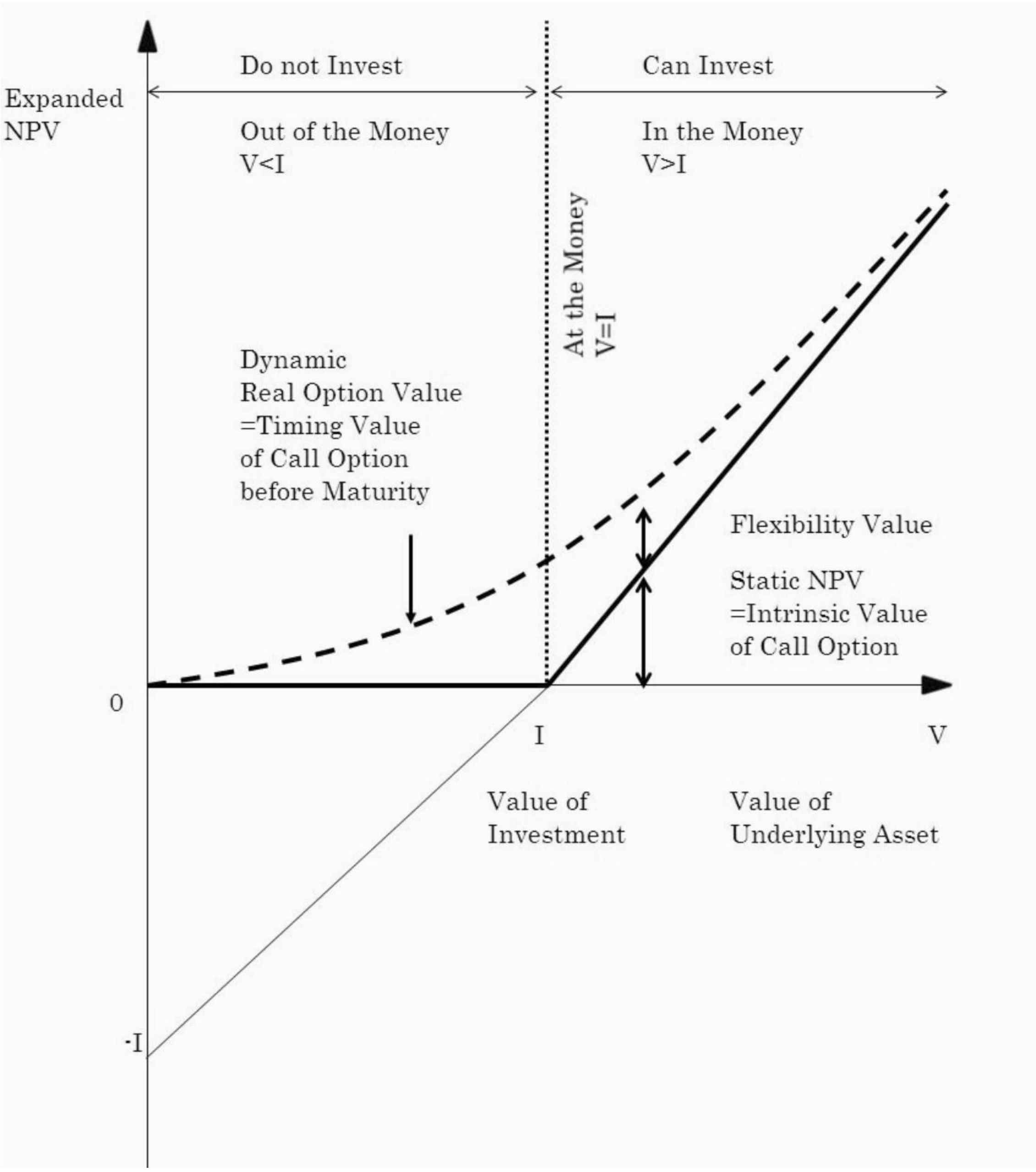


Fig.2-6 Expand NPV structure of a call option

2.7.6 Expanded NPV for Put Option

In contrast to call option, expanded NPV structure of a put option is shown in Figure 2-7 (Smit and Trigeorgis 2004). Note that this figure is also a case without dividend. The relations of call and put options are in mirror figures around vertical axis. If the value of exercise price of put option is equal to the value of underlying asset price, the put is said to be at the money (V=I). The put option is in the money when the value of underlying asset price is below the value of exercise price (V>I). Conversely, the put option is out of the money if the value of underlying asset price is above the value of exercise price (V<I). The dotted line represents the timing value of put option before maturity, which is always higher than the solid line as intrinsic value of put option. At maturity, if the value of underlying asset is lower than the value of exercise price, then put option is exercised and yields ENPV. Otherwise, the put option is not exercised. The price of the put option at that period is flexibility value and calculated by subtracting static NPV from ENPV. Opposite to call option, put option enables to protect from the upward potential of the underlying asset, while benefiting from the downward potential.

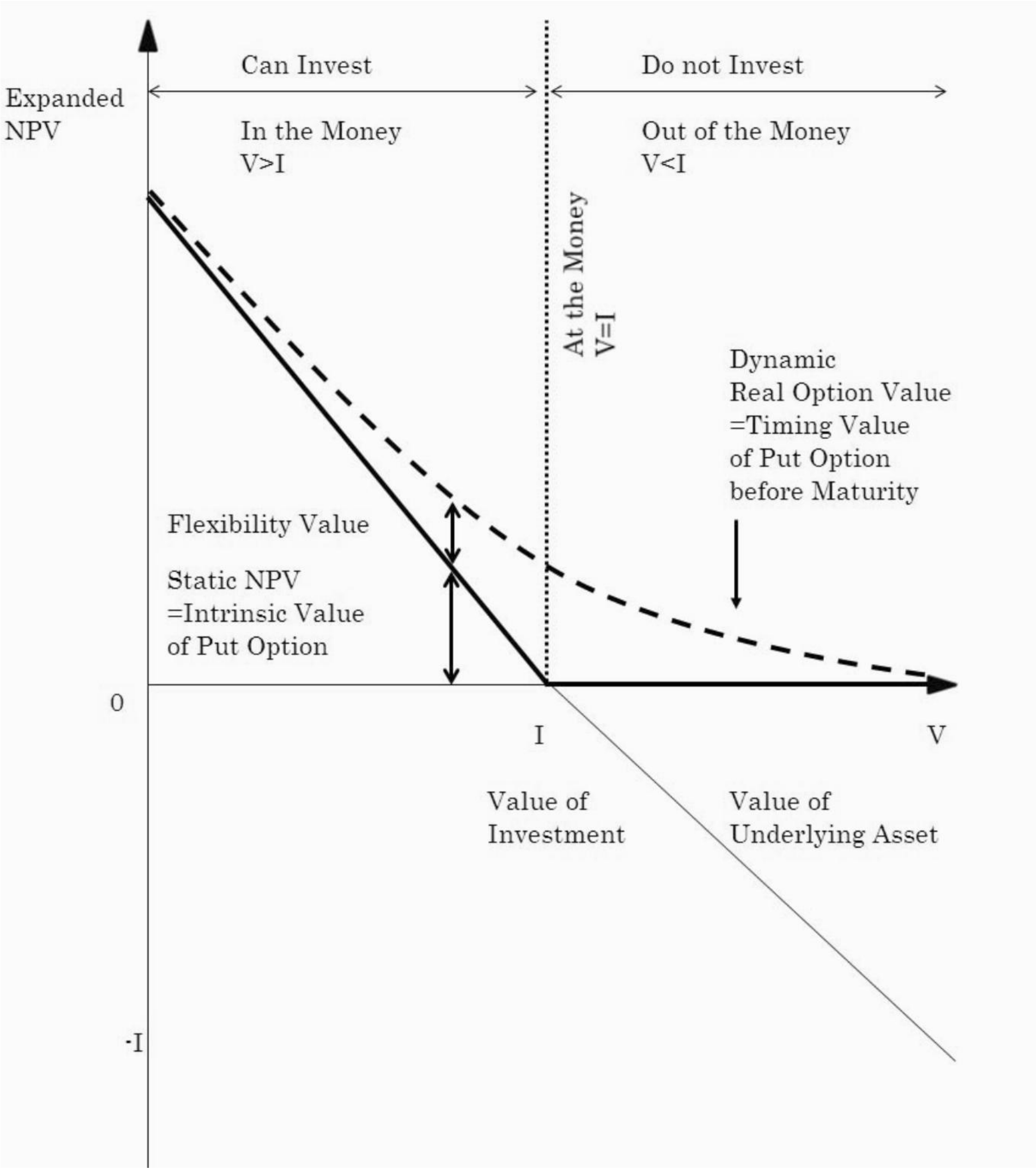


Fig.2-7 Expand NPV structure of a put option

2.7.7 Six Variables to Use in ROA

To be realistic, most of ROA problems require analysis that is capable of relaxing one or more of the standard Black-Scholes assumptions. It is also important to note the six variables to use in ROA (Copeland and Antikarov 2001). The six are:

Variable 1. The value of the underlying risky asset.

Variable 2. The exercise price.

Variable 3. The time to expiration of the option.

Variable 4. The standard deviation of the value of the underlying risky asset.

Variable 5. The risk-free rate of interest over the life of the option.

Variable 6. The dividends that may be paid out by the underlying asset.

2.8 Binomial Lattice Model

2.8.1 Procedure of Binomial Lattice Model

In advance, PV without flexibility using DCF valuation model is completed. There are circumstances in which holder cannot use the Black-Scholes model because of its strict seven assumptions but binomial lattice model will still give the holder a good measure of option value. The binominal lattice model is based on a simple representation of the evolution of the value of the underlying asset (Cox, Ross, and Rubinstein 1979; Cox and Rubinstein 1985). This model is dealt with in discrete time. In each period, the underlying asset can take only one of two possible values. Thus, a binomial lattice within 1 period is created in Figure 2-8. This model is strictly speaking not a lattice because of only 1 period, and has a structure that can only go to either upward or downward by 1 period.

Multi-period binomial model, not binomial lattice model, is a combination of binomial models with multi period. The model can be applied to both backward induction and forward induction; former is suitable for calculation of conditional expectation in backward induction and latter is suitable for both calculation of transition probability and Arrow–Debreu model. The Arrow-Debreu model is central to the theory of general equilibrium, and applies to economies with maximally complete markets without uncertainty, in which there exists no excess demand or supply (Arrow and Debreu 1954). As for the n period, the number of the states at the end is 2n. If n is bigger, a calculation becomes difficult to solve because of the vast data. Therefore multi-period binomial model gives up maintaining the information of all passes and take the recombination of the state node and untie a problem in the lattice model that let the number of the states of the n+1 unit decreases sharply. This is the binomial lattice model.

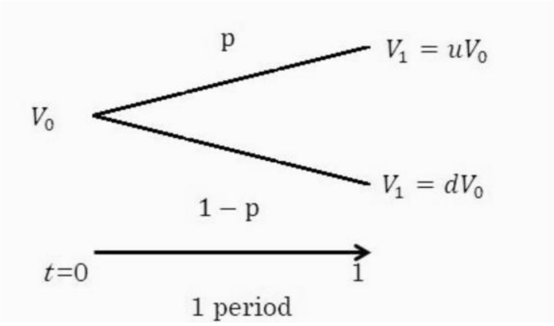


Fig.2-8 Underlying asset movement in binomial model for only 1 period

The binominal lattice model can be solved to calculate option values using two different approaches; one is replicated portfolio approach and the other is risk-neutral probability approach (Copeland and Antikarov 2003; Kodukula and Papudesu 2006). The theoretical framework for both approaches is the same based on the answer, while the mathematics involved are slightly different. The replicated portfolio approach uses a portfolio that consists of a certain number of underlying assets and risk-free bonds that correlates perfectly with the option value. Since the portfolio correlates perfectly with the value of the option, the value of call option at period zero is calculated as the PV of the replicating portfolio. The risk-neutral probability approach involves risk adjusting future FCF throughout the binominal lattice model with risk-neutral probability and discounting the risk-neutral probability at r_f.

For example of the risk-neutral probability approach , if V_0 is the PV of asset value as future FCF at period 0, the asset value could either be uV_0 with a probability of p or dV_0 with a probability of $1-p$ at the next period 1. The factors of u and d are calculated as Equation 2-14 and 2-15, respectively;

$$u = e^{\sigma\sqrt{t}} \qquad (2-14)$$

$$d = \frac{1}{u} \qquad (2-15)$$

where, σ is a periodical volatility of the underlying asset.

The σ which is calculated by logarithmic returns, that is estimated as averaged $LN(FCF\ in\ this\ period/FCF\ in\ previous\ period)$.

By definition, $u \geq 1$ and $0 < d \leq 1$ are settled.

Then an event tree is modeled with the uncertainty.

The probability to increase p means risk-neutral probability, and is calculated with r_f, u and d as Equation 2-16.

$$p = \frac{1 + r_f - d}{u - d} \qquad (2-16)$$

The discount rate for company's option valuation is suitable for WACC (weighted average cost of capital) because activity of company is not risk-free but is contained of particular systematic risk, which arises from the uncertainty faced by all company in the market.

$$p = \frac{1 + \text{WACC} - d}{u - d} \tag{2-17}$$

The probability p is used to identify and incorporate managerial flexibilities for creating a decision tree. If the value of exercise price is X, the value of call option with X of exercise price when V_0 becomes $u\text{V}_0$ will be maximized between zero and $u\text{V}_0 - X$ at period 1. This value is defined as C_u. Like above case, the value of call option when V_0 becomes $d\text{V}_0$ will be maximized between zero and $d\text{V}_0 - X$ at period 1. This value is defined as C_d. The value of call option at period zero is C_0 and be driven by the values at period 1 backward induction, with probabilities linked to each path and divided by WACC as time value instead of r_f. This is an option valuation at present time. Appendix A shows how to calculate the WACC. Then, the ROA is conducted to calculate option value.

Binominal lattice model for a one period call option on an asset is:

$$\text{C}_0 = \frac{1}{\text{WACC}} [p \cdot max(0, u\text{V}_0 - X) + (1 - p) \cdot max(0, d\text{V}_0 - X)] \tag{2-18}$$

Converting the values at period1 to both C_u and C_d,

$$\text{C}_0 = \frac{1}{\text{WACC}} [pC_u + (1 - p)\, C_d] \tag{2-19}$$

The V_0 included time value grows by repeating this step until maturity. With this information, it is possible to set up event tree by generating multiplied asset values as time goes by. The tree shows possible changes in the asset values until maturity. Thus, a binomial lattice within multi-period is created in Figure 2-9.

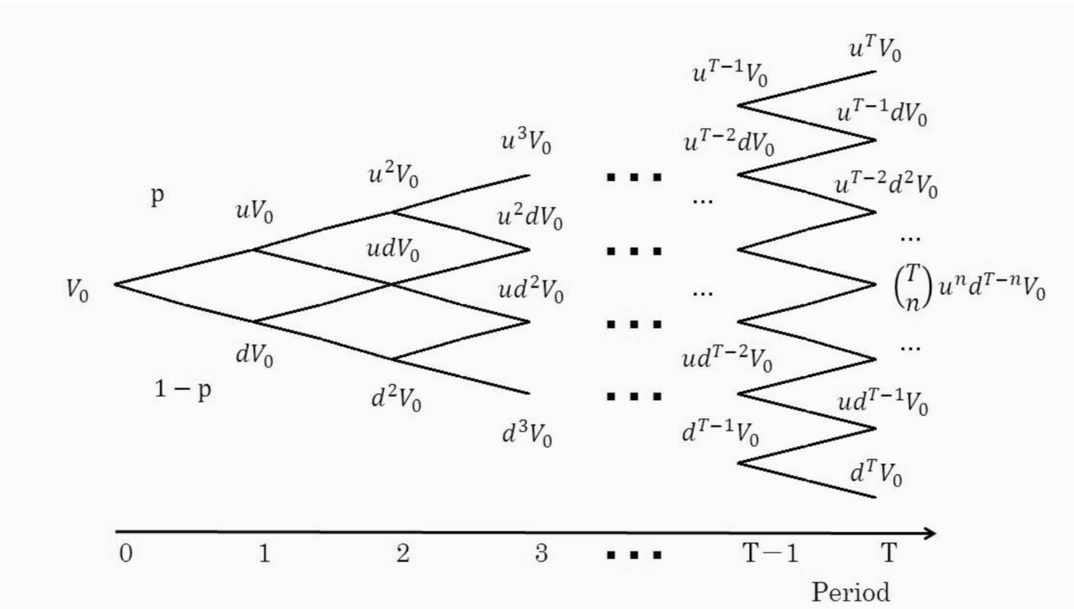
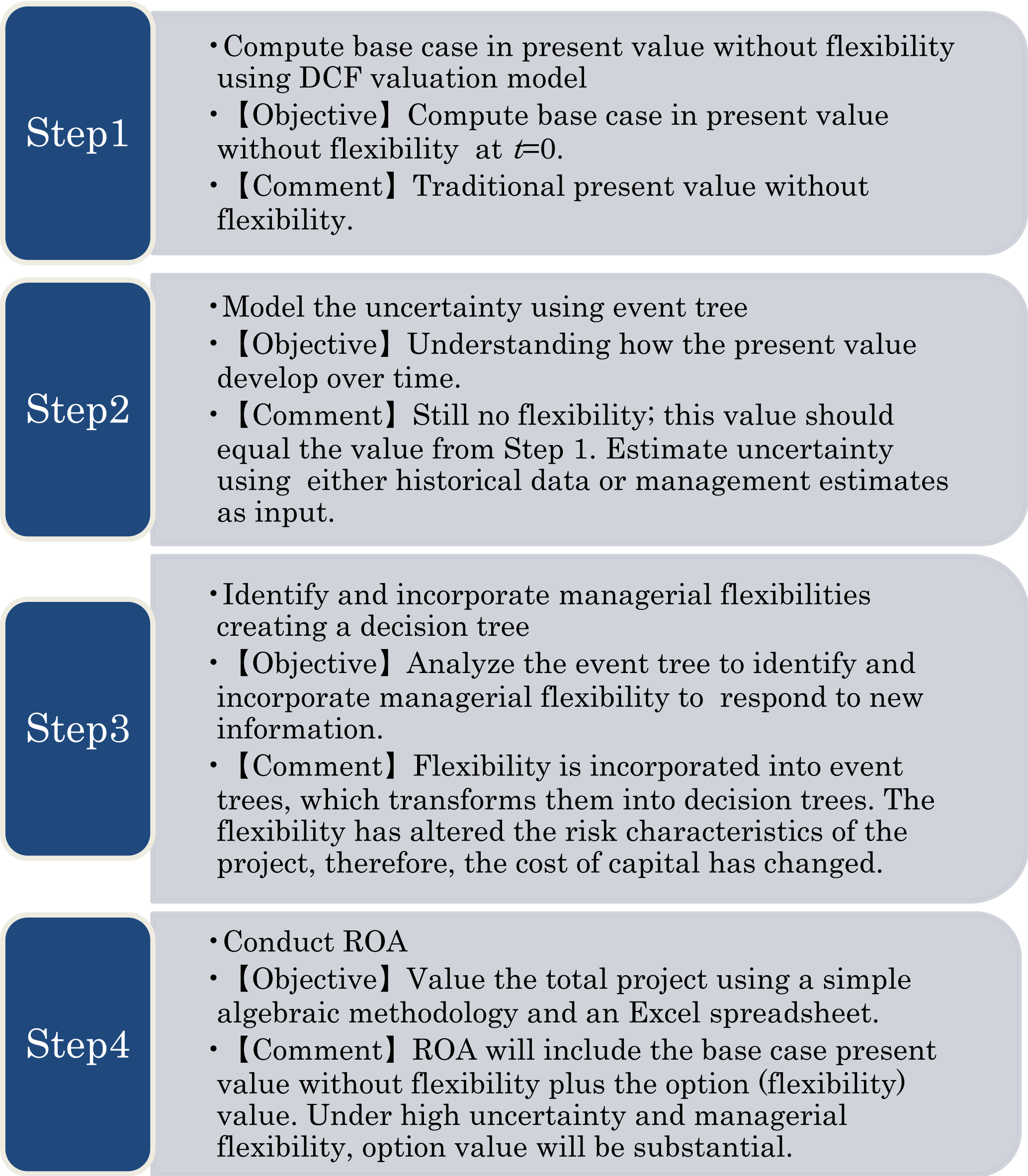


Fig.2-9 Underlying asset movement in binomial lattice model for multi-period

The distribution of outcomes becomes smoother as the number of asset changes per year increases. As the number of asset changes increases, the Binominal lattice model will produce the results similar to those obtained with the Black-Scholes model. In fact, the binominal lattice model provides a good analytical approximation for the movement of the stochastic variable when exact formulas for the stochastic process are not readily available.



*Event trees map out the cash flow explicitly and use objective probabilities and the WACC to calculate the project value without flexibility.

**This value should equal the present value calculated by the valuation model.

Fig.2-10 Four steps process to use in ROA (Sourced by Copeland and Antikarov 2003)

2.8.2 Four Steps Process for Binomial Lattice Model

Figure 2-10 shows the four steps process to use in ROA (Copeland and Antikarov 2003). Step 1 is a standard NPV analysis of the project using traditional techniques mentioned above. FCF over the life of the project should be forecasted under the assumption of no flexibility. Step 2 is to build an event tree, based on the set of combined uncertainties that drive the volatility of the project. An event tree does not have any decisions built into it. Instead, it is intended to model the uncertainty that drives the value of the underlying asset through time. Step 3 is to put the decisions that management may make into the nodes of the event tree to turn it into a decision tree.

Consider the decision to either invest now or defer until the end of optimal period. Once made, the investment is irreversible. So, the decision tree is expected positive with regardless of degree and timing of investment. A value at t in decision tree for scenario "c" is described by $f_{c(t)}$. First, the values at final nodes of the decision tree are calculated. These nodes are calculated as follows;

$$f_{c(t)} = \begin{cases} max\left(ENPV_{cj},\ NPV_j\right) & t = T \\ max\left(ENPV_{cj}, \dfrac{\left(p \cdot f_{cu(t+1)} + (1-p) \cdot f_{cd(t+1)}\right)}{1 + \mathrm{WACC}}\right) & 0 \le t < T-1 \end{cases} \qquad (2-20)$$

Where, j is the number of period, $f_{c(t)}$ is value in decision tree for American option, $f_{cu(t+1)}$ is the value if $f_{c(t)}$ steps to up forward with u at $\mathrm{t}+1$ period, and $f_{cd(t+1)}$ is the value if $f_{c(t)}$ steps to downward with d. In the stream of backward induction, $f_{cu(t+1)}$ and $f_{cd(t+1)}$ are the values from previous node.

The value of $f_{c(0)}$ is same as static NPV without flexibility. The investment at final nodes is only exercised if the $ENPV_{cj}$ is higher than NPV_j. This is a first step to exercise options. If not, investment is not exercised. Second, the value before final nodes are calculated stepwise backwards starting from second last node and ending at the first of all node. Before final node, this procedure is carried on until the first node is reached. Then, present value $f_{c(0)}$ is obtained.

The decision making of Equation 2-21 to investment is as follows:

$$f_{c(t)} = \begin{cases} max(exercise\ now, not\ exercise) & t = T \\ max(exercise\ now, hold\ \ ) & 0 \le t < T-1 \end{cases} \qquad (2-21)$$

The event tree models the set of values that the underlying risky asset may take through time. The decision tree shows the payoff from optimal decisions. Therefore, its payoffs are those that would result from the option. The decision tree shows not only the answer whether invest or not but also investment timing.

Step 4 is the valuation of the payoffs in the decision tree using either the method of replicated portfolio approach, or risk-neutral probability approach. The valuation of the payoffs is called as option value for call option in scenario "c" and is calculated as follows:

$$\text{Option Value}_c = max(f_{c(0)} - V_0,\quad 0) \qquad (2-22)$$

If option value is positive, this option has valuable even if investment is not exercised just now. As for put option, the option value is calculated as follows:

$$\text{Option Value}_c = max(V_0 - f_{c(0)},\quad 0) \qquad (2-23)$$

2.9 Monte-Carlo Simulation

2.9.1 Procedure of Monte-Carlo Simulation

Due to the complexity of the underlying dynamics, analytical models such as Black-Scholes model and binomial lattice model entail many restrictive assumptions. The price of the call option at initial zero period is not obtainable until all parameter of analytical models are known. There are, however, circumstances in which holder cannot use the analytical models for the lack of some assumptions with six variables mentioned above. This difficulty necessitates the use of an approximate numerical method such as Monte-Carlo simulation. In other word, though binomial lattice model is impracticable for purposes of valuing options with more than three uncertain factors, Monte-Carlo simulation is appropriated because this type of technique is indicated for high-dimensionality or stochastic parameter problems (Lazo et al. 2009).

Monte-Carlo simulation is proposed for European options firstly (Boyle 1977), and is a simulation of stochastic natural phenomena, which utilize random numbers in artificial processes (Wright 2002, Glasserman 2003, Schneider and Kirkpatrick 2006, Allen 2011, Chang et al. 2013). Even if problem is hard to be solved analytically, it is possible to obtain a solution approximately by sufficiently repeating the large number of simulations, Monte-Carlo simulation can be applied easily than numerical methods other depending on the problem, but there are also weaknesses that number of calculations become enormous if results need to get a high accuracy.

It is the most important factor for options to choose what and when is the optimal timing. Though American options without dividends prior to its expiration date should not be exercised, the American with dividends shall be exercised (Merton 1973). The Monte-Carlo simulation for European options with simply forward induction is not able to choose these matters correctly. On the other hand, American options can do correctly, but has a difficulty for path-dependent backward induction like binominal lattice method. The Monte-Carlo simulation for American options attempts to combine this problem using the simplicity of forward induction with optimal option exercise of backward induction (Longmann and Schwartz 2001). By repeating simulation runs in discrete models, it is possible to determine the transition probabilities between successive periods, to solve backwards the valuation process using each period as a decision unit, and finally to get expected NPV and option value.

2.9.2 Four Steps Process for Monte-Carlo Simulation

Figure 2-11 shows the example of four steps process for Monte-Carlo simulation (Copeland and Antikarov 2003). All uncertainties driving the PV have been combined into the event tree. Step 1 is to use expected Free Cash Flows (FCF) to estimate PV with a spreadsheet. WACC is used for discount rate. Step 2 is to model the variable uncertainties. The model should capture autocorrelation of each variable with its mean, and cross-sectional correlations among variables. Step 3 is to use the Monte-Carlo simulation to estimate the standard deviation of rate of return based on the distribution of PVs. Step 4 is to construct the event tree like binomial lattice model. Then, the four steps process to use in ROA is completed by putting decisions into the tree and using ROA to solve for the PV of the project with flexibility.

2.9.3 Software for Monte-Carlo Simulation

Some software is available to determine the uncertainty and sensitivity of random variable from simulation (de Neufville et al. 2006; Bhat and Kumar 2008; Chan 2011). Commercial Crystal Ball software is one of the software for Monte-Carlo simulation (Copeland and Antikarov 2003; Mun 2003; Charnes 2007; Bhat and Kumar 2008; Chan 2011; EPM information development team 2012). The Crystal Ball is an analytical tool in spreadsheet form and forecasts that the result from Monte-Carlo simulation helps quantify the uncertainty so that user can facilitate better decision-making.

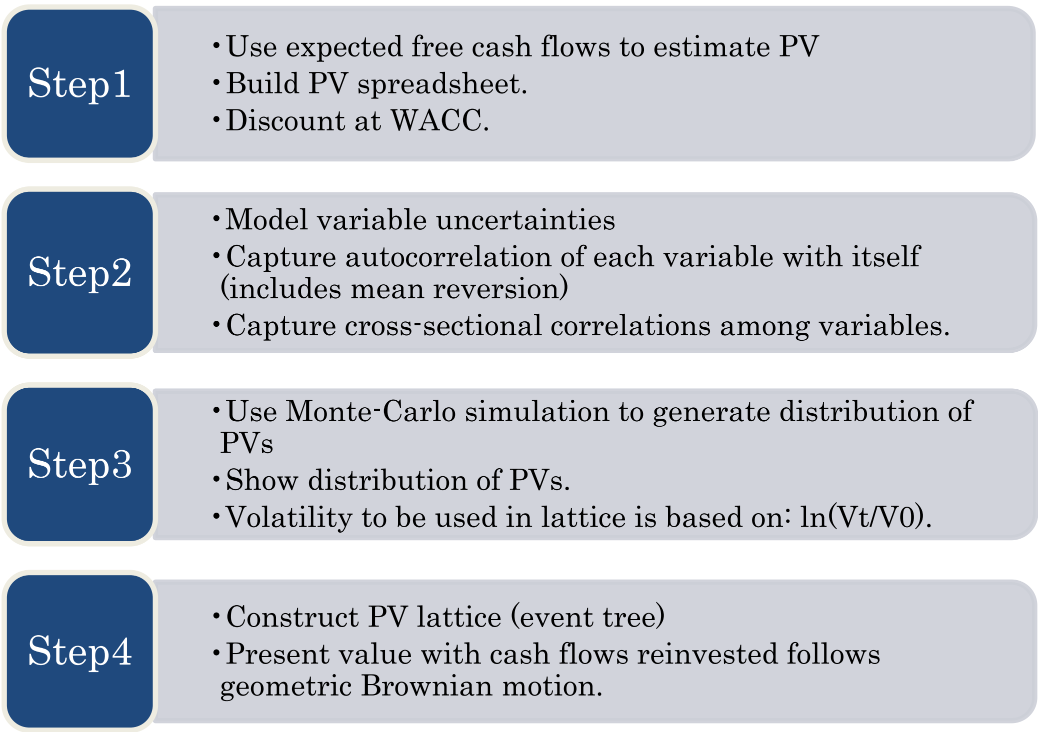


Fig.2-11Example of Monte-Carlo process to use in ROA (Sourced by Copeland and Antikarov 2003)

2.10 Timing option

2.10.1 Inventory

Inventory is held by companies in a supply chain in different forms so as to provide continuous products to the respective downstream customer and finally to products' using customer (Sethupathi et al. 2014). Inventory is usually controlled by companies by using the (s, S) policy with a re-order point (Sethupathi et al. 2014). The (s, S) means (re-order point, base stock). Producers are interested in knowing point of sales data and inventory levels at retail outlets for production planning, material resource planning, logistics planning, and also for avoiding excess inventory (Ramanathan 2014). But there is not enough detail on demand-related information such as point of sales data and inventory levels at retail outlets because of existence of buyers in case of soft drink. Only buyers know point of sales data and inventory levels at retail outlets, and do not transmit the information as it is to producers. Furthermore, soft drink producers receive daily demand from buyers and produce daily to meet demand regardless of efficient and effective flows to minimize total costs. As the number of companies in supply chain increases, received demand is amplified and produces the bullwhip effect (Lee et al. 1997; Quayle 2006; Wisner et al. 2012). The bullwhip effect is firstly appeared as the Forrester effect, and refers to increasing swings in inventory in response to shifts in customer demand as move upstream along the supply chain (Forrester 1961; Giannakis et al. 2004; Naim et al. 2004). The amplified demand causes problems with capacity planning, inventory control, workforce and production scheduling, and ultimately results in lower levels of customer service, greater overall levels of safety stock and higher total supply chain costs (Wisner et al. 2012). If companies know purchase plan for a short intervals, safety stock throughout the supply chain would be reduced drastically, dividing down total supply chain costs.

2.10.2 Timing Option as Inventory

Timing option seeks the optimal timing for the investment, where the waiting turns out to be better than investing immediately. Traditional timing option provides the holder with the option to defer making an investment decision until a later time without much restriction (Mun 2003). It may be that the risk avoided by waiting to invest has greater value than the sales that might be charged a penalty for postponing. Many papers consider when and how much is optimal for timing option to investment (for example, Mun 2003; Fujiwara 2011; Leung and Ludkovski 2012; Hori and Osano 2014). In traditional timing option, delaying soft drink production until more is learned by the strength of demand would be valuable. The author often observes the fact that trading activities in supply chains are accompanied by negotiation involving the demand timing and production timing. It is not an easy task to negotiate a supply contract because parties have to consider market uncertainties which either offer some profits or cause some losses. When parties agree with contracts about real option in supply chain, negotiation is avoided. Author expects that such timing differences will have a new and more significant impact when the supplier has a proprietary access to future opportunities for volume flexibility.

2.11 Limitations of the Past Research

2.11.1 Limitations of Forecasting Problem

In most forecasting problems, mathematical models such as regression analysis are developed in which the forecasts are performed by simple average from the historical data without time series. The mathematical models do not consider the information about the time series analysis. They perform poorly if the data are not time series. Therefore, forecasts derived from simple regression analysis may lead to wrong results about the demand in the future. The forecast of seasonal demand is frequently essential for inventory planning at soft drink industry prior to an active selling season. In demand forecasting, a single model may not be adequate to represent a particular demand series for all times. Further, the chosen model may have been restricted to a certain class of time series. Therefore, a number of forecasting models are studied to provide wider choices to find the best demand forecast of a seasonal product.

2.11.2 Limitations of ROA Problem

The volume flexibility of supply chain requires investments and should be justified on the basis of the potential benefits. For example, with relation to volume flexibility, the benefits changes from daily demand to seasonal demand. If ROA is used to volume flexibility based on daily or seasonal demand, the focus is on what is the potential benefit in supply chain. If the volume flexibility is based on manufacturing, how producer might integrate ROA into volume flexibility in supply chain. There are few studies about volume flexibility in soft drink industry.

ROA enables to protect from the downward potential of the underlying asset, while benefiting from the upward potential. To use ROA, it needs six variables to assess when and how investment should be done. Since most of past researches use the data under hypothesis neither the partial nor whole, and it is uncertain whether ROA can be derived from the four steps using six variables and reducing the hypothesis as little as possible. The research in forecasting problems usually ignores inventory, while the research in inventory problems generally presumes that forecasts are given. Then, inventory problem has a possibility to solve using ROA.

Very little work has been accomplished on demand forecasting, decision-making by ROA and inventory together to determine the best investment model that provides potential benefit during a validity of demand.

2.12 Overcoming the Limitations

2.12.1 Overcoming the Limitations of both Forecasting Problem and ROA

The main goal of this study is to explore whether and how author might integrate ROA into volume flexibility in supply chain in order to overcome the limitations and enhance the benefit of both techniques. So far the author has emphasized that the main advantage of this study consists in developing the learning and adaptive skills of ROA. The author investigates how to develop further these skills. This paper contributes to tactics by manufacturer in mainly three contents.

First, in the forecasting model, demand is evaluated by stochastic model. The forecasts by SARIMA are performed by using a probability distribution to represent the seasonal demand. SARIMA model is extended to ROA to capture the uncertainty of future demand. The parameters of the SARIMA model are static, but the static parameters can be enhanced by combining ROA and Monte-Carlo simulation. The combination of ROA in SARIMA model actually provided additional facilities such as the capacity to use predesigned models forecasting using little data or the data series.

Second, the volume flexibility of supply chain applies to not only daily demand but also seasonal demand by ROA.

Third, ROA gives an inventory problem solution. In inventory problem, uncertain demand is always included in volume flexibility statics and inventory cost is considered as option exercise cost and variable to keep the best volume by ROA.

Chapter 3 Simple ROA by Binomial Lattice Model Using ARIMA Model

3.1 Abstract

To further understanding ROA, this chapter demonstrates binomial lattice models for solving two simple options such as a simple American call option (the option to expand) and a simple American put option (the option to shrink). Annual sales are forecasted for 10 years by autoregressive integrated moving average (ARIMA) model which is one of the methods for time series analysis. The methodology used is based on four step process. If sales of soft drink are favored, the company can exercise the option to expand and is expected to increase the sales from that time by 1.2 times. If the sales are unfavorable, the company can exercise the option to shrink and is expected to shrink down to 0.8 times, and add to 220 million JPY for saving the cost. The option value become the amount of 2,077 thousand JPY when flexible decision-making for irreversible investment is conducted under uncertainty. The results of four step process show the option value in not only simple options but also the combinations. ROA by binomial lattice model can tell us when and what are the best to invest under uncertain sales in the future.

3.2 Introduction

3.2.1 Simultaneous Two Options

To further understanding ROA, this chapter demonstrates binomial lattice models for solving two simple options such as a simple American call option (the option to expand) and a simple American put option (the option to shrink). These simple options are combined finally, because most projects allow all of them to be considered simultaneously. The methodology used here is based on four step process mentioned in previous chapter (Copeland and Antikarov 2003).

3.2.2 ARIMA

The purpose of ARIMA is to identify and estimate the different components of a time series, and for example, forecast future sales (Box et al. 2016). ARIMA model is widely used to deal with cyclic data for time series analysis and forecasting. In a time series$\{Z_t|\mathrm{t} = 1,2,\ldots,\mathrm{k}\}$, ARIMA has a variation which is between consecutive observations. ARIMA $(\mathrm{p},\mathrm{d},\mathrm{q})$ models can be constructed to depict the relationship between consecutive observation values. ARIMA$(\mathrm{p},\mathrm{d},\mathrm{q})$ can be depicted if:

$$\varphi_p(B)(1-B)^d Z_t = \theta_q(B)a_t \qquad (3-1)$$

where t is the number of observations, $p, d, q,$ and s are integers, B are lag operator, d is the number of differences, and a_t is a white noise and the estimated residual at period t that is identically and independently distributed as a normal random variable with $\mu = 0$ and σ^2 (Bouzerdoum et al. 2013).

$$\varphi_p(B) = 1 - \sum_{i=1}^{p} \varphi_i B^i \qquad (3-2)$$

Equation 3-2 is the autoregressive (AR) operator of order p.

$$\theta_q(B) = 1 - \sum_{i=1}^{q} \theta_i B^i \qquad (3-3)$$

Equation 3-3 is the moving average (MA) operator of order q. $(1-B)^d$ is the consecutive dth differencing. One of contributions in this study is to combine ARIMA and ROA. As for ROA, it seems that ARIMA to be rarely used for forecasted future sales.

3.2.3 Evaluation of ARIMA

For fitting a ARIMA model to data, procedures should involves the following four steps: First is to identify the variables of ARIMA(p, d, q), second is to estimate the most efficient variables, third is to validate the models by means of performing goodness-of-fit tests on the estimated residuals, and fourth and final is to forecast future outcomes based on the known data with confidence interval (Box et al. 2016). But in this chapter, the fourth is omitted because of long-term data. It is proposed to use the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the sample data as the basic tools to identify the order of the ARIMA model (Box et al. 2016). Model selection methods have been proposed based on validity criteria, the information-theoretic approaches such as the Akaike's information criterion (AIC) (Shibata 1976). Although there are another three criterions of transformation lambda, the Bayesian information criterion (BIC) and the corrected AIC (AICc), the procedure for selecting model is predominantly based on BIC in this study. The model with the lowest BIC is preferred. It is possible to increase the likelihood function by adding parameters, but doing so may result in over fitting. The penalty term helps both AIC and BIC to inhibit increase in number of parameters, and is larger in BIC than in AIC. Theil's U and Durbin-Watson are also used (Oracle 2009). The Theil's U is a relative accuracy measure that compares the forecasted results with a naïve forecast. If the value is less than 1, the forecasting model is better than guessing. If the value is equal to 1, the model is about as good as guessing. If the value is more than 1, the model is worse than guessing. Durbin-Watson detects autocorrelation at lag 1, and means that each time-series value influences the next value. The value can be any value between 0 and 4, indicates slow-moving, none, or fast-moving autocorrelation. If the value is less than 1, the statistical model has an increase in one period follows an increase in the previous one. If the value is equal to 2, the model is about as good as no autocorrelation. If the value is more than 3, the model has an increase in one period follows a decrease in the previous one.

The analysis and presentation of ARIMA (p,d,q) results are more complex, when p and q are increased. It shall be restricted to only $p \leq 2$ and $q \leq 2$ to forecast demand. Current software packages offer add-in functionally to select between alternative models in an automatic manner. The selection processes mostly relies on BIC. The software Crystal Ball is one of these software and worked on Excel.

3.3 Step 1

3.3.1 Sales Analysis

The first step is to compute base case present value without flexibility using DCF valuation model (Copeland and Antikarov 2003). This result is equal to results of NPV. For sales of the company analysis, historical data from 2008 to 2014 is used. It is assumed that future data from 2015 to 2024 depends on the characteristics of historical data. Figure 3-1 shows historical and forecasted sales which are necessary for calculation of underlying asset that needs to be modeled and on the features of the options are contingent on them. The yearly sales have a tendency to increase until 2024.

SARIMA (2, 1, 1) model statistics shown in Table 3-1, get confident and lowest value 20.57 for BIC. Value of Theil's U is 0.1849; this figure shows forecasted model is same as supposed one. Although result of Durbin-Watson is 0.8227 and is alerted to be less than 1.0, it is due to increase in sales for a long term.

SARIMA (2, 1, 1) model coefficients are also depicted in Table 3-2. As the coefficient of variables has small standard error.

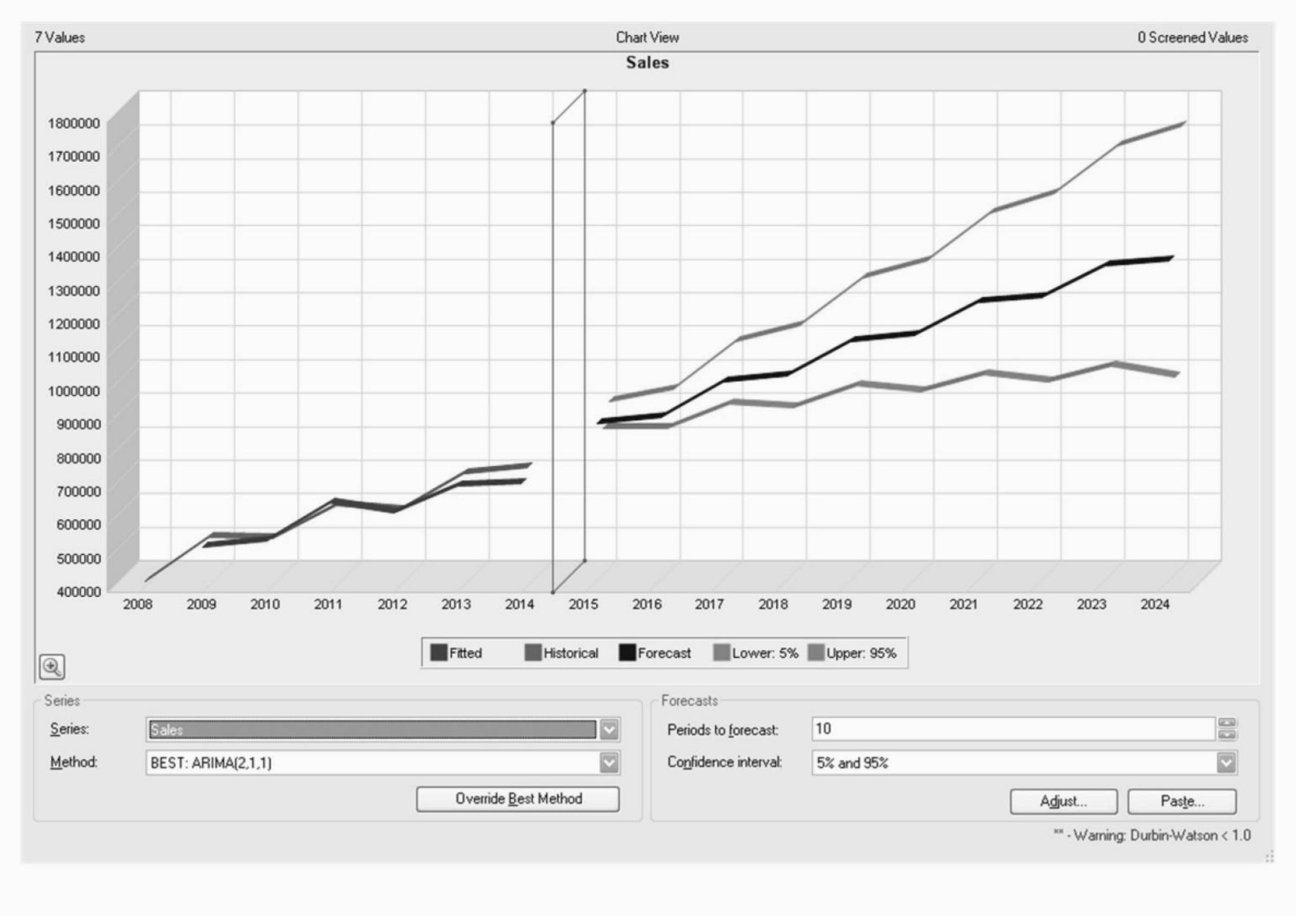


Fig. 3-1 Historical and forecasted sales

Table 3-1 ARIMA (2, 1, 1) model statistics

Items	Figures
Transformation Lambda	1.00
BIC	20.57
AIC	20.67
AICc	22.67
Theil's U	0.1849
Durbin-Watson	0.8227

Table 3-2 ARIMA (2, 1, 1) model coefficients

Variables	Coefficient	Standard Error
$\varphi_1(B)$	-0.0019	0.0171
$\varphi_2(B)$	0.9605	0.0151
$\theta_1(B)$	-0.2368	0.2985

3.3.2 FCF

The yearly FCF of the project is calculated by sales as follows:

$$FCF_n = \mathrm{EBIT}_n \times (1 - \text{Tax rate}) + \text{Depreciation}_n - \text{Investment expenses}_n$$
$$-\Delta\text{Working capital}_n \qquad (3-4)$$

Where, n is yearly periods, EBIT is earning before tax and interest. To avoid confusions between routine and option-targeted investment, an only investment for options is considered. Fluctuation for working capitals is not considered. Convenient calculative methods in this study are shown in Table 3-3.

Table 3-3 Accounting items and conditions

Items	Conditions
Sales	Stochastic process by ARIMA (2,1,1) from 2015 to 2024,
EBIT	Entirely consistent with 32% of sales
Tax rate	Fixed at 40% of EBIT
Depreciations	Fixed at 4,167 (1,000JPY) except for the depreciation of investment expenses using options
Investment expense	Investment expense is paid at once in decision- making period. See investment expense condition.

Underlying asset as V_0 is gained by as follows:

$$V_0 = \sum_{t=1}^{T} \left(\frac{FCF_t}{(1 + WACC)^{t-1}} \right) \qquad (3-5)$$

Where, FCF_t is FCF at t period, $(1 + \text{WACC})^{t-1}$ is a factor for FCF_t to convert from future value at period t to present value V_0, $WACC$ is yearly 1.86% (see Appendix), T is maturity of periods. Duration of T is 10 periods (10years).

The V_0 is calculated by the Equation 3-5 and the DCF model is shown in Figure 3-2.

Step II: DCF

Input Parameters

Discount Rate (WACC)	1.86%
Discount Rate (rf)	1.30%
Tax Rate	40.00%

Results

Present Value (Cash Flow)	1,459,056
Present Value (Investment. Cost)	0
Net Present Value	1,459,056

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Sales	867,492	885,528	993,222	1,010,347	1,113,759	1,130,016	1,229,318	1,244,750	1,340,105	1,354,752
Cost of Sales	607,245	619,870	695,255	707,243	779,631	791,012	860,522	871,325	938,073	948,326
Gross Margin	260,248	265,658	297,966	303,104	334,128	339,005	368,795	373,425	402,031	406,425
Selling and General Administration expense	52,050	53,132	59,593	60,621	66,826	67,801	73,759	74,685	80,406	81,285
Operating Profit	208,198	212,527	238,373	242,483	267,302	271,204	295,036	298,740	321,625	325,140
Depreciation	4,167	4,167	4,167	4,167	4,167	4,167	4,167	4,167	4,167	4,167
Investment Expense	0	0	0	0	0	0	0	0	0	0
Income Before Taxes	204,031	208,360	234,207	238,317	263,135	267,037	290,870	294,573	317,458	320,974
Taxes	81,613	83,344	93,683	95,327	105,254	106,815	116,348	117,829	126,983	128,389
Income After Taxes	122,419	125,016	140,524	142,990	157,881	160,222	174,522	176,744	190,475	192,584
Free Cash Flow	126,586	129,183	144,691	147,157	162,048	164,389	178,688	180,911	194,642	196,751

Volatility Measure:										
Logarithmic Returns		0.0203	0.1134	0.0169	0.0964	0.0143	0.0834	0.0124	0.0732	0.0108
Volatility	4.19%									

Fig. 3-2 DCF model

3.4 Step 2

3.4.1 Volatility

The second step is to build an event tree, based on the set of combined uncertainties that drive the volatility of the project (Copeland and Antikarov 2003). The quantity of yearly sales is identified as the main uncertainty for this project. An event tree does not have any options built into it. The tree is intended to model the uncertainty that drives the value of the underlying asset through time. The uncertainty is expressed as volatility (σ) which is calculated by logarithmic returns as averaged $LN(FCF\ in\ this\ year/FCF\ in\ previous\ year)$.

In this study, the volatility from 2015 to 2024 is calculated as 4.13% in Figure 3-2.

3.4.2 Event Tree

Then the volatility is used to build an event tree. At the beginning of binomial lattice model which is recombining, it is identified to calculate on stepping time and step sizes. Then complete the underlying asset lattice. V_0 moves up or down by multiplying with the factors of u and d. The factors of u and d are calculated for ten years by equations of 2-20 and 2-21 in previous chapter. Note that it is still no flexibility in this model.

$$u = e^{\sigma\sqrt{\Delta t}} = e^{4.13\%\sqrt{1}} = 1.04268 \cong 1.0427 \qquad (3-6)$$

$$d = \frac{1}{u} = 0.9590 \cong 0.9590 \qquad (3-7)$$

The PV of the project is shown in Figure 3-3 as event tree illustrated a ten step recombining underlying asset lattice. The PV is equal to NPV because of no flexibility. The V_0 denoted as node [A] goes up or down by multiplying with the factors of u and d. If, for example, multiplied by u at t=1 and 2, the V_0 moves $u \times u \times V_0 = u^2 V_0$, which is specified by node [B]. If continues to go up until maturity, the V_0 can be reached to the terminal node [C], which is $u^{10}V_0$ from the underlying asset lattice. Similarly, the V_0 can be reached to the terminal node [D], which is $d^{10}V_0$ if continues to go down until maturity.

The values without flexibility at each node are written on Table 3-4. From the table, the value of V_0 which is on node [A] has 1,459 million JPY and grow until the maturity. The intermediate value on node [B] when multiplied by u at t=1 and 2 is 1,586 million JPY. At the maturity of t=10, the event tree is widely ranged from 960 million JPY on node [D] to 2,216 million JPY on node [C]. It is supposed that this company is growing and has a static valuation of future profitability in this event tree.

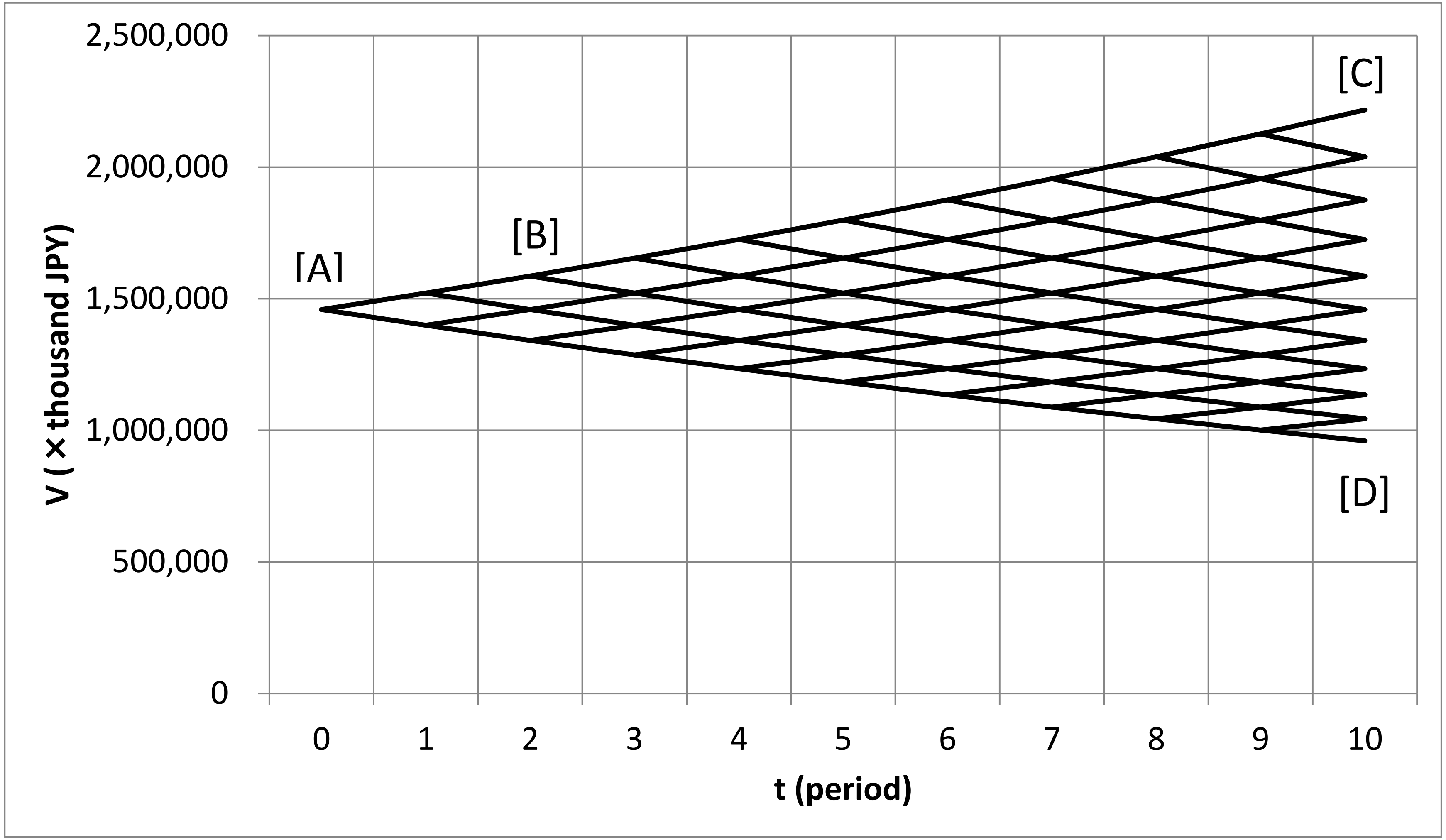


Fig. 3-3 Present value event tree for the underlying asset as binomial lattice

Table 3-4 Present value event tree for the underlying asset

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
1,459,056	1,521,358	1,586,320	1,654,055	1,724,684	1,798,328	1,875,116	1,955,184	2,038,670	2,125,721	2,216,489
	1,399,235	1,458,982	1,521,280	1,586,239	1,653,972	1,724,596	1,798,236	1,875,021	1,955,085	2,038,567
		1,341,866	1,399,164	1,458,908	1,521,203	1,586,159	1,653,888	1,724,509	1,798,145	1,874,926
			1,286,850	1,341,798	1,399,093	1,458,834	1,521,126	1,586,078	1,653,804	1,724,421
				1,234,089	1,286,784	1,341,730	1,399,022	1,458,760	1,521,049	1,585,998
					1,183,491	1,234,026	1,286,719	1,341,662	1,398,951	1,458,686
						1,134,968	1,183,431	1,233,964	1,286,654	1,341,594
							1,088,434	1,134,910	1,183,371	1,233,901
								1,043,808	1,088,379	1,134,853
									1,001,012	1,043,756
										[D]
										959,971

Table 3-5 Option valuation for the option to expand

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
1,461,132	1,524,203	1,590,212	1,659,369	1,731,921	1,808,160	1,888,436	1,973,172	2,062,878	2,158,170	2,259,787
	1,399,542	1,459,422	1,521,910	1,587,139	1,655,259	1,726,438	1,800,871	1,878,791	1,960,477	2,046,280
		1,341,866	1,399,164	1,458,908	1,521,203	1,586,159	1,653,888	1,724,509	1,798,145	1,874,926
			1,286,850	1,341,798	1,399,093	1,458,834	1,521,126	1,586,078	1,653,804	1,724,421
				1,234,089	1,286,784	1,341,730	1,399,022	1,458,760	1,521,049	1,585,998
					1,183,491	1,234,026	1,286,719	1,341,662	1,398,951	1,458,686
						1,134,968	1,183,431	1,233,964	1,286,654	1,341,594
							1,088,434	1,134,910	1,183,371	1,233,901
								1,043,808	1,088,379	1,134,853
									1,001,012	1,043,756
										[D]
										959,971

Table 3-6 Decision tree for the option to expand

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
hold	hold	hold	hold	hold	hold	hold	hold	hold	hold	expand
	hold	hold	hold	hold	hold	hold	hold	hold	hold	expand
		hold	hold	hold	hold	hold	hold	hold	hold	not exercise
			hold	hold	hold	hold	hold	hold	hold	not exercise
				hold	hold	hold	hold	hold	hold	not exercise
					hold	hold	hold	hold	hold	not exercise
						hold	hold	hold	hold	not exercise
							hold	hold	hold	not exercise
								hold	hold	not exercise
									hold	not exercise
										[D]
										not exercise

Table 3-7 Option value for the option to expand

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
2,076	2,846	3,893	5,314	7,237	9,832	13,320	17,988	24,208	32,448	43,298
	308	440	629	900	1,288	1,842	2,635	3,769	5,392	7,713
		0	0	0	0	0	0	0	0	0
			0	0	0	0	0	0	0	0
				0	0	0	0	0	0	0
					0	0	0	0	0	0
						0	0	0	0	0
							0	0	0	0
								0	0	0
									0	0
										[D]
										0

3.5 Step 3

3.5.1 Decision Tree

The third step is to put the decisions that management may make into the nodes of the event tree to turn it into a decision tree (Copeland and Antikarov 2003). The event tree is much valuable if optimal decisions are incorporated though time. In other word, the event tree is analyzed to identify and incorporate managerial flexibility to respond new information as time goes by.

The probability to increase p is calculated as Equation 2-22.

$$p = \frac{1 + \mathrm{WACC} - d}{u - d} = \frac{1 + 0.0186 - 0.9590}{1.0427 - 0.9590} = 0.7121 \qquad (3-8)$$

3.5.2 American Call and Put Options

In this study, two options are identified. The first is an option to expand as American call option. It is decided to use an American call option because the option to expand can be exercised at any discrete time up to the expiration date. It is also decided to evaluate the value of ROA with a binomial lattice model. If sales of soft drink are favored, the company can invest 400 million JPY and is expected to increase the sales from that time by 1.2 times. This increment is equal to a dividend in option theory.

The second is an option to shrink as American put option. If sales of soft drink are not favored, the company can give up to further production in unprofitable soft drinks. In this study, if the company quits produce in partial products such as unprofitable soft drinks, the sales are assumed to shrink down to 0.8 times, and add to 220 million JPY for sparing the cost. To decide what to do, it is important to escape downside risk and know the value of the underlying asset if the decision is not to exercise the option. The company has the option to expand its existing production and not the obligation.

3.5.3 Option to Expand as American Call Option

The option valuation with flexibility is calculated using Equation 2-26. As the stream of calculation is backward induction, first calculations are at terminal nodes of maturity. Here are 4 nodes ([A], [B], [C], and [D]) written in Table 3-5 example to calculate the option valuation. The valuation is ENPV because of considering flexibility. The $f_{e(t)}$ is value in decision tree for Option to Expand as American Call Option. Because of backward induction, authors would like to firstly explain node [C], following node [D], [B], and [A]. The sample terminal node [C] as terminal value in best condition reveals a value of 2,260 million JPY, which can be obtained through the value maximization of exercised option versus no exercise. In detail, on node [C] $f_{e(10)}$ is calculated using Equation 2-26 .

$$f_{e(10)} \text{on node [C]} = max(ENPV_{e10}, NPV_{10}) \text{ on node [C]}$$

$$= max(2{,}259{,}787, \quad 2{,}216{,}489)$$
$$= 2{,}259{,}787 \text{ (thousand JPY)} \qquad (3-9)$$

$ENPV_{e10}$ and NPV_{10} are derived from node [C] in both Table 3-5 and 3-4, respectively. Oppositely, on node [D] as terminal value in worst condition, $f_{e(10)}$ is calculated as same.

$$f_{e(10)}\text{on node [D]} = max(ENPV_{e10}, NPV_{10}) \text{ on node [D]}$$
$$= max(959{,}971, \quad 959{,}971)$$
$$= 959{,}971 \text{ (thousand JPY)} \qquad (3-10)$$

The values of $ENPV_{e10}$ and NPV_{10} are totally same, then option cannot exercise.

At the intermediate from t=1 to 9, the calculation for option valuation is different from at terminal maturity. On node [B] as intermediate value of t=2, $f_{e(2)}$ is calculated using Equation 2-26.

$$f_{e(2)}\text{at node [B]} = max\left(ENPV_{e2}, \frac{\left(p \cdot f_{eu(3)} + (1-p) \cdot f_{ed(3)}\right)}{1 + \text{WACC}}\right) \text{at node [B]}$$

$$= max\left(1.2 \times NPV_2 - 400{,}000, \frac{\left(p \cdot f_{eu(3)} + (1-p) \cdot f_{ed(3)}\right)}{1 + \text{WACC}}\right) \text{at node [B]}$$

$$= max\left(1.2 \times 1{,}586{,}320 - 400{,}000, \frac{(0.7121 \times 1{,}659{,}402 + (1-0.7121) \times 1{,}521{,}939)}{1 + 0.0186}\right)$$

$$= max(1{,}503{,}584, \quad 1{,}590{,}248)$$
$$= 1{,}590{,}248 \text{ (thousand JPY)} \qquad (3-11)$$

where, $f_{eu(\mathrm{t}+1)}$ is the value in decision tree when $f_{e(\mathrm{t})}$ goes upward to $f_{e(\mathrm{t}+1)}$. Oppositely, $f_{ed(\mathrm{t}+1)}$ is the value when $f_{e(\mathrm{t})}$ goes downward to $f_{e(\mathrm{t}+1)}$.

At t=0, the calculation for option valuation does not be effected by the decision at that time, but contains the decision making with flexibility from t=1 to 10. On node [A] as the value of t=0, $f_{e(0)}$ is calculated using Equation 2-18.

$$f_{e(0)}\text{at node [A]} = max\left(ENPV_{e0}, \frac{\left(p \cdot f_{eu(1)} + (1-p) \cdot f_{ed(1)}\right)}{1 + \text{WACC}}\right) \text{at node [A]}$$

$$= max\left(1.2 \times NPV_0 - 400{,}000, \frac{(0.7121 \times 1{,}524{,}241 + (1-0.7121) \times 1{,}399{,}577)}{1 + 0.0186}\right) \text{at node [A]}$$

$$= max\left(1.2 \times 1{,}459{,}056 - 400{,}000, \frac{(0.7121 \times 1{,}524{,}241 + (1-0.7121) \times 1{,}399{,}577)}{1 + 0.0186}\right)$$

$$= max\ (1{,}350{,}867, \quad 1{,}461{,}172)$$
$$= 1{,}461{,}172 \cong 1{,}461{,}173 \text{ (thousand JPY)} \qquad (3-12)$$

A difference occurs to the first column because of rounding off. But this difference does not have a serious influence. All of these results are included and decision tree for the option to expand is shown in Table 3-6.

3.5.4 Option to Shrink as American Put Option

Again, here are 4 nodes ([A], [B], [C], and [D]) written in Table 3-5 example to calculate the option valuation. The $f_{s(t)}$ is value in decision tree for option to shrink.

On node [C] $f_{s(10)}$ is calculated using Equation 2-26.

$$f_{s(10)}\text{on node [C]} = max(ENPV_{s10},\ NPV_{10}) \text{ on node [C]}$$
$$= max(2{,}216{,}489,\ 2{,}216{,}489)$$
$$= 2{,}216{,}489 \text{ (thousand JPY)} \qquad (3-13)$$

$ENPV_{s10}$ and NPV_{10} are derived from node [C] in both Table 3-8 and 3-4, respectively. As the value of $ENPV_{s10}$ is same as that of NPV_{10}, it is no condition to exercise option to shrink. Oppositely, on node [D] as terminal value in worst condition, $f_{s(10)}$ is calculated as same.

$$f_{s(10)}\text{on node [D]} = max(ENPV_{s10},\ NPV_{10}) \text{ on node [D]}$$
$$= max(987{,}977,\ 959{,}971)$$
$$= 987{,}977 \text{ (thousand JPY)} \qquad (3-14)$$

The values of $ENPV_{s10}$ on node [D] is higher than that of NPV_{10}, then the option can be exercised.

On node [B] as intermediate value of t=2, $f_{s(2)}$ is calculated using Equation 2-26.

$$f_{s(2)}\text{at node [B]} = max\left(ENPV_{s2},\quad \frac{\left(p \cdot f_{su(3)} + (1-p) \cdot f_{sd(3)}\right)}{1 + \text{WACC}}\right) \text{at node [B]}$$

$$= max\left(0.8 \times NPV_2 + 220{,}000,\quad \frac{\left(p \cdot f_{su(3)} + (1-p) \cdot f_{sd(3)}\right)}{1 + \text{WACC}}\right) \text{at node [B]}$$

$$= max\left(0.8 \times 1{,}586{,}320 + 220{,}000,\quad \frac{(0.7121 \times 1{,}653{,}992 + (1-0.7121) \times 1{,}521{,}222)}{1 + 0.0186}\right)$$

$$= max(1{,}489{,}056,\quad 1{,}586{,}250\ )$$
$$= 1{,}586{,}250 \text{ (thousand JPY)} \qquad (3-15)$$

The values of NPV_{10} on node [B] is higher than that of $ENPV_{s10}$, then the option cannot be exercised.

At t=0, the calculation for option valuation does not be effected by the decision at that time, but contains the decision making with flexibility from t=1 to 10. On node A as the value of t=0, $f_{s(0)}$ is calculated using Equation 2-18.

$$f_{s(0)}\text{at node [A]} = max\left(ENPV_{s0}, \frac{\left(p \cdot f_{su(1)} + (1-p) \cdot f_{sd(1)}\right)}{1 + \text{WACC}}\right) \text{at node [A]}$$

$$= max\left(0.8 \times NPV_0 + 220{,}000,\right.$$

$$\left.\frac{(0.7121 \times 1{,}521{,}358 + (1 - 0.7121) \times 1{,}399{,}239)}{1 + 0.0186}\right) \text{at node [A]}$$

$$= max\left(0.8 \times 1{,}459{,}056 + 220{,}000, \quad \frac{(0.7121 \times 1{,}521{,}358 + (1 - 0.7121) \times 1{,}399{,}239)}{1 + 0.0186}\right)$$

$$= max\,(1{,}387{,}245, \quad 1{,}459{,}061)$$

$$= 1{,}459{,}061 \cong 1{,}459{,}057 \text{ (thousand JPY)} \qquad (3-16)$$

A difference occurs to the first column because of rounding off. But this difference does not have a serious influence. All of these results are included and decision tree for the option to shrink is shown in Table 3-9.

3.6 Step 4

3.6.1 Option Value for the Option to Expand

After calculation of the option valuation with flexibility, the decision-making such as “hold”, “exercise” and “not exercised” in the decision tree is cleared in Table 3-9. Decision-maker can see his behavior from present to the future based on the option valuation with flexibility. Furthermore, option value on each node is shown in Table 3-7. The option value in the decision tree is calculated using Equation 2-26. Especially, when the option value is mentioned, it means that the value is calculated at $t = 0$. In Table 3-4, the value of V_0 which is on node [A] in event tree has 1,459 million JPY. The value of $f_{e(0)}$ in Table 3-5 is on node [A] in option valuation has 1,461 million JPY.

$$\text{Option value(e)} = \max(f_{e(0)} - V_0, \quad 0)$$

$$= max\,(1{,}461{,}132 - 1{,}459{,}056, \quad 0)$$

$$= 2{,}076 \text{ (thousand JPY)} \qquad (3-17)$$

This option value for the option to expand is shown on node [A] in Table 3-7. The Table 3-7 is given by subtracting event tree in Table 3-4 from option valuation in Table 3-5. If the subtraction is negative, then option value turn to zero. Note that option value is only at $t = 0$. If option value is positive, this option has valuable even if investment is not exercised just now. By not exercising the option to expand just now but still having the option to acquire bigger option value, the value of the investment is worth more than its static value of 1,459,056 thousand JPY on node [A] shown in Table 3-4. It is a reason for the value of keeping the option hold at $t = 0$.

But as time goes by, the value is changed and some case has an increment, and the other case is decreased. Whereas the option value on node [A] is 2,076 thousand JPY, node [B] moving on to the intermediate nodes is calculated as 3,898 million JPY. It is wise to continue the existing condition and hold the option. The value on node [C] as terminal value in best condition grows to be a value of 43,298 million JPY. It is high condition to exercise option because the investment will have a high flexibility value at the period. If, however, the option value goes to the value on node [D] as terminal value in worst condition, the option value is diminished. It is more optimal not to exercise option right now because the investment will be a loser at the period.

The option value is worth to an additional 0.15 percent of existing sales. If a ROA is not used, the sales will be undervalued because it has an opportunity to expand its current sales but not be conscious to do so and will most likely not to expand under optimal conditions. The investment has a defensible hedge against any potential downside risk because of the uncertain what may potentially happen in the future. It is valuable to have the option under an uncertain demand until it come favorable condition. The option should be exercised when decision–maker chooses the node to invest under the possibility of option value in the future. Next is opposite American put option as option to shrink.

3.6.2 Option Value for the Option to Shrink

The option value for the option to shrink is shown in Table 3-10.

$$\begin{aligned} \text{Option value(s)} &= \max(f_{s(0)} - V_0, \quad 0) \\ &= max\,(1{,}459{,}057 - 1{,}459{,}056, \quad 0) \\ &= 1 \ \ \text{(thousand JPY)} \end{aligned} \qquad (3-18)$$

But as time goes by, the value is changed and some case has an increment, and the other case is diminished. Whereas the option value on node [A] is 1 thousand JPY, node [B] moving on to the intermediate nodes is calculated as zero. It is wise to continue the existing condition and hold the option until the put option become large flexibility value. The value on node [C] as terminal value in best condition is also zero. It is optimal not to exercise option because the value without option is higher than the value with the option at the maturity. If, however, the option value goes down to the value on node [D] as terminal value in worst condition, it is high condition to exercise option because the investment will have a high flexibility value at the period.

3.6.3 Combinations of Option Values

Author considers the possibility of a projects that allows any one of the above two simple options to be exercised at each node. That is, the options are combined finally, because, in general, most projects allow all of them to be considered simultaneously. The event tree for the underlying asset and option valuations for the options remain the same as before. However, the decision trees as shown in both Table 3-6 and 3-9 contain at each node all two possible options; the option to expand, and to shrink. These options are mutually exclusive alternatives. The combinations begin to solve the decision tree problem by comparing the optimal decisions between each at nodes based on option valuation in both Tables 3-5 and 3-8. Here are 4 nodes ([A], [B], [C], and [D]) written in Table 3-11 example to calculate the option valuation. The option valuations from four mutually exclusive nodes are evaluated at each node, and the decision that results in the highest option valuation is chosen as optimal by working backward from the maturity to node [A]. Once author determines the optimal decisions, it is ready to show the decision tree at each node shown in Table 3-12.

From Table 3-11, the optimal option valuation from node [A] is 1,461,133 thousand JPY. At node [B] is decided to "hold" with the option valuation of 1,590,212 thousand JPY. At node [C] where decided to expand, the option valuation is 2,259,787 thousand JPY. At node [D] where decided to shrink, the option valuation is 987,977 thousand JPY. Next, option value is calculated

The binomial lattice model makes it easy to evaluate a project with two simultaneous options on underlying asset. The following values of the separate options and of the combinations of simultaneous options make it easy to draw conclusions:

Option value to the option to expand	2,076 thousand JPY
Option value to the option to shrink	1 thousand JPY
Option value to the combinations of options	2,077 thousand JPY

The option value become the amount of 2,077 thousand JPY when flexible decision-making for irreversible investment is conducted under uncertainty. ROA by binomial lattice model can tell us when and what are the optimal to invest under uncertain sales in the future.

3.7 Conclusion

ARIMA model for forecasting future sales helps ROA to conduct four step analysis process, especially sales analysis in step 1. If sales of soft drink are favored in the future, the option to expand is exercised to increase the sales at that time by 1.2 times. If the sales are unfavorable, the option to shrink is exercised to scale down to 0.8 times for sparing the cost. Not NPV but ROA can evaluate simultaneous projects on the same spreadsheet and tell when and what are the optimal decision to invest under uncertain sales in the future. The values of combined simultaneous options (chooser option) make it easy to draw conclusions. Note that it is seems that the option to shrink will not be used here . However, it values 1 thousand JPY to hold the option. The results are based on only one time and cannot tell what and how often the options are exercised in the future. This point can be cleared if the ROA is used on the basis of repeatedly simulated results.

Table 3-8 Option valuation for the option to shrink

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
1,459,057	1,521,358	1,586,320	1,654,055	1,724,684	1,798,328	1,875,116	1,955,184	2,038,670	2,125,721	2,216,489
	1,399,239	1,458,982	1,521,280	1,586,239	1,653,972	1,724,596	1,798,236	1,875,021	1,955,085	2,038,567
		1,341,879	1,399,165	1,458,908	1,521,203	1,586,159	1,653,888	1,724,509	1,798,145	1,874,926
			1,286,890	1,341,804	1,399,093	1,458,834	1,521,126	1,586,078	1,653,804	1,724,421
				1,234,217	1,286,805	1,341,730	1,399,022	1,458,760	1,521,049	1,585,998
					1,183,896	1,234,098	1,286,719	1,341,662	1,398,951	1,458,686
						1,136,221	1,183,685	1,233,964	1,286,654	1,341,594
							1,092,239	1,135,809	1,183,371	1,233,901
								1,055,047	1,091,559	1,134,853
									1,020,810	1,055,004
										[D]
										987,977

Table 3-9 Decision tree for the option to shrink

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
hold	hold	hold	hold	hold	hold	hold	hold	hold	hold	not exercise
	hold	hold	hold	hold	hold	hold	hold	hold	hold	not exercise
		hold	hold	hold	hold	hold	hold	hold	hold	not exercise
			hold	hold	hold	hold	hold	hold	hold	not exercise
				hold	hold	hold	hold	hold	hold	not exercise
					hold	hold	hold	hold	hold	not exercise
						hold	hold	hold	hold	not exercise
							hold	hold	hold	not exercise
								abandon	hold	not exercise
									abandon	abandon
										[D]
										abandon

Table 3-10 Option value for the option to shrink

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
1	0	0	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0	0
		13	2	0	0	0	0	0	0	0
			40	6	0	0	0	0	0	0
				129	20	0	0	0	0	0
					404	72	0	0	0	0
						1,253	254	0	0	0
							3,805	899	0	0
								11,238	3,180	0
									19,798	11,249
										[D]
										28,006

Table 3-11 Option valuation for combinations

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
1,461,133	1,524,203	1,590,212	1,659,369	1,731,921	1,808,160	1,888,436	1,973,172	2,062,878	2,158,170	2,259,787
	1,399,546	1,459,422	1,521,910	1,587,139	1,655,259	1,726,438	1,800,871	1,878,791	1,960,477	2,046,280
		1,341,879	1,399,165	1,458,908	1,521,203	1,586,159	1,653,888	1,724,509	1,798,145	1,874,926
			1,286,890	1,341,804	1,399,093	1,458,834	1,521,126	1,586,078	1,653,804	1,724,421
				1,234,217	1,286,805	1,341,730	1,399,022	1,458,760	1,521,049	1,585,998
					1,183,896	1,234,098	1,286,719	1,341,662	1,398,951	1,458,686
						1,136,221	1,183,685	1,233,964	1,286,654	1,341,594
							1,092,239	1,135,809	1,183,371	1,233,901
								1,055,047	1,091,559	1,134,853
									1,020,810	1,055,004
										[D]
										987,977

Table 3-12 Decision tree for combinations

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
hold	hold	hold	hold	hold	hold	hold	hold	hold	hold	expand
	hold	hold	hold	hold	hold	hold	hold	hold	hold	expand
		hold	hold	hold	hold	hold	hold	hold	hold	not exercise
			hold	hold	hold	hold	hold	hold	hold	not exercise
				hold	hold	hold	hold	hold	hold	not exercise
					hold	hold	hold	hold	hold	not exercise
						hold	hold	hold	hold	not exercise
							hold	hold	hold	not exercise
								shrink	hold	not exercise
									shrink	shrink
										[D]
										shrink

Table 3-13 Option value for combinations

Unit: thousand JPY

0	1	2	3	4	5	6	7	8	9	10
[A]		[B]								[C]
2,077	2,846	3,893	5,314	7,237	9,832	13,320	17,988	24,208	32,448	43,298
	311	440	629	900	1,288	1,842	2,635	3,769	5,392	7,713
		13	2	0	0	0	0	0	0	0
			40	6	0	0	0	0	0	0
				129	20	0	0	0	0	0
					404	72	0	0	0	0
						1,253	254	0	0	0
							3,805	899	0	0
								11,238	3,180	0
									19,798	11,249
										[D]
										28,006

Chapter 4 Options in Case of Seasonal High Demand Using SARIMA Model

4.1 Abstract

The demand of soft drink may not be satisfied in the summer because the supply is often too short to meet the unexpected demand. For this circumstance, this chapter proposes the optimal investment that integrates demand uncertainty, based on real options approach (ROA) and seasonal autoregressive integrated moving average. Two alternative options are compared and evaluated, one is Bermudan options to employ additional part-time workers to elevate efficiency in summer and dismiss in winter, this attitude is repeated each year. The other is American option to replace equipment to elevate machine ability throughout the depreciation year. We use these options in binomial lattice on Monte-Carlo simulation.

Results in ROA show that employing additional workers has an advantage to replace equipment under uncertainty. But, the highest improvement is gained if the two options are simultaneously used. Soft drink producers should search for replacing equipment, using the employing repeatedly. A limited life decision is not equal to infinite going-concern decision.

4.2 Introduction

4.2.1 Food Hygiene Standards

In recent years, food sanitation as food hygiene standards has attracted as HACCP (Hazard Analysis and Critical Control Point) system (e.g. Codex 2003; Mortimore and Wallace 2013). FSSC 22000 is one of the food hygiene standards using HACCP system (Foundation for food safety certification 2014a), and be based on existing ISO Standards such as ISO 22000:2005 and ISO/TS22002-x series (Foundation for food safety certification 2014b). ISO/TS22002-x series include requirements for establishing, implementing and maintaining pre-requisite programs (PRP) to assist in controlling food safety hazards.

Furthermore, soft drink producers intrinsically manage their plants in consideration of not only the food sanitation but also upgrade to enlarge the capacity. If the investment for the upgrade is accompanied with food sanitation, it is easy to recover the investment expenses. However, this irreversible investment is critical to sunk costs if soft drink producers cannot fully recover the expenses.

4.2.2 Investment for Upgrade in Production Capacity

The investment decision-making depends on expectations about uncertain future demand and profits. Sales of soft drink have been affected by seasonal change in Japan. For example, so far as statistical results of both 2013 and 2014 of Japan, monthly productive indicators of soft drinks are enhanced in summer, and lowered in winter (Food marketing research and information center 2015).

Then, there is a case study that the demand of soft drink in the summer can be often too high for production capacity. Producer has a plan to upgrade in the summer by means of investment for either plant (facility and equipment) modification or added temporary human resources. The former needs huge amount of investment at once and the latter needs small labor costs repeatedly. If the shortage of production capacity is prolonged for years, plant modification is superior to added temporary human resources. If the shortage is not prolonged enough to depreciate, the plant modification may be overinvested and the added temporary human resources are better for the uncertainty. This investment contains of not only upgrade but also evaluation of food sanitation.

As the design of plants has been predicted on a known and constant production rate over the life of the plant, plant capacity should be considered by anticipated growth in product demand (Coleman and York 1964), and uncertain of seasonal production (Coleman et al. 1964). As for capacity management of a plant, it is a prerequisite for achieving the optimal capacity in a production plant to provide opportunistic value based on current demand or on demand and supply forecasts using ROA (Rosqvist 2010). In an environment in which the underlying stochastic structure is itself subject to random change, events whose long run implications are uncertain can create an investment cycle by temporarily increasing the returns to waiting for information (Bernanke 1983).

4.2.3 SARIMA

The purpose of SARIMA is to identify and estimate the different components of a time series, and forecast future sales (Box et al. 2016). SARIMA model is widely used to deal with seasonal data for time series analysis and forecasting. In a seasonal time series$\{Z_t|\mathrm{t}=1{,}2,\dots,\mathrm{k}\}$, SARIMA has two types of variations: the first type is between consecutive observations, while the second type is between pairs of corresponding observations belonging to consecutive seasons. The first is ARIMA $(\mathrm{p},\mathrm{d},\mathrm{q})$ models which can be constructed to depict the relationship between consecutive non-seasonal observation values, whereas the second is ARIMA $(\mathrm{P},\mathrm{D},\mathrm{Q})\mathrm{s}$ models which can be formed to show the relationship between corresponding observation values of consecutive seasons. SARIMA$(\mathrm{p},\mathrm{d},\mathrm{q})(\mathrm{P},\mathrm{D},\mathrm{Q})\mathrm{s}$ can be depicted if:

$$\varphi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^{\mathrm{D}}Z_t=\theta_q(B)\Theta_Q(B^s)a_t \qquad (4-1)$$

where t is the number of observations, p,d,q,P,D,Q,B and s are integers, B and B^s are lag operator, s is the seasonal period length, d is the number of non-seasonal differences, D is the number of seasonal differences, and a_t is a white noise and the estimated residual at period t that is identically and simply distributed as a normal random variable with $\mu=0$ and σ^2 (Bouzerdoum et al. 2013).

$$\varphi_p(B)=1-\sum_{\mathrm{i}=1}^{p}\varphi_i B^i \qquad (4-2)$$

Equation 4-2 is the non-seasonal autoregressive (AR) operator of order p.

$$\Phi_P(B^s) = 1 - \sum_{\mathrm{i=1}}^{P} \Phi_P B^{s^i} \qquad (4-3)$$

Equation 4-3 is the seasonal AR (SAR) operator of order P.

$$\theta_q(B) = 1 - \sum_{\mathrm{i=1}}^{q} \theta_i B^i \qquad (4-4)$$

Equation 4-4 is the non-seasonal moving average (MA) operator of order q.

$$\Theta_Q(B^s) = 1 - \sum_{\mathrm{i=1}}^{Q} \Theta_i B^{s^i} \qquad (4-5)$$

Equation 4-5 is the seasonal MA (SMA) operator of order Q.

$(1-B)^d$ and $(1-B^s)^{\mathrm{D}}$ are the consecutive non-seasonal dth differencing and the seasonal Dth differencing at s number of lags, respectively.

One of contributions in this study is to combine seasonal change and ROA. As for ROA, it seems that SARIMA to be rarely used for forecasted future sales. The interval of ROA is targeted for over a few years and do not considered seasonal movement whereas the interval of SARIMA is basically targeted within a years; e.g. quarterly or monthly.

4.2.4 Evaluation of SARIMA

For fitting a SARIMA model to data, procedures should involves the four steps as is the same of ARIMA. Tracking signal method is also used and is one of the measurements using for evaluating a difference between actual demands and forecasted ones. The formulas for tracking signal can be depicted if: where n is the order of periods, $A_t$is the actual sales of the value being forecasted, and $T_t$is the forecasted sales.

$$\text{Tracking signal } = \frac{\sum_{t=1}^{n}(A_t - T_t)}{\sum_{t=1}^{n}|A_t - T_t|/n} \qquad (4-6)$$

Equation 4-6 is the formula of tracking signal and its denominator is called as mean absolute deviation (MAD). Tracking signal is used as a ratio of the cumulative sum of deviations between A_t and T_t to mean absolute deviation. The tracking signal is designed and developed for forecast control (Brown 1963; Trigg 1964). The forecasting error can be tracked with a tracking signal in order to identify any unexpected patterns as quickly as possible.

4.2.5 Three Option Types by Restriction for Exercise Timing

Main option type is divided into three by the restriction for exercise timing; European, American, and Bermudan options. Although explained in chapter 2, American and European options are reviewed briefly for the comparison with the new added Bermudan option. A European option is only exercised on maturity, and exercised nodes are at maturity nodes in binomial lattice. An American option is exercised one time at any time before or on maturity, and exercised nodes are all in binomial lattice. Though American options without dividends prior to its expiration date should not be exercised, the American with dividends shall be exercised (Merton 1973).

A Bermudan option is one of the exotic options, and is exercised at the frequency with same intervals. This frequency includes maturity date. Bermudan option can be exercised at chosen nodes in binomial lattice and not in any of intermediate nodes. Though the European and the American could be exercised at only one time, the Bermudan can be exercised more than two within decided frequency.

4.2.6 Research Questions

This chapter proposes optimal investment for seasonal high demand that integrates the uncertain, based on ROA and SARIMA model. Decision-maker can invest only when he sees that investment is valid by ROA. It means that decision-making is not conducted right now and can be delayed to get optimal conditions. The SARIMA model forecasts future values of a seasonal time series with a relationship between current and past (Box et al. 2016). The forecasting future values by SARIMA are meaningful for ROA.

Main goal is to decide on what and when is investment according to information from ROA. The existence of the managerial contribution can be examined, based on which the applicability and effectiveness of ROA can be assessed. The questions considered in the study are: (1) Conducting time series analysis for forecasting sales by SARIMA model; (2) Application of models of SARIMA combined with ROA to forecasting; (3) Identifying correlation type of ROA and decision-making; (4) Interpretation of the results within and out of ROA.

4.3 Problem Description

4.3.1 Soft Drink Plant

The demand of soft drink may not be satisfied in summer because the supply is frequestly too short to meet the expected demand. It becomes the excess capacity when a productive capacity is more than a demand of the summer. On the other hand, it cannot satisfy the demand in summer when productive capacity is based on a demand of another seasons. This is dilemma for the producer. There are alternative two methods to meet the demand in summer, one is to employ additional workers to elevate efficiency in summer and dismiss in winter, this attitude is repeated each year. The other is to replace equipment to elevate machine ability throughout the life years. The former is Bermudan options and the latter is American option. Of course, if periods are the multiple years, it is possible to combine them so that after employment of additional workers in first and second years, producer embarks on replacement of equipment in third year. That is, Bermudan options are exercised until American option is exercised.

4.3.2 ROA Combined Binominal Lattice Method with Monte-Carlo Simulation

ROA method has mainly three types; binominal lattice method, continuous method, and Monte-Carlo simulation method. The former two methods are analytical and the latter is simulated. Monte-Carlo simulation can get stochastic model with frequency at each value, but binominal lattice method can get only one analytical answer. So, we propose new method that combines the binomial lattice method and Monte-Carlo simulation. Monte-Carlo simulation repeatedly creates a lot of PV and the each PV is used to analyze option value by binomial lattice method based on four step process. One of our contributions is to analyze the binomial lattice method repeatedly and show the stochastic model.

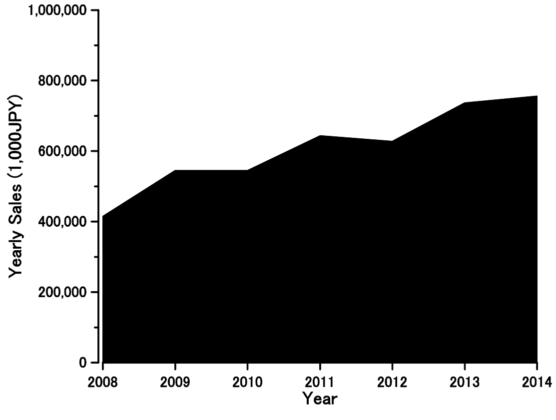
4.4 Step 1

4.4.1 Sales Analysis

Basically, ROA is based on four step processes for valuing real options. Some different points from original processes are to incorporate Monte-Carlo simulation into binominal lattice method, resulting in more practical decision-making.

The present year is end of 2014 and come to start 2015. Though sales are multiplied by volume and unit price, author assumed that the increase is only dependent of volume, not unit price. The sales of soft drink from 2008 to 2014 are shown in Figure 4-1 based on both yearly (a) and monthly (b) in the targeted plant. Yearly sales are gradually increased and monthly sales are also increased in perspective, whereas, monthly sales within year are cyclically moved with high and low sales in summer and winter, respectively. Volatilities for the monthly sales are calculated as $LN(sales\ in\ this\ period/sales\ in\ previous\ period)$, and averaged historical monthly volatilities are shown in Table 4-1.

(a) yearly sales



(b)monthly sales

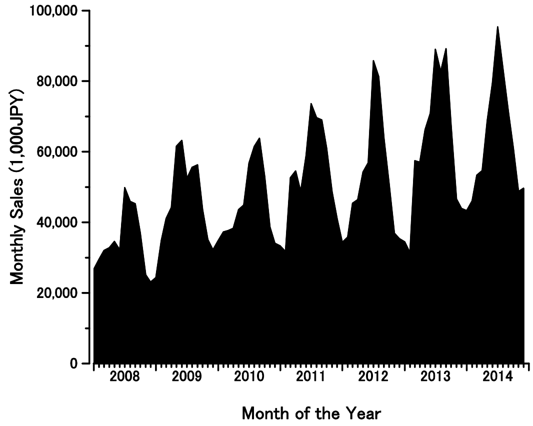


Fig. 4-1 Soft drink sales in targeted plant based on yearly (a) and monthly (b)

Mean value (%) ± S.D. of yearly and monthly volatilities are 8.59±11.43 and 0.73±15.50, respectively.

Table 4-1 Averaged historical monthly volatilities from 2008 to 2014

Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Volatility(%)	-1.8	7.1	25.0	2.7	13.4	6.2	19.5	-1.4	-4.2	-20.5	-29.3	-8.0

4.4.2 FCF

Future sales are forecasted by SARIMA model with monthly interval. The variable of SARIMA is adjusted, and the effect should be removed from the original series to allow for a correct analysis of the current sales conditions. The sales include products sales only. Suppose the only available historical data on sales are 84 monthly data equal to 7 years in Figure 4-1 (b). Using these historical data, author use Crystal Ball Predictor to choose the best fitting SARIMA model which is incorporated into Excel spreadsheet. The forecasted sales for 60 months are taken into FCF model.

The FCF is calculated by the Equation 3-1 in chapter 3. Author attempt that historical monthly FCF turn out to be forecasted yearly FCF based on each December.

Fluctuation for working capitals is not considered. The accounting items are detailed in Table 4-2.

Table 4-2 Accounting items and conditions

Items	Conditions
Sales	SARIMA model
EBIT	Entirely consistent with 32% of sales
Tax rate	Fixed at 40% of EBIT
Investment expenses	Investment expenses are paid at once in decision- making period at April of investment year.
Depreciation	If American option is exercised, additional depreciation is yielded within the year.
	If, however, Bermudan option is exercised, no additional depreciation is needed.

4.4.3 Investment Expenses

Investment expenses mean only option expense for both the American and Bermudan in this study. There are two scenarios for investment: facility and equipment for the American and Human resource for the Bermudan. Effect of both exercised investments is to increase sales in summer (from June to October). Relevant information for each scenario is given in Table 4-3. Timing of decision-making is in April, every year. Investment expenses are paid at the same time. Additional depreciation for the American is covered from May to December constantly, and finished within the year. Expense for the American is made up for depreciation in the future, but for the Bermudan is not. Both expenses may become sunk costs when sales are dull.

If investment is exercised, forecasted sales will be increased by 1.18 times of monthly sales 100,000 (1000JPY) with upper limitation. But duration of the effect of two options is different. Effect of the Bermudan on sales is limited within the summer of the year, so right for the Bermudan is once per year for five years. On the other hand, effect of the American is prolonged for each summer before arriving maturity.

Table 4-3 Two scenarios for investment

Scenario	Option type	Investment expenses （1,000 JPY）	Rate of multiplication （times）	Upper limitation of monthly sales (1,000 JPY / month)	Duration of option effect
Human resource	Bermudan options	10,000/year for 5 years	1.18	100,000	Within year
Facility and equipment	American option	50,000	1.18	100,000	Before maturity

4.4.4 Forecasting Standard NPV and Expanded NPV

Forecasting standard NPV without investment and expanded NPV (ENPV) when investment occurs is depicted in following Equation 4-1 and 4-2, respectively.

$$\mathrm{NPV}_j = \sum_{t=1}^{T} \left(\frac{V_{tj}}{(1 + WACC)^{t/12}} \right) \qquad (4-7)$$

$$\mathrm{ENPV}_{cj} = \sum_{t=1}^{T} \left(\frac{eVc_{tj}}{(1 + WACC)^{t/12}} - \frac{\mathrm{Xc}_{\mathrm{k}j}}{\left(1 + r_f\right)^{t/12}} \right) \qquad (4-8)$$

where, V_t is monthly FCF_t at t period. j means j^{th} simulation number, $(1 + WAAC)^{t/12}$ is a factor for V_t to convert from future value at period t to present value V_0, $\left(1 + r_f\right)^{t/12}$ is a factor for Xc_t to convert from future value at period t as month to present value, $WACC$ is yearly 1.86% derived from other companies in the same business and CAPM theory (Brealey and Myers 2003, Copeland and Antikarov 2003), r_f is risk free rate as yearly 0.10%, T is maturity of 60 periods (5 years). $\mathrm{e}Vc_t$ and Xc_k are asset value as monthly FCF_t with options, and investment expenses in scenario c at April of k^{th} year, respectively. The "c" is alternative "a" or "b" for American option or Bermudan options, respectively.

Using Monte-Carlo simulation, author can get Expected value for NPV (E[NPV]) and ENPV(E[ENPV]) as:

$$\mathrm{E[NPV]} \approx \frac{1}{J} \sum_{j=1}^{J} NPV_j \qquad (4-9)$$

$$E[\text{ENPV}] \approx \frac{1}{J}\sum_{j=1}^{J} ENPV_{cj} \qquad (4-10)$$

Where, J is 10,000 as total simulation number.

4.5 Step 2

4.5.1 Volatility

The uncertainty is expressed as volatility (σ) which is calculated by logarithmic returns as averaged $LN(FCF\ in\ this\ year/FCF\ in\ previous\ year)$.

In this study, the volatility for 5 years is calculated each simulation and results of all the volatility are shown as stochastic model.

4.5.2 Event Tree

The second step is to build an event tree as a binominal lattice using the results from the DCF and simulation analyses into the real options paradigm. The resulting PV of future FCF now becomes the starting asset value in ROA. Binominal lattice is recombining because FCFs generated at the end of each year are constant proportion of the value at the end of the year. It is assumed that in each step of the tree the PV of future FCF can develop either to a higher or to a lower value.

The up (u) and down (d) factors jump in the lattice are annual and the length of time between nodes is 1 year. The factors of u and d are calculated as using Equation 2-20 and 2-21, respectively.

4.6 Step 3

4.6.1 Decision Tree

The third step is to consider a decision that food producer must either invest now or defer until the end of optimal period. Once made, the investment is irreversible. So, food producer expects decision tree is positive with regardless of degree and timing of investment. Decision tree can be generated based on the asset values in previous event tree. A value at t in decision tree for scenario "c" is described by $f_{c(t)}$. First, for American option, the values at final nodes of the decision tree are calculated. These nodes are calculated as follows;

$$f_{a(t)} = \begin{cases} max\left(ENPV_{aj},\ NPV_j\right) & t = T \\ max\left(ENPV_{aj}, \dfrac{\left(p \cdot f_{au(t+1)} + (1-p) \cdot f_{ad(t+1)}\right)}{1 + r_f}\right) & 1 \le t < T-1 \end{cases} \qquad (4-11)$$

where, $f_{a(t)}$ is value in decision tree for American option, $f_{au(t+1)}$ is the value if $f_{a(t)}$ steps to up forward with u at $t+1$ period, and $f_{ad(t+1)}$ is the value if $f_{a(t)}$ steps to downward with d.

In the stream of backward induction, $f_{au(t+1)}$ and $f_{ad(t+1)}$ are the values from previous node. The investment at final nodes is only exercised if the $ENPV_{aj}$ is higher than NPV_j. This is a first step to exercise options. If not, investment is not exercised. Second, the value before final nodes are calculated stepwise backwards starting from second last node and ending at the first of all node. Before final node, this procedure is carried on until the first node is reached. Then, present value $f_{a(0)}$ is obtained. In this study, American option is applied to Equation 4-11 without any limitation.

As for Bermudan options, basic method for calculation is same as the American. But exercise opportunity of Bermudan options is repeated and exercised once per a year. The Bermudan options are simple each other, and exercised like European options having five different maturities. Each improvement opportunity is calculated as follows;

$$f_{bk(t)} = \begin{cases} max\left(ENPV_{bkj},\ NPV_j\right) & t = \dfrac{T}{M} \\ \dfrac{\left(p \cdot f_{bku(t+1)} + (1-p) \cdot f_{bkd(t+1)}\right)}{1 + r_f} & 1 \leq t \neq \dfrac{T}{M} \end{cases} \qquad (4-12)$$

where, $f_{bk(t)}$ is value in decision tree for Bermudan option on k^{th} year $(k = 1,2,3,4,5)$, M is multiplied times prior to its expiration date. As maturity is five years and exercise opportunity is once per a year, T and M are k and one, respectively. Total improvement is calculated as follows;

$$f_{b(0)} = \sum_{k=1}^{5} f_{bk(0)} \qquad (4-13)$$

where, $f_{b(0)}$ is total present value in decision tree for all of five Bermudan options.

4.7 Step 4

4.7.1 Valuation to the American or Bermudan Options

The fourth and final step is to calculate payoff by subtracting $f_{c(0)}$ of decision tree from V_0 asset value of event tree. If $f_{c(0)}$ is bigger than V_0, the payoff turns to option value.

$$\text{Option Value}_c(\text{JPY}) = \max\left(f_{c(0)} - V_0, 0\right) \qquad (4-14)$$

As PV, volatility, up factor, down factor and risk-neutral probability in this study are changed by each simulation, the option value is evaluated by improvement calculated as following;

$$\text{Improvement}_c(\%) = \frac{Option\ Value_c}{PV} \times 100 \qquad (4-15)$$

After determining multiplicative factors and risk-neutral probability, option value can be obtained through a binominal lattice.

4.7.2 Valuation to the American and Bermudan Options

Next is the test for effect of combination of simultaneous options between American and Bermudan options. It is assumed that American and Bermudan are simultaneous, and until exercising American option, soft drink producer has a right to exercise Bermudan options every year. All of possible types is shown in Table 4-4. The option value of simultaneous options by adding the effect of simple the American and the Bermudans is calculated as;

$$\text{Option Value}_{\text{ab}}(\text{JPY}) = \max\left(f_{a(0)} - V_0 + f_{b(0)} - V_0, 0\right) \qquad (4-16)$$

The option value of simultaneous options is evaluated by improvement calculated as following;

$$\text{Improvement}_{ab}(\%) = \frac{Option\,Value_{ab}}{PV} \times 100 \qquad (4-17)$$

The goal of this study is to identify scenario allowing the best adaption to an uncertain demand.

Table 4-4 Combination of simultaneous options between American and Bermudan options

Type	1st year	2nd year	3rd year	4th year	5th year
B0A5	American	None	None	None	None
B1A4	Bermudan	American	None	None	None
B2A3	Bermudan	Bermudan	American	None	None
B3A4	Bermudan	Bermudan	Bermudan	American	None
B4A1	Bermudan	Bermudan	Bermudan	Bermudan	American
B5A0	Bermudan	Bermudan	Bermudan	Bermudan	Bermudan

4.7.3 Valuation to Finite Annuity

In the following sections, even after the time range of ROA, comparison between simple American and Bermudan options is tested. Note that usual ROA does not contain this procedure of ROA, but this study tries to face this original further extended challenge.

For five years using finite annuity method (Luenberger 2009), there are two values; one is for the Bermudan, the other is for American. It is assumed that sales are repeated from sixth to tenth year in the same constant sales condition of fifth year without any option. American option can be exercised and depreciated at sixth year as maturity. After seventh year, the American cannot exercise. The Bermudan pay investment expenses every year if invest, though the American cannot pay furthermore. For the sake of brief calculation, finite annuity method for seventh to tenth year is used and calculated based on December ($\mathrm{t} = 72$) of sixth year.

Finite improvements for American option and Bermudan options are calculated as follows;

$$\text{Improvement}_{Fa}(\%) = \frac{f_{Fa(t)}}{f_{F(t)}} \times 100 = \left(\frac{f_{a(6)} + \frac{f_{a(7)}}{WACC} \cdot \frac{1}{1+WACC}}{f_{(6)} + \frac{f_{(7)}}{WACC} \cdot \frac{1}{1+WACC}} \right) \times 100 \qquad (4-18)$$

$$\text{Improvement}_{Fb}(\%) = \frac{f_{Fb(t)}}{f_{F(t)}} \times 100 = \left(\frac{f_{b(6)} + \frac{f_{b(7)}}{WACC} \cdot \frac{1}{1+WACC}}{f_{(6)} + \frac{f_{(7)}}{WACC} \cdot \frac{1}{1+WACC}} \right) \times 100 \qquad (4-19)$$

Where, $f_{Fa(t)}, f_{Fb(t)}$ and $f_{F(t)}$ are finite value for the American, the Bermudan, and base case respectively. $f_{(6)}$ and $f_{(7)}$ are annual base case value at sixth and seventh. To get accuracy, 10,000 simulations are conducted (J =10,000).

$$\mathrm{E}\left[\frac{f_{Fa(t)}}{f_{F(t)}} \times 100\right] \approx \frac{1}{J}\sum_{j=1}^{J}\left(\frac{f_{Fa(t)j}}{f_{F(t)j}}\right) \times 100 \qquad (4-20)$$

$$E\left[\frac{f_{Fb(t)}}{f_{F(t)}} \times 100\right] \approx \frac{1}{J}\sum_{j=1}^{J}\left(\frac{f_{Fb(t)}}{f_{F(t)}}\right) \times 100 \qquad (4-21)$$

4.8 Results

4.8.1 Forecasted Sales

The graph shown in Figure 4-2 illustrates in the gallery of monthly time-series, vertical and horizontal axis are expressed as sales based on unit 1,000 JPY and month of the years, respectively. These monthly point forecasts are based on SARIMA (2, 1, 2) (1, 0, 1)$_{12}$ model as the best fitting line in the gallery of time-series approaches. The historical data and model fitted data until December of 2014 show as dotted line and solid line, respectively. The forecasts indicate three lines: mean value (dark solid line), upper 95% confidence interval (upper dotted line) and lower 5% confidence interval (lower dotted line). Sales have a tendency to be cyclic movements with the highest and the lowest in summer and winter of each year, respectively. The difference between the highest and the lowest in same year is biggest in 2015 and gradually decreases. This tendency will continue after 5 years by forecasting data.

It is assumed that forecasted monthly sales after 2020 are always same as the results of 2019. SARIMA (2, 1, 2) (1, 0, 1)$_{12}$ model statistics shown in Table 4-5, get confident and lowest value 17.84 for AIC. Value of Theil's U is 0.7589; this figure shows forecasted model is same as supposed one. The Value of Durbin-Watson is 2.13, which is close to 2, and means that there is no over- and under- moving average. SARIMA (2, 1, 2) (1, 0, 1)$_{12}$ model coefficients are also depicted in Table 4-6. As the coefficient of variables has small standard error, this model has good harmony with seasonality. Averaged forecasted monthly volatilities from 2015 to 2019 are shown in Table 4-7. It is reasonable to assume that the sales have a stochastic process with a certain amount of volatility and drift.

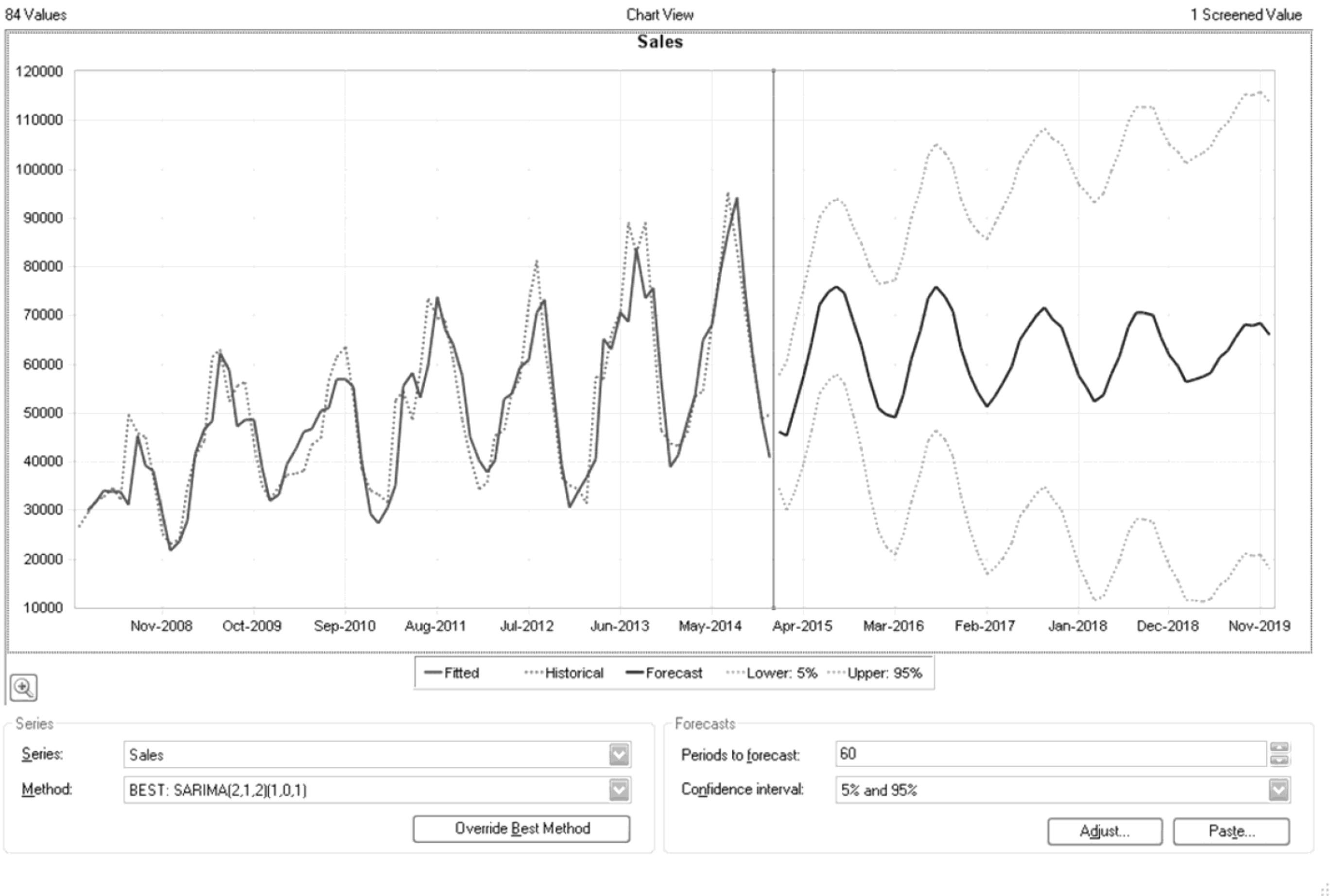


Fig.4-2 Monthly sales results from historical and forecasted data

Table 4-5 SARIMA (2, 1, 2) $(1, 0, 1)_{12}$ model statistics

Items	Figures
Transformation Lambda	1.00
BIC	18.02
AIC	17.84
AICc	17.86
Theil's U	0.7589
Durbin-Watson	2.13

Table 4-6 SARIMA (2, 1, 2) $(1, 0, 1)_{12}$ model coefficients

Variables	Coefficient	Standard Error
$\varphi_1(B)$	1.7200	0.0290
$\varphi_2(B)$	-0.9653	0.0285
$\theta_1(B)$	1.8400	0.0306
$\theta_2(B)$	-0.9549	0.0335
$\Phi_1(B^s)$	-0.9999	0.0582
$\Theta_1(B^s)$	-0.9729	0.0909

Table 4-7 Averaged forecasted monthly volatilities from 2015 to 2019

Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Volatility(%)	-7.6	-4.0	2.2	5.8	7.7	8.2	5.7	3.4	0.4	-3.4	-5.3	-7.3

Furthermore, to validate the forecasting models, the forecasts in 2015 are compared with actual data. The performance of forecasting models can be validated by tracking signal at each period ranged from 1 to 12. The tracking signal is also shown in Figure 4. As the relation of 1 standard deviation =approximately 1.25 MAD is known, control limits are set at plus or minus 4 MAD to meet 95 percent of standard deviation (Ravi Mahendra 2009). It seems that the result of tracking signal is well within the control limits.

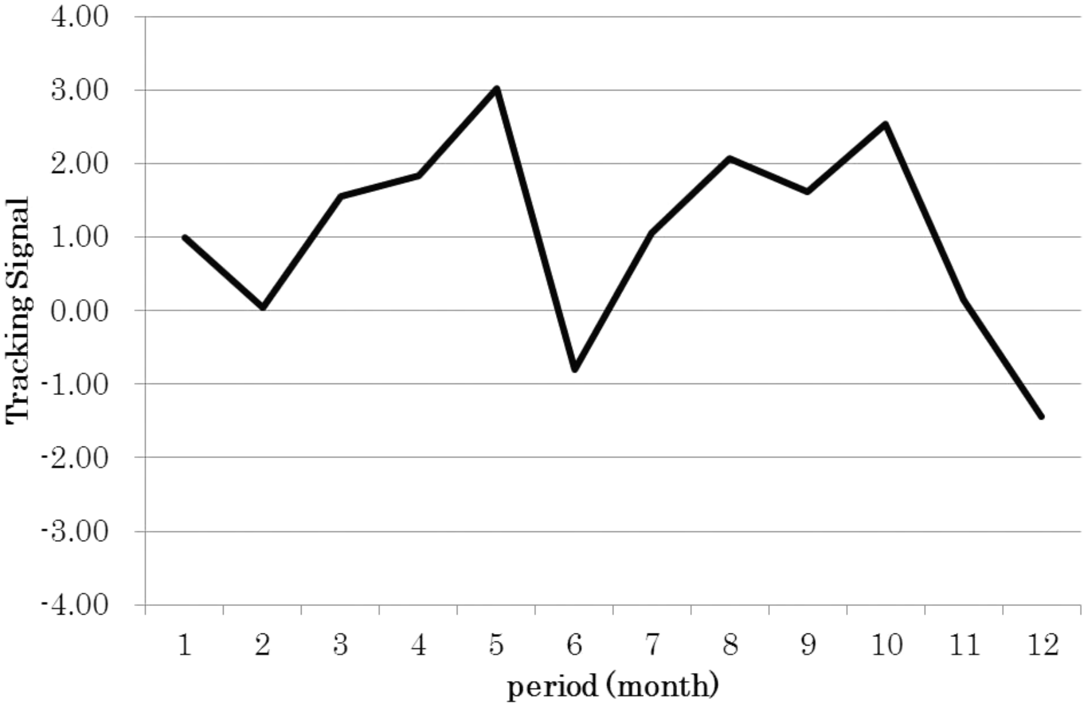


Fig.4-3 Tracking signal

The SARIMA (2, 1, 2) $(1, 0, 1)_{12}$ model which is using Equation 4-1 is expanded as following;

$$(1-\varphi_1 B^1-\varphi_2 B^2)(1-\Phi_1 B^{12})(1-B)\mathrm{Y}_t=(1-\theta_1 B^1-\theta_2 B^2)(1-\Theta_1 B^{12})a_t \qquad (4-16)$$

The coefficients of variables shown in Table 4-6 were inserted into Equation 4-16.

$$(1-1.7200B^1+0.9653B^2)(1+0.9999B^{12})(1-B)\mathrm{Y}_t$$
$$=(1-1.8400B^1+0.9549B^2)(1+0.9729B^{12})a_t \qquad (4-17)$$

Thus, Equation 4-17 is solved for Y_t as follows:

$$\mathrm{Y}_t=\frac{(1-1.8400B^1+0.9549B^2)(1+0.9729B^{12})}{(1-1.7200B^1+0.9653B^2)(1+0.9999B^{12})}\times\frac{a_t}{(1-B)} \qquad (4-18)$$

4.8.2 PV

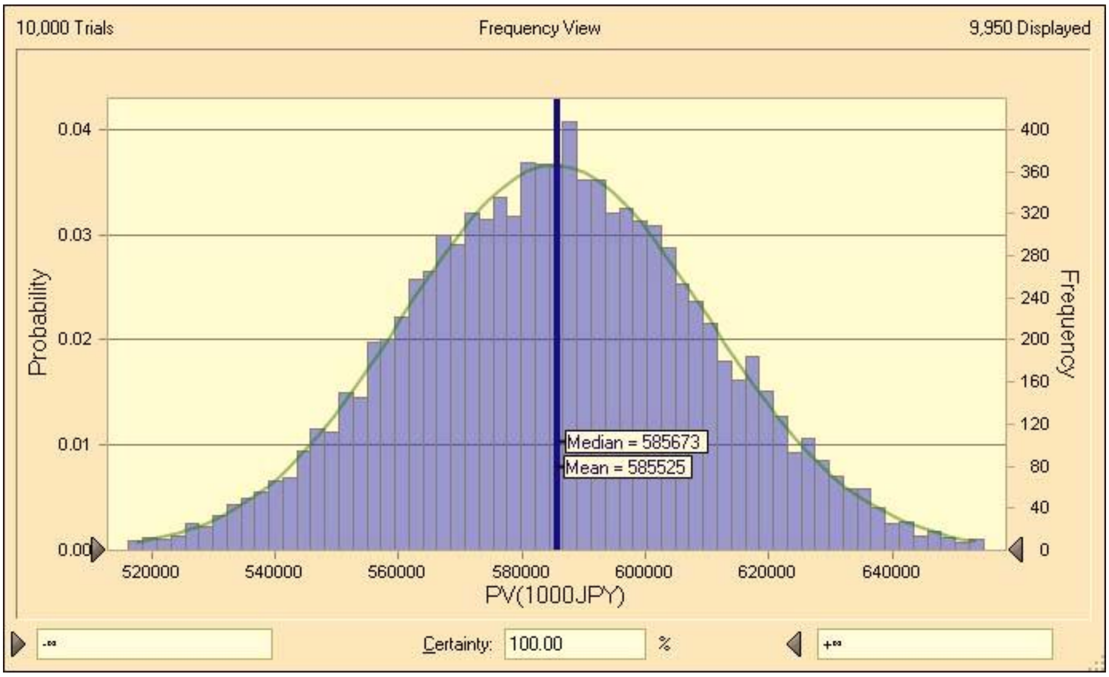


Fig.4-4 Probability distribution of PV for NPV

Figure 4-4 shows results of probability distribution of PV with expected mean value of 585 million JPY and median value of 585 million JPY. Although the behaviors of PV are like normal distribution orbit, goodness of fit shows best relation with lognormal distribution, having Anderson-Darling test of 0.1983 and P-value of 0.823, respectively. The parameters of this distribution are estimated as location of -2,509,428 and standard deviation of 24,728.

4.8.3 Volatility

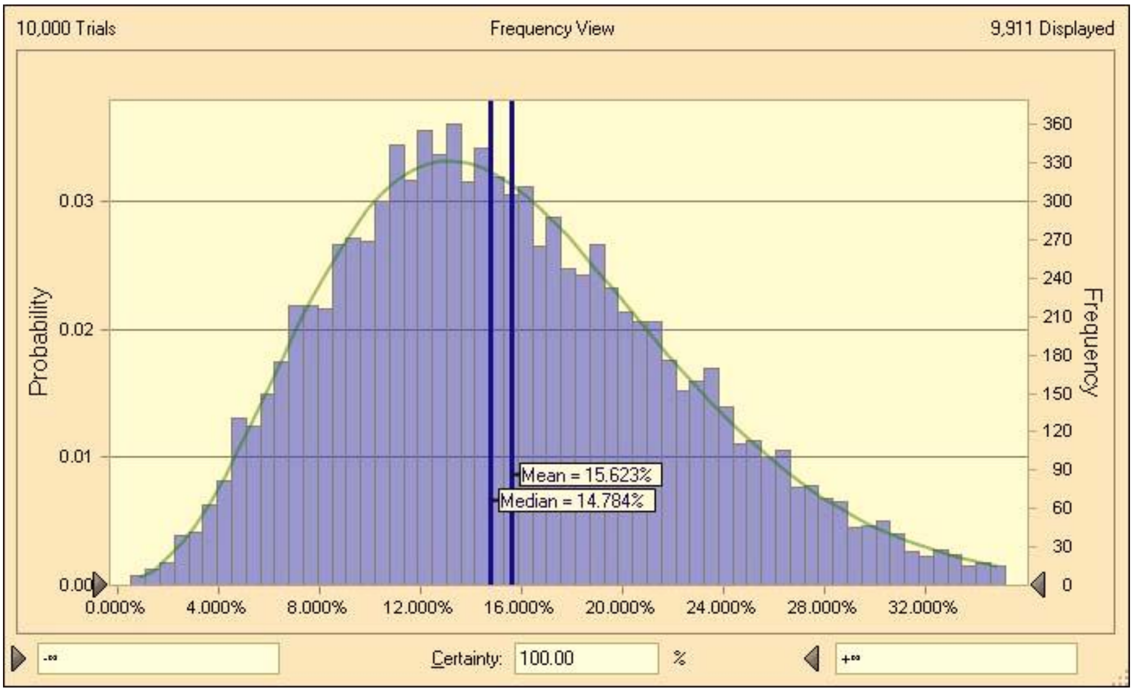


Fig.4-5 Probability distribution of volatility

Volatility σ is changed by each simulation, and the result of probability distribution of σ is shown in Figure 4-5. Two thick solid lines represent the results of mean and median value as 15.623% and 14.784%, respectively. The goodness of fit in this distribution shows best relation with beta distribution with alpha of 4.67549 and beta of 21.26313. The value of σ is ranged from 0.569% to 35.106%. As σ moves, values of u, d, p and q are also calculated at each simulation. Then, the σ is positively correlated with the option value. The probability distribution of σ should be used as a tool for decision-making to assess whether there exists any flexibility in sales.

4.8.4 Improvements of American and/or Bermudan Options

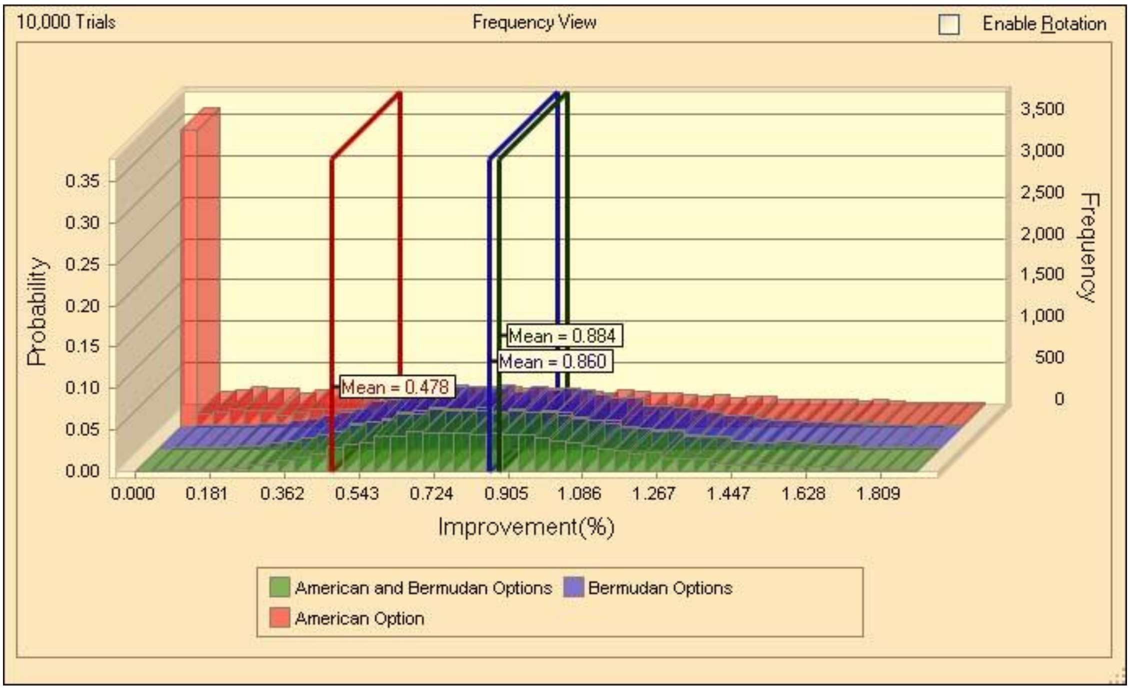


Fig.4-6 Probability distribution of American and/or Bermudan options by ROA

Figure 4-6 indicates the improvement effects with comparisons in American and Bermudan options, and simultaneous options. The result shows that mean value of the Bermudan (0.860%) has an advantage to that of the American (0.478%). It is seen that about 35% of simulations American option cannot exercise and only the residue can do. But, the highest improvement is gained if the two options are simultaneous; choosing both American and Bermudan options. By using simultaneous options, lower risk is averted and higher opportunity is gained.

4.8.5 Timing for Exercising American Option in Simultaneous options

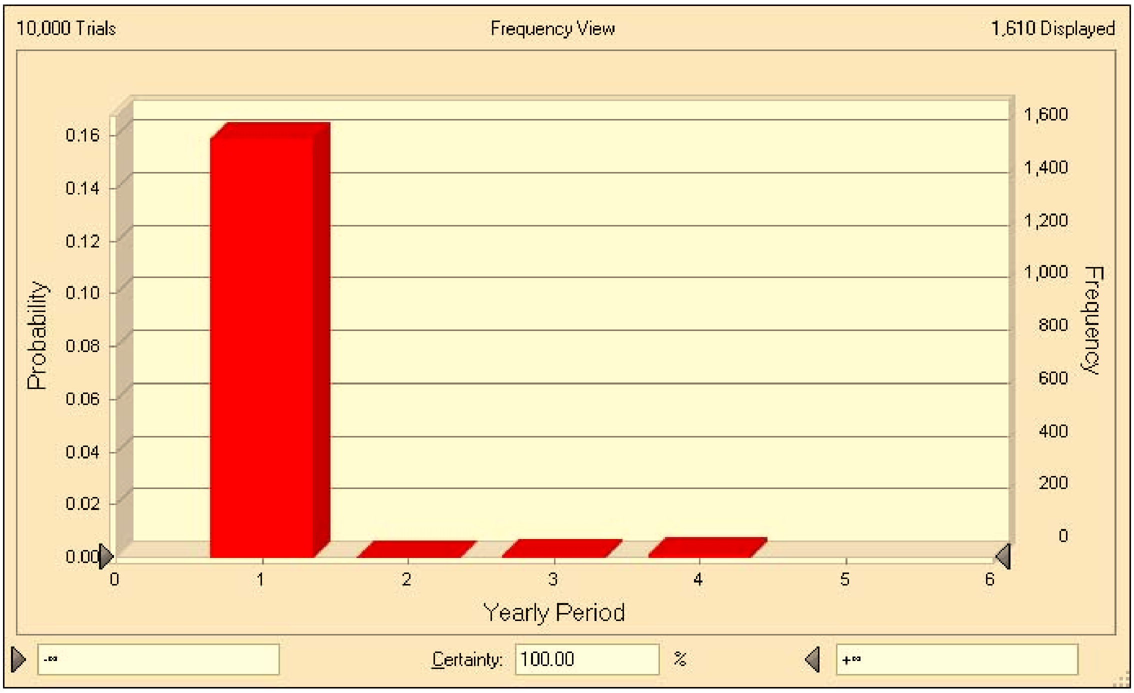


Fig.4-7 Timing for exercising American option in simultaneous options

Figure 4-7 shows timing for exercising American option in simultaneous options. The result shows that only 1,692 of 10,000 times can exercise American option on the basis of choosing the most profitable decision-making. High opportunity for the American exists in first yearly period, following very low opportunities in second, third and fourth periods and no opportunity in fifth period. If no American exercise in first period, the results imply that the Bermudan can exercise for the rest of periods.

4.8.6 Improvements by Finite Annuity

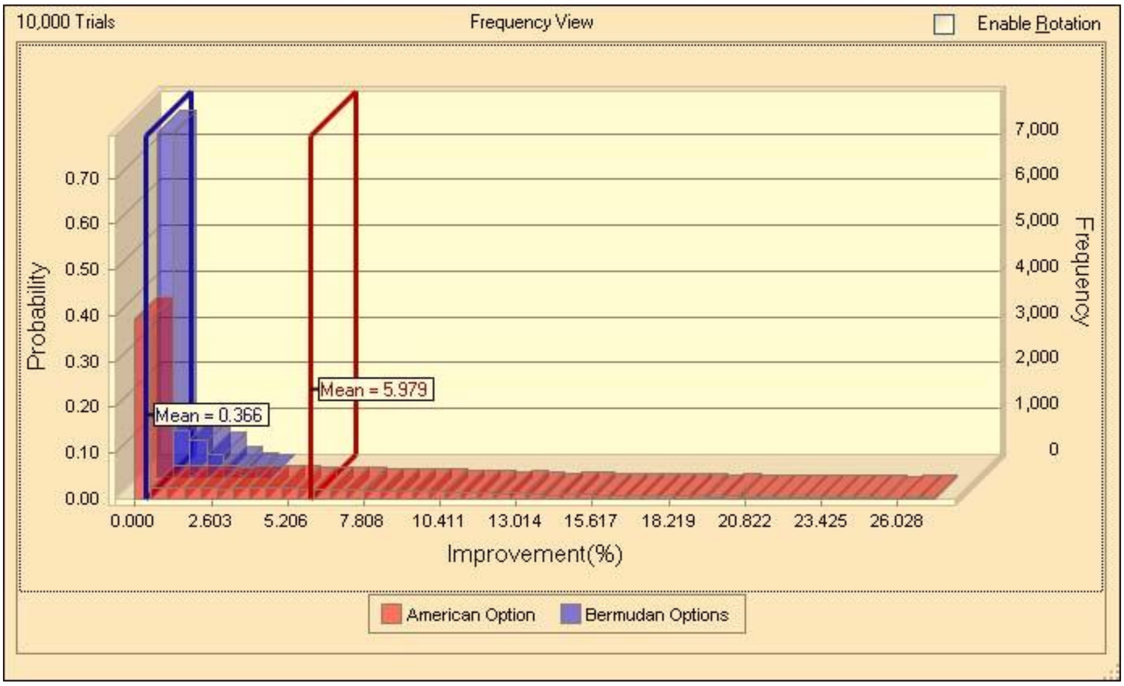


Fig.4-8 Probability distribution of simple American and Bermudan options by finite annuity

Figure 4-8 shows probability distribution of simple American and Bermudan options by finite annuity. In opposite to prior results shown in Figure 8, it is higher mean improvement for the American with 5.979% than the Bermudan with 0.366%. If American option is exercised, effect of investment is to be effective until maturity. The depreciation and upgrade by the American will yield in favor of FCF. If, on the other hand, Bermudan option is exercised each year, upgrade by the Bermudan will increase sales as the American without depreciation. If sales are constant and the uncertain is cleared, it is possible to aim upside opportunity and avoid downside risk.

4.9 Conclusion

If the investment for upgrade leads to food sanitation, it is easy to recover the investment expenses. However, this irreversible investment is critical to sunk costs if future sales are uncertain.

Decision-maker can decide on what and when is investment according to information from ROA. Each simulation can show the stochastic condition according to the forecasted sales. As statistical information based on 10,000 simulations, most of all use the Bermudan for five years, and 16% of the case can exercise the American. It means that producer would tend to invest in added temporary human resources rather than plant modification. If, however, sales are constant and the uncertain is cleared after the duration of ROA, producer would tend to invest in plant modification rather than added temporary human resources. Even if choosing the human resources by ROA, the producer should not repeatedly choose the Bermudan for infinity without ROA. ROA keeps the evaluation period constant, and it is 60 periods (5 years) in this SARIMA model. Any extension beyond this will reduce the forecasting accuracy. If decision-maker is assuming going-concern even after the maturity, it is better to consider the possibilities after that as well.

A temporary decision cannot be unreasonably continued and should be reviewed in the long-term forecasting. The producer knows that the plant modification has a potentially advantage than just added temporary human resources in the long term. But, in practice, there is an uncertain about sales. It is wise for the producer to forecast the sales, have the simultaneous American and Bermudan options, and seek for the opportunity for the American. ROA can help the producer make his right decision.

There is little possibility of perfectly fitting the forecast based on SARIMA to reality in sales. Future researches are to elevate capability of ROA decision-making based on more accurate sales forecasting combining another time series analysis.

Chapter 5 Signal Prior to Optimal Investment Timing

5.1 Abstract

The decision-making for investment is usually subject to time lags before factual investment can be completed. This matter may affect the effective expiry date of the decision-making. If manager makes a decision like ROA without a confidence in consideration to the time lag, it might be uncertain to invest successfully or not. If, oppositely, decision-maker waits to make a decision until ROA can tell the optimal timing, it may be too late to invest because of time lag for preparation. In this perspective, the aim of this chapter is to propose a model for more optimal and dynamic decision-making for investment and long term valuation of ROA in the presence of uncertain demand.

Under the independent American call option based on SARIMA model forecasting, signal of monthly sales prior to the optimal investment timing is evaluated. The correlation coefficient of improvement based on between signal and real option valuation (ROV), which is the third process of four steps process, in this chapter shows good value when the signal is within ranged from 10 million to 40 million JPY in the threshold of monthly sales, and in the targeted month from January to April. Then it may be possible to provide robust signal in decision-making for exercising the option. The remaining problem is that the improvement based on signal is relatively lower with compared to that based on ROA.

5.2 Introduction

5.2.1 Time Lags between Decision-making and Investment

Investment complement naturally takes some time after its decision-making. Many companies face ordinal delays, which need to be taken into account when the companies make decisions under uncertainty (Bayraktar and Egami 2007). For the supply chain operations, the decision-making for investment is usually subject to time lags before investment can be completed (Nembhard et al. 2005). This matter affects the expiry date of the decision-making. If manager makes a decision like ROA without a confidence in consideration to the time lag, it might be uncertain to invest successfully or not. If, oppositely, decision-maker waits to make a decision until ROA tells the optimal timing, it may be too late to invest because of time lag from decision-making to exercising for preparation. The opportunity cost of time lag is the foregone FCF from the project, which depends on the lost sales during the delay. The decision-making at ROA involves the optimal exercising timing under uncertainty, but usually does not consider the delay. In many cases, ROA assumes that investment effect comes out at the same time as decision-making. However, in reality there is a time lag as mentioned above. Therefore, we need signal as the estimated correlation coefficients by assuming time gap.

5.2.2 Needs for Signal

Static signals may not work during persistent periods, and dynamic signals have been necessary in ROA. If signal based on valuation by ROV shows higher correlation with option value, it is possible to provide robust signal in decision-making for exercising options.

It is discussed about the rational signal for decision-making prior to the optimal investment timing and their criteria. Although, with few exceptions, models of irreversible investment assume that a project is brought immediately after the decision to invest is made, the effects of investment lags has been studied in the simple possible model of an uncertain, and irreversible investment (Bar-Ilan and Strange 1996). As to ROA, the optimal stopping with exponentially distributed exercise-lag was studied using one-dimensional diffusion dynamics (Lempa 2012). The valuation and rational exercise of irreversible investment opportunities in the presence of sales uncertainty and delivery lag have demonstrated and found that typically increased uncertainty decreases the investment incentives by increasing the value of waiting (Alvarez and Keppo 2002).

5.2.3 Financial Factors

Experimental methods have often been used to study the condition of stock prices. These methods still be discussed when investment is considered and have a possibility to apply to ROA. Arbitrage pricing theory explains that expected return of financial asset can be modeled as a function of various economic factors, but doesn't state what these factors should be (Ross 1976; Luenberger 2009). There are three main categories of the factors: macroeconomic, statistical, and fundamental (Connor 1995). The capital asset pricing model (CAPM) is used to examine systematic risk which arises from exposure to the market and is captured by beta, shows the sensitivity of return to the market (Luenberger 2009). One of the key signals of investment is cyclicality. While CAPM has showed the risk adjusted returns over the long period, the market exhibits cyclic movement over the short period. Some investments require long term perspectives, but also include short term perspective. Investors with short term sight would not be able to benefit from long term stance such as full range of cyclic movement.

In financial theory, long term equity portfolio performance can be explained by stock prices because of risk premium and systematic risk. The risk premium is identified by six equity factors; value, low size, low volatility, dividend yield, quality and momentum (Bender et al. 2013). The factor of value captures excess returns to stocks that have low prices relative to their fundamental value. Value-related variables might be dominant factor of value and explain violations of the CAPM. An example is presented as alpha that is one of the variables and measures of the active return on an investment. The factor of low size captures excess returns of smaller companies relative to their larger counterparts. The factor of low volatility captures excess returns to stocks with lower than average volatility, beta, and/or idiosyncratic risk. The factor clearly contradicts the assumptions of the CAPM. It means that investors often overpay for volatility and underpay for low volatility due to unreasonable preference for the stocks. The factor of dividend yield that captures excess returns to stocks has higher-than-average dividend yields. The factor of quality that captures excess returns to stocks is characterized by low debt, stable earnings growth, and other “quality” metrics. These might trigger a positive feedback loop making the companies more competitive in the eyes of their customers and investors. The factor of momentum reflects excess returns to stocks with stronger past performance. Although these factors are thought to be effective, there are very little literatures on why the factors work. Further studies are necessary to fill up the matter of extensive discussions and to apply the factors to decision-making. Therefore, it is difficult to apply these financial factors to ROA as they are.

5.2.4 ROA Factors

A candidate factor is correlation which is one of the important factors to measure the consistency. This factor is used to find signal value to apply the ROA. The correlation is seen by Least-Squares liner regression, and time series modeling such as SARIMA.

In stochastic control problem, a feedback control policy is used for energy system’s flexible generation assets, and shows a map which takes as input the current system state and whose output is an operational state to be applied (Kitapbayev et. al 2015). The map at any given point in time takes the form of a scatter plot with the number of price paths sampled. In order to estimate the numerical error introduced by backward simulation, the same set of simulation are used in a forward simulation.

In robust design, signal-to-noise ratio, which is the ratio of the signal over the noise, is used to measure robustness (Wang et.al 2015). When the signal-to-noise ratio is large, the performance is more robust. The purpose of robust design is to use an experimental approach in order to choose the combination of parameter values that maximizes the signal-to-noise ratio.

A firm’s entry and exit decisions when the output price follows a random walk are resolved by a pair of trigger prices for entry and exit (Dixit 1989). It is found that the exit price 13 percent below the variable cost and the entry price 15 percent above the full cost. The entry trigger exceeds the variable cost plus the interest on the entry cost, and the exit trigger is less than the variable cost minus the interest on the exit cost.

5.2.5 Research Questions

The aim of this chapter is to propose a signal for the optimal and dynamic decision-making for investment and long term valuation of correlation between the signal and ROV in the presence of uncertain demand using the model in the previous chapter. With reference to beta in CAPM theory, the sensitivity of signal to ROV might be used to confirm unique risk which arises from exposure to the cyclical demand.

This chapter is organized as follows: the following section provides a problem description: the proposed ROV based signal framework is developed in section “Problem Description”; Results of an experimental study of signal are illustrated in section “Results” and experimental results and managerial implications are also discussed as well; Section “Conclusions” concludes this chapter.

5.3 Problem Description

5.3.1 Time Lag Problem

The aim of forecasting in this study is to analyze the sales in the future by determining the relationship among historical data. The SARIMA model shown in Equation 4-18 could not forecast the sales of the current month until it knows the previous sales. Suppose the situation that it is necessary to make decisions at least before one month, considering the preparation period for options exercising. In order to obtain the effect of options at the beginning of June, decision-making is finished at the end of April and the preparation period is set up. To forecast sales in June, it is necessary for SARIMA model shown in Equation 4-18 to get sales in May just before one month of June. However, it is late to know the sales at the end of May considering the preparation period. It is necessary to find good conditions that can correlate the sales of June with the sales of the month before that. Since white noise can overlap as time gets away, the uncertainty of correlation might increase. If the good conditions are found how much and when sales are required, it is a candidate to be a signal of investment.

The value of signal lies in its ability to effectively relate with ROA through time. In the presence of SARIMA model and needs for prepared period of investment, the value creates an opportunity to gain the optimal option value by ROA, and in particular due to uncertain demand. Details of the problem and the model developed are provided in Figure 5-1 below.

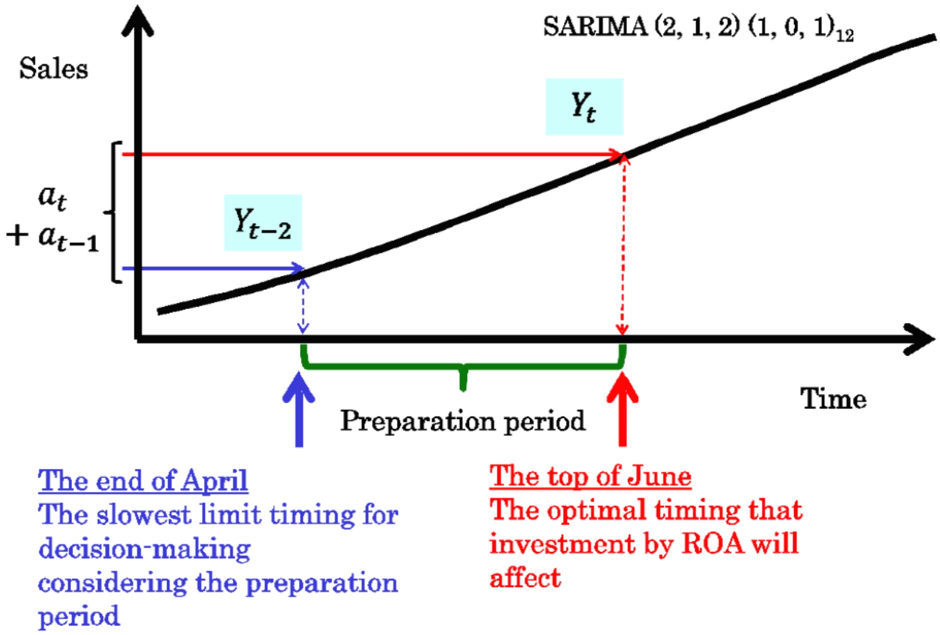


Fig. 5-1 Signal and investment model

5.3.2 Signal for ROA

In previous chapter 4, model for sales is forecasted as SARIMA (2, 1, 2) (1, 0, 1)$_{12}$ model in Equation 4-18 and each coefficients of variables are determined. After that, Y_t is calculated by Equation 4-18. The value of coefficients for 1 period is very close between p and q, the order of p and q is the same as second. For 12 periods as seasonality, the value of coefficients is very close between P and Q, the order of P and Q is the same as first. Therefore, when Equation 4-18 is assumed that the fraction of the first term on the right side is 1, following Equation 5-1 can be obtained.

$$Y_t = \frac{a_t}{(1-B)} \qquad (5-1)$$

Replacing $Y_t B$ with Y_{t-1} and solving for Y_t, Equation 5 - 1 turns to Equation 5 – 2.

$$Y_t \approx Y_{t-1} + a_t \qquad (5-2)$$

In this Equation, Y_t depends on Y_{t-1}, added to a constant white noise a_t like a random walk model. Furthermore, Equation 5-3 is obtained by substituting Y_{t-2} for Y_{t-1}.

$$Y_t \approx Y_{t-2} + a_t + a_{t-1} \qquad (5-3)$$

Since a_t and a_{t-1} are white noise with mean of zero and constant variance, Y_t in June may be larger than Y_{t-2}. This is robust procedure based on high precision of the SARIMA model. And there is also a high possibility that Y_t in June becomes larger than Y_{t-2} because of the model of the SARIMA with higher value in summer. It is natural for Y_{t-3} and Y_{t-4} to repeat the replacement to forecast Y_t. A key element is cyclicality movement in the SARIMA model. The monthly fluctuations in sales used in this study are shown in Figure 5-1. The forecasted sales profile, based on monthly intervals, are generated through the SARIMA (2, 1, 2) (1, 0, 1)$_{12}$ model. This model has a tendency to be higher value in summer and lower value in winter. Sales fluctuations may be an indication of the potential value given by the exercise of options to increase sales. Especially when their rising from spring to summer, it is considered to be true.

5.3.3 Robustness of Signal

The purpose of robust signal is to tell the time point of investment decision before the optimal timing by ROA in order to make an enough preparation of investment completion. The signal is applied to evaluate and select the decision-making with less sensitivity sources of uncertain demand. The basic model of robust signal is outlined below. In the signal model, a number of variables can affect the performance of sales and they can be classified into the decision variables and the non-decision variables. Decision variables are to be varied in a controlled way during the simulations, and include targeted performance levels that are expected to be achieved. Non-decision variables are variables that cannot be explicitly controlled, and are typically modeled by white noise with mean of zero and constant variance. For a targeted performance, many combinations of parameter values may be possible to yield the desired results, and some combinations may be more sensitive to uncertain variation than others. In this sense, the signal needs more precise decision variables, whereas white noise has constant variance.

5.4 Preparation for Signal

5.4.1 Threshold Value of Monthly Sales

For the purpose of robust signal, the decision at April of first year is considered. Robust signal types are evaluated with respect to their combinations of targeted month and threshold monthly sales shown in Table 5-1. The numbers in each lattice indicate signal type by the name of figures from 1 to 28. The four targeted months are January, February, March, and April because the latest month is April. The threshold value of monthly sales is calculated by Equation 5-4, based on the same monthly FCF between when investing and otherwise.

$$\text{Monthly FCF when investing} = \text{Monthly FCF when not investing} \qquad (5-4)$$

Equation 5-4 can be calculated by the financial indices and conditions shown in Tables 5-2 and 5-3. Since the result of above-mentioned Figure 4-7 shows that the high opportunity for exercising American option exists in first yearly period, the concern about the optimal signal is focused on first year regardless of five-year duration. Thus, the following procedure is restricted to first year. Although the American option which has the maturity of five years can be exercisable only for five months in each year, it is considered that 55 periods from March of 2015 to December of 2019 need to pay the divided investment expenses equally if exercised. These conditions are inserted into Equation 5-4, and Earnings Before Interest After Taxes yield:

$$(1-\text{Tax rate}) \times EBIT$$
$$= (1-\text{Tax rate}) \times EBIT \times Rate\ of\ multiplication - Investment\ expenses \div 55 \qquad (5-5)$$

$$0.32 \times (1-0.4) \times \text{Sales}$$
$$= 0.32 \times (1-0.4) \times 1.18 \times \text{Sales} - 50{,}000 \div 55 \qquad (5-6)$$

$$\text{Sales} = 50{,}000 \div 1.9008 = 26{,}305 \approx 30{,}000\ (1{,}000\text{JPY}) \qquad (5-7)$$

Note that fluctuation for working capitals and depreciation are not considered. Investment expenses are limited to the investment related to American option, and are evaluated as an equal load for 55 periods even if the amount of the expenses is a lump sum payment. Now, assuming investment period is June of 2015 and Equation 5-5 is substituted by numbers except for sales. Then, sales are obtained.

The value of 30 million JPY is determined as threshold value of monthly sales. Then, three levels including higher, medium, and lower were chosen as representative successful criteria for each parameter. Since there are seven levels for one parameter and four different timing for decision-making, 28 different types shown in Table 5-1 are classified to seek for the optimal signal.

Table 5-1 Total 28 combinations of timing and value as signal

Targeted month	Threshold of monthly sales(×1000JPY) 20,000	30,000	40,000	50,000	60,000	70,000	80,000
January	1	2	3	4	5	6	7
February	8	9	10	11	12	13	14
March	15	16	17	18	19	20	21
April	22	23	24	25	26	27	28

5.4.2 Calculation for Statistical Data

The improvement is calculated for each simulation to determine the effect of each parameter on option value. The objective of this chapter is to propose a signal for the optimal and dynamic decision-making for investment and long term estimation of correlation between the signal and the ROV in the presence of uncertain demand. Then, more precise covariance is necessary to evaluate the robustness of signal.

The covariance investment based on between signal ($Singal_{mv}$) and ROV is defined as

$$Cov(Signal_{mv},\quad ROV) = \frac{1}{n}\sum_{j=1}^{n}\left(Signal_{mvj} - E(Signal_{mv})\right)\left(ROV_j - E(ROV)\right) \qquad (5-8)$$

where $E(Signal_{mv})$ is the expected value of investment based on Signal, and also known as the mean of $E(ROV)$, The "m" means signal month of sales, "v" means threshold value of sales, and j means j^{th} simulation of total n simulation run number.

$Signal_m$ is calculated as Equation 5-9, using Equation 4-1 and 4-2. The signal is a special case of NPV that assumes low flexibility in decision making with compared to ROV because of predetermined threshold and timing. If the sales at m month are higher than threshold value, investment "a" is exercised and expanded NPV ($ENPV_a$) is gained. If the sales are not, the investment is not exercised and NPV is gained.

$$Signal_{mv} = \begin{cases} ENPV_a & if\ Sales\ at\ m\ month > Threshold\ value \\ NPV & if\ Sales\ at\ m\ month \leq Threshold\ value \end{cases} \qquad (5-9)$$

where $Signal_m$ is sales of one month out of January, February, March, or April in 2015.

ROV is calculated by Equation 4-5.

$$ROV = \begin{cases} max\left(ENPV_{aj},\ NPV_j\right) & t = T \\ max\left(ENPV_{aj}, \dfrac{\left(p \cdot f_{au(t+1)} + (1-p) \cdot f_{ad(t+1)}\right)}{1 + r_f}\right) & 1 \leq t < T - 1 \end{cases} \qquad (5-10)$$

After that, the correlation coefficient ($r_{Signal_{mv}\quad ROV}$) between $Singal_{mv}$ and ROV is obtained by the following Equation 5-11

$$r_{Signal_{mv}\quad ROV} = \frac{Cov(Signal_{mv},\quad ROV)}{\sqrt{Var(Signal_{mv})}\sqrt{Var(ROV)}} \qquad (5-11)$$

Variances are defined as Equations 5-12 and 5-13.

$$Var(Signal_{mv}) = \frac{1}{n}\sum_{j=1}^{n}\left(Signal_{mvj} - E(Signal_{mv})\right)^2 \quad (5-12)$$

$$Var(ROV) = \frac{1}{n}\sum_{j=1}^{n}\left(ROV_j - E(ROV)\right)^2 \quad (5-13)$$

Thus, $Cov(Signal_{mv},\ ROV)$, $Var(Signal_{mv})$, $r_{Signal_{mv}\ ROV}$, number of $ENPV_a$, and improvement are calculated.

5.5 Results

5.5.1 Results of Statistical Data in ROV

Results of $Var(ROV)$, number of $ENPV_a$, and averaged improvement in ROV are shown in Table 5-2. From the ratio of case number of $ENPV_a$ 6,625 to total simulation runs 10,000, about 66% of simulation trials could exercise American options. In Figure 4-6 of previous chapter, about 35% of the simulation could not exercise the American. Then, there is no contradiction between both results.

Table 5-2 Results of ROV

Indices	Figures
$Var(ROV)$	0.2485
Number of $ENPV_a$	6,625
Improvement (%)	0.474

Table 5-3 Results of combinations of timing and value in signal

	Targeted	Threshold of monthly sales (×1,000JPY)							
	month	10,000	20,000	30,000	40,000	50,000	60,000	70,000	80,000
$Cov(Signal_{mv},\ ROV)$	January	0.3487	0.3487	0.3446	0.2844	0.1106	0.0134	0.0001	0.0000
	February	0.3488	0.3477	0.3333	0.2552	0.1146	0.0269	0.0016	0.0001
	March	0.3485	0.3474	0.3386	0.2869	0.1720	0.0583	0.0111	0.0009
	April	0.3487	0.3484	0.3457	0.3230	0.2558	0.1354	0.0386	0.0059
$Var(Signal_{mv})$	January	0.6359	0.6359	0.6267	0.5026	0.1965	0.0230	0.0002	0.0000
	February	0.6354	0.6327	0.6064	0.4737	0.2250	0.0541	0.0038	0.0002
	March	0.6355	0.6324	0.6134	0.5264	0.3260	0.1131	0.0211	0.0016
	April	0.6359	0.6351	0.6283	0.5904	0.4819	0.2615	0.0767	0.0136
$r_{Signal_{mv}\ \ ROV}$	January	0.8772	0.8772	0.8732	0.8049	0.5007	0.1779	0.0104	0.0000
	February	0.8773	0.8771	0.8587	0.7439	0.4845	0.2322	0.0509	0.0144
	March	0.8770	0.8764	0.8673	0.7934	0.6044	0.3476	0.1533	0.0435
	April	0.8772	0.8771	0.8750	0.8434	0.7392	0.5311	0.2796	0.1012
Number of $ENPV_a$	January	10,000	9,998	9,840	7,776	2,706	246	3	0
	February	9,999	9,965	9,494	7,228	3,328	700	52	4
	March	9,997	9,961	9,637	8,157	4,901	1,660	283	26
	April	10,000	9,992	9,919	9,310	7,362	3,949	1,176	198
Improvement (%)	January	0.263	0.263	0.263	0.239	0.110	0.583	0.000	0.000
	February	0.263	0.264	0.256	0.197	0.090	0.269	0.000	0.000
	March	0.263	0.264	0.262	0.224	0.135	0.290	0.009	0.001
	April	0.263	0.264	0.266	0.267	0.261	0.266	0.262	0.112

5.5.2 Results of Statistical Data in Signal

Table 5-3 shows the results of $Cov(Signal_{mv},\ ROV)$, $Var(Signal_{mv})$, $r_{Signal_{mv}\ \ ROV}$, number of $ENPV_a$, and averaged improvement in signal. The higher the values of $Cov(Signal_{mv},\ ROV)$, $Var(Signal_{mv})$, and $r_{Signal_{mv}\ \ ROV}$, the lower the threshold of monthly sales. There is no tendency among target months in these indices. An effective and valid signal is considered within the rage from 10 million to 40 million JPY in sales where $r_{Signal_{mv}\ \ ROV}$ is always 0.7 or more. Under that condition, the value of $Var(Signal_{mv})$, which is ranged from 0.4737 to 0.6359, is larger than that of $Var(ROV)$, 0.2485. Whereas ROA induces backward to avoid downside risk and gain upside opportunity, signal moves forward with criteria for current result regardless of the future. It means that signal cannot avoid the downside risk as much as ROA. The higher case number in $ENPV_a$, the lower threshold in monthly sales. The number of $ENPV_a$ in ROV means the frequency of option exercised and is shown in Table 5-2 as 6,625 in 10,000 simulations. If the threshold of monthly sales ranged from 10 million to 40 million JPY in sales, the frequency of $ENPV_a$ is more in signal than in ROV. It means that $ENPV_a$ is chosen by not ROV but the signal. Therefore, it is considered that $Var(Signal_{mv})$ is larger than $Var(ROV)$.

If the value of improvement is large, the threshold of monthly sales is small. Since the improvement by ROV is 0.474%, the improvements of signal ranged from 10 million to 40 million JPY in sales are less than 0.267% and lower than those of improvement by ROV. Investment based on signal has somewhat low, but the performance is much smoother. Then, it is meaningful for signal to have a high correlation coefficient with ROV.

Within the range in this study from 10 million to 40 million JPY in the threshold of monthly sales, and from January to April in the targeted month, any signal cam be judged to be effective and valid. Signals other than this range should be avoided. That is, when the thresholds of monthly sales are big and ranged from 50 million to 80 million JPY, high correlation coefficient cannot be obtained and the improvement will be low. Although the expected threshold of monthly sales is about 30 million JPY, the examined result of the effective and valid threshold is ranged from 10 million to 40 million JPY. The difference among the values of both thresholds is not so large.

5.6 Conclusions

The aim of this chapter is to propose a signal for the optimal and dynamic decision-making. It is for investment and long term valuation of the correlation between the signal and ROV under uncertain demand using the model in the previous chapter. This chapter is only focused on investment with American call option in first year.

The correlation coefficient of the improvement based on between signal and ROV shows effective value when the signal is ranged from 10 million to 40 million JPY in the threshold of monthly sales, and from January to April in the targeted month.

In entry and exit decisions problem, Dixit shows that entry trigger exceeds the variable cost plus interest in the entry cost (Dixit 1989). Thus, when the 40 million JPY as threshold in monthly sales is higher than the 30 million as the expected value, it can be due to lack of interest.

It is possible to provide robust signal in decision-making for exercise options. In practice, since calculation can become complicated, it is usually difficult to make many lattices in ROA. Then, in many studies, ROA assumes that investment effect comes out at just the same time as decision-making, and usually neglects the necessity for a time lag. It is valuable for ROA using to find a suitable condition for signal and make an enough time for preparation prior to optimal investment implementation timing. However, the remaining problem is that the improvement with signal is lower with compared to the improvement based on ROA.

Chapter 6 Gap between Daily Demand and Optimal Production

6.1 Abstract

As the shelf life of carton soft drink is shorter than other packaging systems, it is difficult to carry its inventory and then is necessary to repeat daily production by order. In particular, at the final batch in daily production, it is unavoidable to discard the excess drink over the minimum volume necessary for final one batch processing. Hence, this chapter's research question is how some flexible before and behind shifts of order timing can reduce such kinds of discard based on an agreement with the customer. A key phrase is 'Virtual Inventory' by flexible orders-received timing for a buffer between supply and demand without any physical inventory for discard reduction. The methodology to the above research questions is real options analysis for a flexible shift decision of demand timing. The objectives are is to 1) build a two-stage supply-chain model for call and put options for positive and negative daily production flexibility to "real demand," 2) draw an option selection policy to each gap between supply and demand, 3) apply a sensitivity analysis to find important conditional and decision variables at a decision tree, and 4) confirm the effectiveness of this scheme by using practical demand data. Thus, timing option can be considered as Virtual Inventory by its buffer function between supply and demand in daily order production.

6.2 Introduction

6.2.1 Optimal Production Batch Size as Volume Flexibility

The soft drink industry has been facing with technological and market uncertainties. Because of this, an improvement in a more cooperative supply chain between the buyer and supplier is required in order to build a productive system for commercial production. This chapter focuses on the gap between daily demand and optimal production, and on ROA effectiveness in daily delivered products. Some of the challenges in the soft drink industry include the following: The buyer orders soft drinks filled in the cartons every day to supplier to avoid the unfortunate dead stock and to adjust the inventory under their short shelf life and uncertain demand. Therefore, the supplier should produce the soft drinks to meet this daily demand. However, the varying uncertain demand is not necessarily suitable to a technically optimal amount for the supplier. The supplier sometimes faces with the case that needs irreversible and inefficient production. In particular, decreases of demand usually lead to higher increases of costs per unit because of utilization reduction of the production capacity. Thus, the supplier has the optimal production batch size and needs approaches to quantify his operational limits of volume flexibility. In this chapter, the volume flexibility is defined by changeability of both upper and lower bounds of order quantity between supplier and buyer under changing demand conditions.

The economic order quantity (EOQ) model serves as the model for fixed order cost and inventory holding costs. The EOQ model deals with a single stage of inventory with a constant and continuous demand rate. Producer is willing to stock the products in order to ensure that all demands are met from stock. This is possible because the demand rate is deterministic and the inventory is not deteriorated. If not, the uncertainty for demand and deterioration should be considered. It is hard for EOQ to deal with the economic order quantity under uncertain demand.

Inventory of the carton drinks does not work well for short shelf life, and daily-repeated buyer's demands and supplier's production, thereby maintaining a balance in the supply chain. Such daily amounts of small product are less efficient than the amounts of large production at one time together. As a consequence, increase in production volume is still the more attractive argument in drink with carton container. Flexibility related to such as batch-sizing and lot-sizing, has been featured as a problem about productivity (Kenyon et al. 2005; Jönsson et al. 2011; Amorim et al. 2013; Stadtler and Sahling 2013; Schulz and Voigt 2014; Seebacher and Winkler 2014; Almeder et al. 2015).

Possibility of the increase in production size tends to be evaluated as vacant capacity of batch. In response to increasingly drastic and competitive environments, organizations want to manage their resource and utilize their capacity in the best possible way (Singh and Acharya 2014). ROA is a proposed method to coordinate between demand and equipment to meeting supplier's efficiency.

6.2.2 Virtual Inventory

For example, when a supplier has an option to increase volume within agreed proportion, the production can be increased as efficient as possible. The volume added is not demand for this timing, but as shortly surplus. The redundancy will be absorbed by future demand-supply coordination. This redundancy is not so-called inventory if it is out of risk management for supply chain. For this case, the redundancy can be used to fill the demand in different timing. Such a redundancy in this study is called as 'Virtual Inventory' which has no physical stock place but just timing flexibility. Thus, even at daily repeated order-production system, in which inventory is prohibited. 'Virtual Inventory' system can be identified as a buffer between demand and supply. Figure 6-1 shows the relation by illustration between timing option, 'Virtual Inventory,' and buffer without stock. All of them are equal in volume but different from each perspective.

Unlike a traditional timing option, novel timing option proposed as 'Virtual Inventory' is a right to invest. So it is convenient to oneself, if it is possible to prevent the delay of decision timing. Supplier as decision maker can get the 'Virtual Inventory' by the timing option, and pull out the conditions under which can be produced efficiently. ROA with timing options make modulate the supply chain as 'Virtual Inventory' under uncertain demand. This notion is novel for daily traded supply chain.

Timing Option = Virtual Inventory = Buffer between Demand and Supply without Stock

Fig.6-1 Illustration between timing option, virtual inventory and buffer without stock

6.2.3 Sensitivity Analysis

Apart from 'Virtual Inventory', the results of ROA are uncertain because they are based on the project risk that future values of variables are not known with certainty at present. The aim of a sensitivity analysis is to describe how much model-output-values are affected by changes in model-input-values. Sensitivity analysis is considered to be an important step in model validation, and it can increase confidence in a model with experimental test. The sensitivity analysis can be distinguished from uncertainty analysis. The uncertainty analysis shown as frequencies of model-input-values can be used to visualize probability distributions of model-output-values and system performance indicators.

Simple sensitivity-analysis procedures can be used to illustrate either graphically or numerically the consequences of alternatives assumptions about the future. It can identify the important parameters and variables. Sensitivity analysis is one of the tools for the strategic analysis in worst case and here then focused on the optimization in worst case.

6.2.4 Research Questions

This chapter's research question is how some flexible before-and-behind shift of demand timing can enhance productivity and reduce waste based on agreement between both buyer and supplier. The objective of this study stands as a first step to theory building. We believe supplier who has options to adjust production volume can play a role to solve the research questions. However, the demand is ordered by the buyer and buyer has no possibility to optimize the production volume for the supplier. It is suitable for supplier to negotiate with buyer about production affected by productivity and waste. If there is some flexibility for manufacturing in response to the demand even for daily production, it may be some chance to coordinate both profits. But, little researches have been made from the perspective of supplier.

This study differs from previous research in the following four points. First, the player who exercises options is not buyer but supplier. Many of previous studies have optimized just buyer's perspective. Buyer is to estimate the expected the under or over-stocking risks with respect to the demand decision. On the other hand, supplier is passive at a perspective only to receive the demand, but not to modulate. This perspective assumes that supplier is perfectly difficult to exercise the option's flexibilities to escape from an uncertainty in supply chain. It is focused on the impact of

ROA to tight relationship between buyer and supplier. That is, if buyer tries to avoid the disadvantageous contract, supplier can expect to exercise the options for considering of win-win relations. Second, two-stage model is adapted to this study, is used in many previous studies and often regarded as no-multi business deal. This two-stage model, however, is regarded as a partial of multi-stage model, which is more complicated.

Third, the supplier has not only call option but also put option for volume flexibility in second stage. The call and put as timing option is novel ideas in supply chain. The options can make the supplier hold 'Virtual Inventory'. That is, supplier should consider not only production efficiency but also inventory shortage in supply chain.

Fourth, this model is evaluated by sensitivity analysis as well as functions. The model is applied to realistic business deals with ROA.

6.3 Necessity of ROA to Supply Chain

6.3.1 ROA in Supply Chain

The flexibility of supply chain has already been studied (Bertrand 2003). The Flexibility requires investments and should be justified on the basis of the potential benefits. Most manufacturing flexibility has dealt within the internal each company level, not supply chain coordination level (Bertrand 2003). Furthermore, manufacturing flexibility is difficult to measure (Beskese et al. 2004; Giachetti 2003; Mishra et al. 2014).

The soft drink industry should be informed daily order production from buyer just before the manufacturing day. The industry has daily multi orders with a very short interval. Even such daily reorder production, supplier can have some flexibility for manufacturing. The manufacturing flexibility is widely recognized as a critical component to achieving an optimal advantage for the manufacturer, i.e. supplier. Volume is a one of the major dimensions in flexibility (Koste et al. 1999; Beach et al. 2000; Vokurka et al. 2000; Zhang et al. 2003; Raturi et al. 2004; Ali and Ahmad 2014; Singh and Acharya 2013; Kundi and Sharma 2015). The key problem in developing a response to volume flexibility is making balance between the order demand from buyer and the production supply from supplier at the same time. The lack of coordination in supply chain can cause various inefficiencies like bullwhip effect and inventory instability (Costantino et al. 2014).

Company could implement the optimal actions, but usually lack the incentive to do so (Cachon 2003). Company might adjust their trade to create the incentives via a contract. Private information that the other companies do not possess is very important to implement own optimal actions in supply chain coordination. Due to the high uncertainty in manufacturing process, a method to increase the flexibility needs to be used (Kleinert and Stich 2010). One method increasing suppliers' flexibility that has been used in recent years is ROA (Lander and Pinches 1998).

6.3.2 ROA in Manufacturing Flexibility

Many studies have examined the ROA for investment in projects with irreversibility and uncertainties (for example, Dixit and Pindyck 1994; Trigeorgis 1996; Copeland and Antikarov 2003; Mun 2003; Jaina et.al. 2013; Fujiwara 2012; Fujiwara 2013; Aye and Fujiwara 2014). If ROA applies to flexible decision making of investment with irreversibility to be equated with the sunk costs under uncertainties, the focus is on the value of information (Pindyck 2008). Further studies on ROA in manufacturing flexibility have shown their effectiveness to evaluate the flexibility (Bengtsson 2001; Bengtsson and Olhager 2001; Bengtsson and Olhager 2002a; Bengtsson and Olhager 2002b; Yeo and Qiu 2003; Zhang et al. 2003; Lloréns et al. 2005). Supply chain has a significant effect on manufacturing flexibility. Especially it is expected that the informational adaptation of operating decisions to changing conditions can be modeled by using ROA. The possibility of co-operation between buyer and supplier in ROA has been studied to allocate profits (Moon 2011).

Although ROA and flexibility of supply chain have recently become to be dealt together, research number has been still limited. That is, the theory building of ROA on the supply chain which consists of buyer and supplier has just started and been introduced to be divided into three types (Wang et al. 2006; Zhao et al. 2013). First, there are studies only on the call option that allows the buyer to adjust the order upwards (Barnes-Schuster et al. 2002; Wang et. al. 2012; Gabrel et.al. 2014). Second, there are studies only on the put option that allows the buyer to adjust the order downwards (Pasternack et al. 1985; Emmons et al. 1998). And thirdly, there are studies on bidirectional option adjustments over the initial order (Wang et al. 2006; Zhao et al. 2013). The second studies included just the contract, but did not sufficiently account for the monetary idea of ROA about their value. A theoretical test for an option contract is more limited. A simulation for the option contract between multiple suppliers and one buyer has examined an option contract on a wholesale price and a buyback for retailer (Gomez_Padilla et al. 2009).

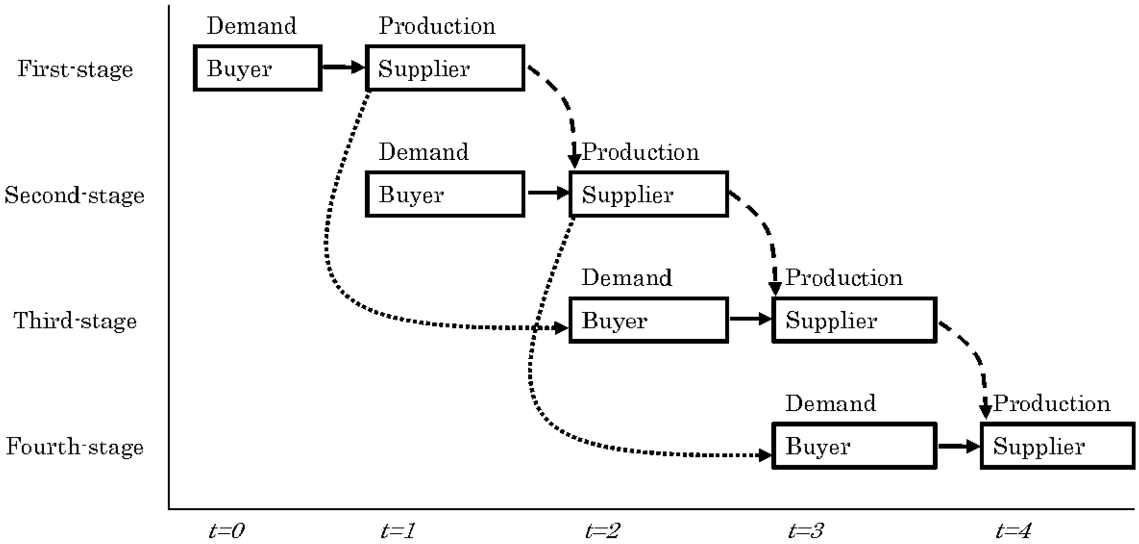
Thus, even at daily order-production system which is prohibiting inventory, it is possible to identify ‘Virtual Inventory’ system as a buffer between demand and supply. Supplier as decision maker can get the 'Virtual Inventory' by the timing option, and pull out the conditions under which can be produced efficiently. ROA with timing option makes modulate uncertain demand by ‘Virtual Inventory’ in supply chain. This notion is novel for daily traded supply chain.

6.4 Problem Description

6.4.1 Model Building

In this model building, the author considers, from the supplier's viewpoint, a general framework of multi-stage supply contracts between one supplier and one buyer. Especially, it is focused on first and second-stages in multi-stage. The supplier gets orders from the buyer, then produces and sells the ordered beverage to the buyer. At starting point, the buyer is not assumed to permit the supplier to change production volume from the ordered carton pieces because the buyer decides the order for his own optimal condition. However, there is another case that the supplier can change and modify the pieces to control the uncertainty in supply chain by option contracts.

Figure 6-2 shows an illustration of informational feedback between buyer and supplier with respect to production from first-stage to fourth-stage based on multi-stage. Production information at first-stage is transmitted from supplier to buyer at initial time point in third-stage. This means that production information is reported from supplier to buyer after one period necessary for manufacturing. This enables buyer to modulate the supply and the demand at third-stage based on the delivery from production at first-stage. On the other hand, production information at first-stage also must be used at second-stage inside supplier to decide on next production after one period. This enables supplier to plan the production in second-stage based on production in first-stage. Condition in second-stage is the same as that in first-stage except for receiving production information from first-stage. Production information from supplier is input to the demand processing to buyer after two-stage and the production to supplier after one-stage.



Demand information from buyer to supplier（pieces/stage）

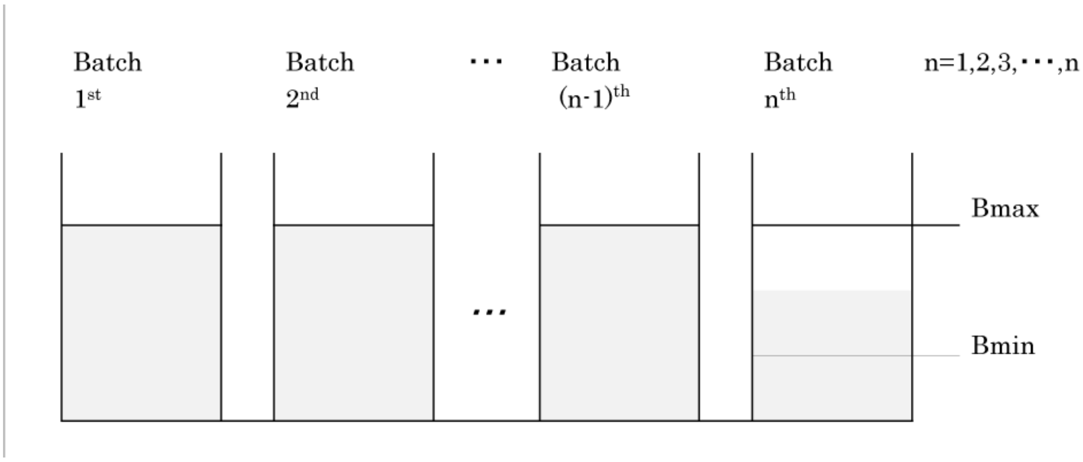
Production information from supplier to supplier (pieces/stage)

Production information from suppler to buyer (pieces/stage)

Fig.6-2 Illustration of informational feedback between buyer and supplier

However, a wide range of uncertainties might affect the activity of supplier. Analytically, a typical formulation batches are shown in Figure 6-3. There are arrangement links with the characteristics of batch capacity and buyer’s demand. The maximum carton pieces mean full capacity that is not produced further more. The minimum pieces are the least capacity that is not produced in pieces below this level.

It is assumed that demand is distributed into several batch, each batch has same capacity and is formulated at full capacity until just one before the last batch (Batch n^{th}). The last batch has uncertainty to be formulated between full and minimum requirement capacities due to meet the demand. Formulation of the last batch pieces is considered as the uncertainty for the supplier and has an opportunity for them to exercise options.



B_{max}: maximum pieces for batch, B_{min}: minimum pieces for batch

Fig.6-3 Illustration of formulation batches

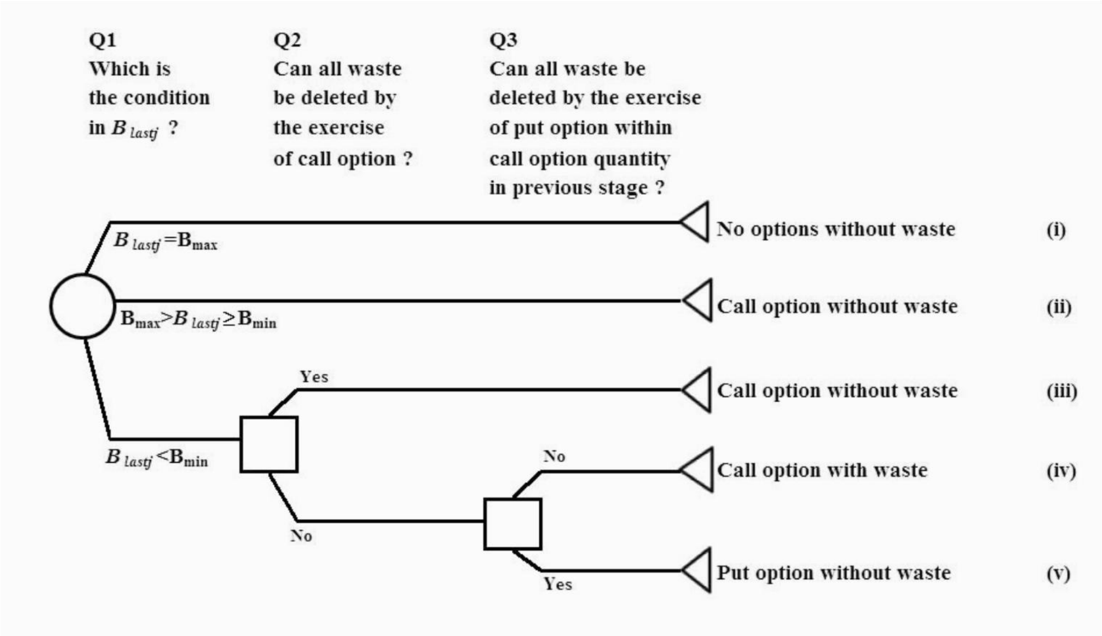
The capacity of the last batch is divided into three cases: equal to maximum carton pieces, middle range pieces, or less than minimum necessary pieces in Figure6-3.

(1) The maximum pieces: it is the most desirable conditions, not afford to be increased further. Waste pieces are not occurred.

(2) The middle range pieces: it is more desirable conditions than the minimum necessary pieces, has afford to be increased further. Waste pieces are not occurred.

(3) The minimum necessary pieces: it is the most undesirable conditions, has afford to be increased further. Waste pieces are occurred if demand in the last batch is less than and needed to increase up to the minimum necessary pieces. It is a condition of uncertainty that had better be avoided strongly.

Waste means a part of amount that must be discarded from the gap between demand and minimum necessary amount for last batch processing while a usable state. The management of 'wastivity' which means a ratio of waste to input would affect all the three dimensions of sustainability, for example, economic, environmental, and social (Sushil 2015). It is difficult for buyer to prevent waste at daily order production. Supplier can, however, shift some damage into the more desirable condition with options. Supplier should make a decision to obtain economic benefits while environmentally friendly.



Note: For first-stage, Q (Question) 3 is omitted because of no acceptance of put option, effective choices are limited to the range from (i) to (iv). If answer of Q2 is No, the choice goes to (iv). For second-stage, Q3 also becomes effective.

Fig.6-4 Decision tree to exercise call and put options

In order to evaluate the ROA for supplier, a systematic decision tree is formulated. Figure 6-4 shows a decision tree to exercise call option under the condition of last batch in both first-stage and second-stage. The difference of second-stage from first-stage is whether put option can be exercised. Supplier is assumed to be able to exercise put option in second stage within the range of exercised call option in previous first-stage. Thus, supplier can utilize flexibility while preventing shortage for buyer.

The main objective of this methodology is the comprehensive analysis of the underlying investment project, by using ROA. The ROA views an investment opportunity in volume flexibility as the call option which is the right, but not the obligation, to invest in a certain increase of carton pieces and thereby claim the profits from the investment. On the other hand, as put option the ROA views an escape opportunity to postponing the duty to produce and claim the profits. The ROA is regarded as the timing decision to invest immediately or not. The decision-making is clarified by the systematic decision tree. The ROA has a possibility of bringing forward or postponing the investment, and the associated flexibility has a positive value if uncertainty exists in last batch.

If the quantity of call option provides an additional new batch to exercise a full option quantity, the option is likely introducing the new uncertainty in the additional batch again. In order to accommodate the uncertainty, it is assumed that the quantity of call option should be restricted within the affordance in last batch and is not permitted to exercise in additional batch.

If the carton pieces in last batch are equal to the tank maximum, it has no opportunity to exercise the call option because the maximum case has no afford to be increased further. Decision tree goes to the optimal (i) in Figure 6-4, resulting in neither call option nor waste.

If the demand in last batch is less than the maximum, it has the opportunity to exercise the call option especially in the first stage. The author assumes that supplier will exercise the call option to produce more efficiently and escape waste. If the demand in the middle pieces in last batch, supplier prefers to produce more with call option (ii) in Figure 6-4. If the demand is in less than the minimum carton pieces in last batch, supplier prefers to exercise call option regardless of non- waste (iii) or waste (iv) in Figure 6-4.

Of course, there is a better case that a put option can produce more efficiently and escape waste. If the waste is occurred even with the call option, the waste can be prevented because of production reduction in last batch with a put option. This is true especially when the demand is in less than the minimum in last batch. Put option is able to exercise only in second-stage within the range of the increased volume produced by call option in first-stage. If the put option is exercised, decision tree goes to (v) in Figure 6-4. Fundamentally from a perspective of sustainable supply chain, supplier has to think not only profits but also environmental problems in exercising options.

In Japan, supplier has been required reducing the waste of food by domestic law (Japanese Government 2001; Japanese Ministry of Agriculture, Forestry and Fisheries 2013). In another area, the reduction in the waste of food is also paid attention to food and agriculture organization of the United Nations (FAO 2011), European Commission (EC 2011) and European Union (EU 2011), and United States of America (EPA 2016; USDA 2016). To make supply chain capable to bear simultaneously regular and risk condition, producer requires proactive planning and flexibility in the decisions making (Mangla et al. 2014). If the waste is produced, priority gives the reduction in the waste than the profit. But, the priority for supplier is to evaluate productivity, adhering to Japanese environmental laws and regulations. Supplier should make a decision to obtain economic benefits while environmentally friendly.

6.4.2 Mathematical Model

6.4.2.1 NPV

The Notation and assumptions for modeling are shown in Table 6-1.

Table 6-1 Notation and assumptions

j	= subscript indicates the stage of j^{th}, ($j = 1{,}2$)
Π_j	= the profits per j stage (JPY: Japanese Yen /stage)
D_j	= the carton pieces of demand per j stage (piece/stage)
r	= the sales price per piece (JPY/piece)
n_j	= the number of batches per j stage (group/stage)
Fc	= the processing cost per batch (JPY / batch) which is treated as a fixed cost per batch and semi-fixed costs per stage
B_{max}	= the maximum pieces of production in one batch (pieces/batch)
$B_{last\,j}$	= the pieces of production only in the last batch of j stage before options exercised (pieces/batch)
Vc	= the direct material cost (JPY / piece), which is treated as variable costs per piece
B_{min}	= the minimum pieces of production in one batch (pieces/batch)
Wq_j	= the waste pieces per j stage (piece/stage)
Wc	= the waste cost per piece(JPY/piece)
di_j	= the increase (the call; di_j>0) or decrease (the put; di_j<0) in the ratio of the pieces of demand to the option exercise per j stage (in case of no option is di_j=0)
Oc	= the exercise cost of both call and put option per piece (JPY / piece)
Oq_j	= the exercise quantity of call option or put option per j stage (piece/stage)

The model applied in this simulation takes the ROA as the guideline that will help the supplier's decision making. The option value (OV) is measured by the difference between NPV and ENPV throughout the stages. It is ignored the effect of the time value as dealing with daily production (Milner and Rosenblatt 2002). Tax is also omitted to simplify the model. The following equations are referenced by the mathematical formulation to value the real options (Kume and Fujiwara 2016a, 2016b).

First, the NPV at stage j is given by Equation 6-1.

$$\mathrm{NPV_j} = \mathrm{Tsales_j} - \mathrm{TVc_j} - \mathrm{TFc_j} - \mathrm{TW_j} \qquad (6-1)$$

where

j – Subscript indicates the stage of $\mathrm{j^{th}}$, ($\mathrm{j} = 1{,}2{,}3{,}\cdots \mathrm{N}$)

$\mathrm{NPV_j}$ – NPV(JPY / stage) at stage j

$\mathrm{Tsales_j}$ – Total sales (JPY / stage) at stage j

$\mathrm{TVc_j}$ – Total direct material costs (JPY / stage) at stage j, which is treated as variable costs

$\mathrm{TFc_j}$ – Total processing cost (JPY / batch) at stage j, which is treated as semi-fixed costs because of a fixed cost per batch

$\mathrm{TW_j}$ – Total waste cost (JPY / stage) at stage j

The $\mathrm{Tsales_j}$ is given by equation 6-2.

$$\mathrm{Tsales_j} = \mathrm{r}D_j \qquad (6-2)$$

where

r – Sales price (JPY/piece)

D_j – Demand (piece/stage) at stage j

The TVc_j is given by Equation 6-3, according to the number of $\mathrm{B_{max}}$ batches and the condition of $B_{last\,j}$

$$\mathrm{TVc_j} = \left\{(n_j - 1)\mathrm{B_{max}} + \max\left(B_{last\,j}, \mathrm{B_{min}}\right)\right\}\mathrm{Vc} \qquad (6-3)$$

Equation 6-3 can be changed into two cases of Equation 6-4.

$$\mathrm{TVc_j} = \begin{cases} \left\{(n_j - 1)\mathrm{B_{max}} + B_{last\,j}\right\}\mathrm{Vc} & if\ B_{last\,j} \geq \mathrm{B_{min}} \\ \left\{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}}\right\}\mathrm{Vc} & if\ \mathrm{B_{min}} > B_{last\,j} \end{cases} \qquad (6-4)$$

where

n_j – Number of batches (group) at stage j

$\mathrm{B_{max}}$ – Maximum pieces of production in one batch (pieces/group)

$B_{last\,j}$ – Pieces of production only in the last batch before options exercised at stage j

$\mathrm{B_{min}}$ – Minimum pieces of production in one batch (pieces/group)

Vc – Direct material costs (JPY / piece), which are treated as variable costs

The $\mathrm{TFc_j}$ is given by Equation 6-5.

$$\mathrm{TFc_j} = n_j\mathrm{Fc} \qquad (6-5)$$

where

Fc – Processing cost per batch (JPY / group) which is treated as fixed cost

The $\mathrm{TW_j}$ is given by equation (6-6).

$$\mathrm{TW_j} = \mathrm{Wc}Wq_j \qquad (6-6\ )$$

where

Wc – Waste cost per piece (JPY/piece)

Wq_j – Waste pieces per stage (piece/stage) at stage j

The waste without any options can occur only in the case of $\mathrm{B_{min}} > B_{last} > 0$,

then

$$Wq_j = \max(\mathrm{B_{min}} - B_{last\,j}, 0) \qquad (6-7)$$

Equation 6-7 can be changed into two cases of equation (6-8).

$$\mathrm{TW_j} = \begin{cases} 0 & if B_{lastj} \geq \mathrm{B_{min}} \\ (\mathrm{B_{min}} - B_{lastj})\mathrm{Wc} & if \mathrm{B_{min}} > B_{lastj} \end{cases} \qquad (6-8)$$

6.4.2.2 ENPV

The ENPV is given by Equation 6-9.

$$\mathrm{ENPV_j} = \mathrm{eTsales_j} - \mathrm{eTVc_j} - \mathrm{eTFc_j} - \mathrm{eTW_j} - \mathrm{Opt_j} \qquad (6-9)$$

where

$\mathrm{ENPV_j}$ – ENPV (JPY / stage) at stage j

$\mathrm{eTsales_j}$ – Expanded total sales (JPY / stage) at stage j

$\mathrm{eTVc_j}$ – Expanded total direct material costs (JPY / stage) at stage j, which is treated as variable costs

$\mathrm{eTFc_j}$ – Expanded total processing cost (JPY / batch) at stage j, which is treated as semi-fixed costs because of a fixed cost per batch

$\mathrm{eTW_j}$ – Expanded total waste cost (JPY / stage) at stage j

$\mathrm{Opt_j}$ – Options cost (JPY / stage) at stage j

The $\mathrm{eTsales_j}$ is given by Equation 6-10.

$$\mathrm{eTsales_j} = \mathrm{r}(1 + di_j)D_j \qquad (6-10)$$

where

di_j – Differential increase (the call; $di_j > 0$) or decrease (the put; $di_j < 0$) in the ratio of the option exercise quantity to the demand pieces at stage j (in case of no option; $di_j = 0$)

The $\mathrm{eTVc_j}$ is given by Equation 6-11, according to the number of $\mathrm{B_{max}}$ batches and the condition of B_{lastj} with options.

$$\mathrm{eTVc_j} = \begin{cases} n_j\mathrm{B_{max}}\mathrm{Vc} & if\ B_{lastj} = \mathrm{B_{max}} \\ \{(n_j - 1)\mathrm{B_{max}} + B_{lastj} + di_jD_j\}\mathrm{Vc} & if\ \mathrm{B_{max}} > B_{lastj} \geq \mathrm{B_{min}} \quad and\ \mathrm{B_{max}} \geq B_{lastj} + di_jD_j \\ \{(n_j - 1)\mathrm{B_{max}} + B_{lastj} + di_jD_j\}\mathrm{Vc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ B_{lastj} + di_jD_j \geq \mathrm{B_{min}} \\ \{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}}\}\mathrm{Vc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ \mathrm{B_{min}} > B_{lastj} + di_jD_j > 0 \\ (n_j - 1)\mathrm{B_{max}}\mathrm{Vc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ B_{lastj} + di_jD_j = 0 \end{cases} \qquad (6-11)$$

Especially, if $di_j < 0$, supplier expects not the simple decrease in production but the decrease of inefficient processing cost and production. Then, optimal condition in $di_j < 0$ is $B_{lastj} + di_jD_j = 0$.

The $\mathrm{eTFc_j}$ is given by Equation 6-12.

$$\mathrm{eTFc_j} = \begin{cases} n_j\mathrm{Fc} & if\ B_{lastj} = \mathrm{B_{max}} \\ n_j\mathrm{Fc} & if\ \mathrm{B_{max}} > B_{lastj} \geq \mathrm{B_{min}} \quad and\ \mathrm{B_{max}} \geq B_{lastj} + di_jD_j \\ n_j\mathrm{Fc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ B_{lastj} + di_jD_j \geq \mathrm{B_{min}} \\ n_j\mathrm{Fc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ \mathrm{B_{min}} > B_{lastj} + di_jD_j > 0 \\ (n_j - 1)\mathrm{Fc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ B_{lastj} + di_jD_j = 0 \end{cases} \qquad (6-12)$$

The $\mathrm{eTW_j}$ is given by Equation 6-13.

$$\mathrm{eTW_j} = \mathrm{Wc}Wq_j \qquad (6-13)$$

where

If $di_j \geq 0$, the waste with call option can occur only in the case of

$\mathrm{B_{min}} > B_{lastj} + di_jD_j > 0$, then

$$Wq_j = \max(\mathrm{B_{min}} - B_{lastj} - di_jD_j, 0) \qquad (6-14)$$

If $di_j < 0$, the waste with put option can occur only in the case of

$B_{lastj} + di_jD_j = 0$, and it is not necessary to prepare B_{lastj}, then

$$Wq_j = 0 \qquad (6-15)$$

$$\mathrm{eTW_j} = \begin{cases} 0 & if\ B_{lastj} = \mathrm{B_{max}} \\ 0 & if\ \mathrm{B_{max}} > B_{lastj} \geq \mathrm{B_{min}} \quad and\ \mathrm{B_{max}} \geq B_{lastj} + di_jD_j \\ 0 & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ B_{lastj} + di_jD_j \geq \mathrm{B_{min}} \\ (\mathrm{B_{min}} - B_{lastj} - di_jD_j)\mathrm{Wc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ \mathrm{B_{min}} > B_{lastj} + di_jD_j > 0 \\ 0 & if\ \mathrm{B_{min}} > B_{lastj} > 0 \quad and\ B_{lastj} + di_jD_j = 0 \end{cases} \qquad (6-16)$$

The Opt_j is given by Equation 6-17.

$$Opt_j = \mathrm{Oc}Oq_j \qquad (6-17)$$

where

Oc – Option exercised cost (JPY / piece)

Oq_j– Option exercised quantity (piece) at stage j

Value of the Oc for both call option and put option is same. Oq_j is given with di_j and D_j by Equation 6-18.

$$Oq_j = di_jD_j \qquad (6-18)$$

Then, using Equations 6-18, Equation 6-17 can be changed into Equation 6-19.

$$Opt_j = \mathrm{Oc}di_jD_j \qquad (6-19)$$

6.4.2.3 Option Value

The OV at stage j can be calculated from Equation 6-20 using Equation 6-1and 6-9.

$$\mathrm{OV}_j = \mathrm{ENPV}_j - \mathrm{NPV}_j \qquad (6-20)$$

Equation 6-20 can be divided into five cases of Equation 6-21, according to the conditions of B_{lastj} and di_j.

$\mathrm{OV}_j =$

$$
\begin{cases}
0 & if\ B_{lastj} = \mathrm{B_{max}} & \\
(\mathrm{r} - \mathrm{Vc} - \mathrm{Oc})di_jD_j & if\ \mathrm{B_{max}} > B_{lastj} \geq \mathrm{B_{min}} & and\ \mathrm{B_{max}} \geq\ B_{lastj} + di_jD_j \\
(\mathrm{r} - \mathrm{Vc} - \mathrm{Oc})di_jD_j\ + (\mathrm{B_{min}} - B_{lastj})(\mathrm{Vc} - \mathrm{Wc}) & if\ \mathrm{B_{min}} > B_{lastj} > 0 & and\ B_{lastj} + di_jD_j \geq \mathrm{B_{min}} \\
(\mathrm{r} + \mathrm{Wc} - \mathrm{Oc})di_jD_j & if\ \mathrm{B_{min}} > B_{lastj} > 0 & and\ \mathrm{B_{min}} > B_{lastj} + di_jD_j > 0 \\
(\mathrm{r} + Oc)di_jD_j + \mathrm{B_{min}Vc} + \mathrm{Fc} + (\mathrm{B_{min}} - B_{lastj})\mathrm{Wc} & if\ \mathrm{B_{min}} > B_{lastj} > 0 & and\ B_{lastj} + di_jD_j = 0
\end{cases}
\quad (6-21)
$$

In Equation 6-21, the solutions of first, second, third and fourth from the top are all in case of positive di_j. Equation 6-21 shows that if $di_j > 0, \mathrm{r} > \mathrm{Vc} + \mathrm{Oc}, \mathrm{Vc} > \mathrm{Wc},$ and $(\mathrm{r} - \mathrm{Oc}) > \mathrm{Wc}$, supplier always can get positive OV_j in direct proportion to the di_jD_j. This means that supplier can get an additional OV_j when maximizing di_jD_j. The r is greater than the Vc as a general rule, as it is determined by the magnitude of the Oc whether supplier makes OV_j positive or negative,

In Equation 6-21, the solution of the fifth and final is only in case of a negative di_j. In the case of a put option, it is best to eliminate the inefficient B_{lastj} to enhance the profit even if production is reduced. Equation 6-21 shows that if $di_j < 0,$ and $(\mathrm{r} + Oc)di_jD_j < \mathrm{B_{min}Vc} + \mathrm{Fc} + (\mathrm{B_{min}} - B_{lastj})\mathrm{Wc}$, the supplier can always get positive OV_j.

6.4.3 Case of No Option

Behavior of the supplier who cannot exercise any option is just enough to meet the demand. The NPV are calculated by subtracting direct raw material cost, processing cost and the waste cost from sales.

$$
\mathrm{NPV}_j(D_j) = \begin{cases}
\mathrm{r}D_j - n_j\mathrm{Fc} - \{(n_j - 1)\mathrm{B_{max}} + B_{lastj}\}\mathrm{Vc} \\
\quad if\ B_{lastj} \geq \mathrm{B_{min}} \\
\mathrm{r}D_j - n_j\mathrm{Fc} - \{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}}\}\mathrm{Vc} - \{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}} - D_j\}Wc \\
\quad if\ B_{lastj} < \mathrm{B_{min}}
\end{cases}
\quad (6-22)
$$

Equation 6-22 is the profits equation per stage with no options and corresponds to conditions (i) in Figure 6-3 except the possibility of the imperfect operational ratio and existing of waste. If $B_{lastj} \geq \mathrm{B_{min}}$, the first term is sales, the second term is the supplier's processing cost (total Fc_j), and the last term is the direct material cost. The sales are equal to the multiplication of the unit price and pieces. The processing cost is directly proportional to the numbers of batch.

If $B_{lastj} < \mathrm{B_{min}}$, this condition yields waste which is the difference between formulation and demand. The last term is the waste cost. The waste quantity (Wq_j) is calculated by subtracting demand pieces (D_j) from formulated pieces $\{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}}\}$.

6.4.4 Case with Options

Behavior of the supplier who has the options is different according to the condition in B_{lastj}. As already discussed above, it can be classified into following three cases; $B_{lastj} = \mathrm{B}_{\max}$, $\mathrm{B}_{\max} > B_{lastj} \geq \mathrm{B}_{\min}$, and $B_{lastj} < \mathrm{B}_{\min}$. For each case, the author seeks for the maximum profits function and the optimal or targeted $B_{lastj} \equiv B^*_{lastj}$.

Case 1 $B_{lastj} = \mathrm{B}_{\max}$

In the case, there is no affording to exercise call option as the optimum (i) in Figure 6-3. Then always $B^*_{lastj} = B_{lastj} = \mathrm{B}_{\max}$. Undoubtedly, waste cost does not occur. If B_{lastj} is replaced with $\mathrm{B}_{\max}$ in the Equation 6-22, Equation 6-23 can be obtained.

$$\Pi_j(D_j) = \begin{cases} \mathrm{r}D_j - n_j\mathrm{Fc} - n_j\mathrm{B}_{\max}\mathrm{Vc} \\ \quad if\ B_{lastj} = \mathrm{B}_{\max} \end{cases} \qquad (6-23)$$

Case 2 $\mathrm{B}_{\max} > B_{lastj} \geq \mathrm{B}_{\min}$

In the case, there is affording to exercise call option. The targeted B_{lastj} is $B^*_{lastj} = B_{lastj} + di_jD_j$. In addition, waste cost is not occurred. In the Equation 6-22, D_j and B_{lastj} are replaced with $(1 + di_j)D_j$ and $B_{lastj} + di_jD_j$, respectively, and subtract the exercised option cost$\left(\mathrm{Oc}Oq_j = \mathrm{Oc} \cdot di_jD_j\right)$. Here, D_j and $B_{lastj} = D_j - (n_j - 1)\mathrm{B}_{\max}$ are random variables, and di_j is a decision variable. The range of di_j shall be determined by the contract between a suppler and a buyer. The targeted condition is subject to following formula.

$$\Pi_j(di_j, D_j) = \begin{cases} \mathrm{r}(1 + di_j)D_j - n_j\mathrm{Fc} - \{(n_j - 1)\mathrm{B}_{\max} + B_{lastj} + di_jD_j\}\mathrm{Vc} - \mathrm{Oc}Oq_j \\ \quad if\ \mathrm{B}_{\max} > B_{lastj} \geq \mathrm{B}_{\min} \end{cases} \qquad (6-24)$$

Thus, the targeted profit is dependent on not only variables di_j and D_j but also the range of di_j and the exercised option cost $(\mathrm{Oc}Oq_j)$. Hence it is just discussed about option selection policy at each facing condition for the supplier. However, it is basically assumed that Oc is relatively lower than the unit cost of waste and divided processing cost.

Case 3 $B_{lastj} < \mathrm{B}_{\min}$

The Case 3 is different by each stage. Supplier can exercise call option only in first-stage, but can adopt either call option or put option in second-stage. To reduce more aggressively waste, the supplier can choose either case3.1 or case3.2 as follows.

Case 3.1 $B_{lastj} < \mathrm{B}_{\min}$ and the exercise of call option

This case corresponds to (iii) and (iv) in Figure 6-3. The B^*_{lastj} has following two results: option selection policies of (iii) and (iv) are $B_{lastj} + di_j D_j \geq \mathrm{B_{min}}$ and $B_{lastj} + di_j D_j < \mathrm{B_{min}}$ respectively. As discussed already, waste cost occurs only in the latter case. The targeted profit is formulated by the following Equation 6-25. If $B_{lastj} + di_j D_j \geq \mathrm{B_{min}}$, the profit is equal to the Equation 6-24. If $B_{lastj} + di_j D_j < \mathrm{B_{min}}$, from the case of $B_{lastj} < \mathrm{B_{min}}$ in the Equation 6-22, D_j is replaced with $(1 + di_j)D_j$ and the exercised option cost $\mathrm{Oc}Oq_j$ is subtracted. But as still $B^*_{lastj} < \mathrm{B_{min}}$ and necessary production has to accompany waste for minimum batch size, then modified $B^*_{lastj} = B^{M*}_{lastj} = B^*_{lastj} + (\mathrm{B_{min}} - B^*_{lastj}) = \mathrm{B_{min}}$. Then, following Equation 6-25 is the targeted profit equation per stage in case of call option exercising with possible di_j size.

$$\Pi_j(di_j, D_j) = \begin{cases} \mathrm{r}(1 + di_j)D_j - n_j\mathrm{Fc} - \{(n_j - 1)\mathrm{B_{max}} + B_{lastj} + di_j D_j\}\mathrm{Vc} - \mathrm{Oc}Oq_j \\ \ if\ B_{lastj} < \mathrm{B_{min}}\ and\ B_{lastj} + di_j D_j \geq \mathrm{B_{min}} \\ \mathrm{r}(1 + di_j)D_j - n_j\mathrm{Fc} - \{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}}\}\mathrm{Vc} \\ -\{(n_j - 1)\mathrm{B_{max}} + \mathrm{B_{min}} - (1 + di_j)D_j\}Wc - \mathrm{Oc}Oq_j \\ \ if\ B_{lastj} < \mathrm{B_{min}}\ and\ B_{lastj} + di_j D_j < \mathrm{B_{min}} \end{cases} \qquad (6-25)$$

Case3.2 $B_{lastj} < \mathrm{B_{min}}$ and the exercise of put option

It corresponds to put option decision at (v) of second-stage in Figure 6-3, which means only for keeping balance between the demand and the supply within first- and second-stages. The case of put option exercise and expanding waste is nonsense and meaning-less at all. The reasonable case of (v) is just the time when supplier can cancel completely the production of last batch by exercising put option. It is possible to save waste cost and processing cost of full 1 batch, then total batch number becomes to $(n - 1)$. If the put cannot remove waste completely, supplier should return back to above the case 3.1. The objective of the put option is to remove both inefficient processing cost of the last batch and waste. Therefore, $B^*_{lastj} = 0$. The targeted profit is calculated in equation 6-26.

$$\Pi_j(di_j, D_j) = \begin{cases} \ \mathrm{r}(1 + di_j)D_j - (n_j - 1)\mathrm{Fc} - (n_j - 1)\mathrm{B_{max}}\mathrm{Vc} - \mathrm{Oc}Oq_j \\ if\ B_{lastj} < \mathrm{B_{min}}, \quad B_{lastj} + di_j D_j \leq 0,\ di_{j-1}D_{j-1} + di_j D_j \geq 0 \\ \quad and\ \ di_j < 0 \end{cases} \qquad (6-26)$$

Summarized option selection policy

From above three cases; $B_{lastj} = \mathrm{B_{max}}$, $\mathrm{B_{max}} > B_{lastj} \geq \mathrm{B_{min}}$, and $B_{lastj} < \mathrm{B_{min}}$, the targeted B_{lastj} (including modified target B_{lastj}), B^*_{lastj}, is given by:

$$B^*_{lastj} = \begin{cases} \mathrm{B}_{\max} & if\ B_{lastj} = \mathrm{B}_{\max} \\ B_{lastj} + di_j D_j & if\ \mathrm{B}_{\max} > B_{lastj} \geq \mathrm{B}_{\min} \\ B_{lastj} + di_j D_j & if\ B_{lastj} < \mathrm{B}_{\min}\ and\ B_{lastj} + di_j D_j \geq \mathrm{B}_{\min} \\ \mathrm{B}_{\min} & if\ B_{lastj} < \mathrm{B}_{\min}\ and\ B_{lastj} + di_j D_j < \mathrm{B}_{\min} \\ 0 & if\ B_{lastj} < \mathrm{B}_{\min}\ ,\ \ B_{lastj} + di_j D_j < 0, \\ & di_{j-1} D_{j-1} + di_j D_j \geq 0\ and\ \ di_j < 0 \end{cases} \qquad (6-27)$$

Thus, to find better targeted $B_{lastj,}$ B^*_{lastj} for improving profits Π_j, the suitable decision variable as option di_j is needed to be determined by considering a random variable, demand D_j, the agreed range of di_j between the supplier and the buyer, and the exercised option cost $\left(\mathrm{Oc}Oq_j\right)$. Such optimization problems will be left and focused on next chapter 7. Even so, Equation 6-27 is useful for option selection policy for a supplier according to each facing conditional parameter values discussed here.

6.5 Sensitivity Analysis

6.5.1 Conditions of the Sensitivity Analysis

The supplier has to modulate the last batch by optimizing di_j with reference to D_j, $\mathrm{B_{min}}$, $\mathrm{B_{max}}$, the agreed range of call option, option cost, and potential range of put option depend on previous call exercised, for leading to lower unit cost, maximum profits, and maximized OV with the flexibility in timing of operating. The production facilities have fixed costs as sunk costs. Then effective application of ROA to the above problem can be expected. Especially here, as a scenario analysis in ROA, sensitivity analysis is discussed about how the optimal di_j should be selected mainly depending on condition of random variable, daily demand D_j.

The sensitivity analyses for optimal profits in first- and second-stages were performed according to Equation 6-27. The difference between first and second-stages is the possibility of put option exercise only in second-stage. The sensitivity analysis is here focused on the impact of random variable D_j and decision variable di_j on dependent variables as processing costs, waste cost, option exercised cost, OV, and profits.

The model is validated by both using spreadsheets and drawing parameter values from actual supply conditions except for Oc is shown in Table 6-2. The Oc is the cost tentatively assumed for ROA.

Table 6-2 Model parameters for sensitivity analysis

Symbols	Value	Symbols	Range of value	Type
$\mathrm{B_{max}}$	5,000	di_j	$0.10 \geq di_j \geq -0.10$	Discrete (2nd decimal)
$\mathrm{B_{min}}$	3,000	D_j	$20{,}000 \geq D_j \geq 0$	Discrete (Integer)
R	60			
Vc	20			
Fc	30,000			
Wc	5			
Oc	1			
$\mathrm{Oc}Oq$ in previous stage	1,000			

6.5.2 Results in Sensitivity Analysis of Second-stage

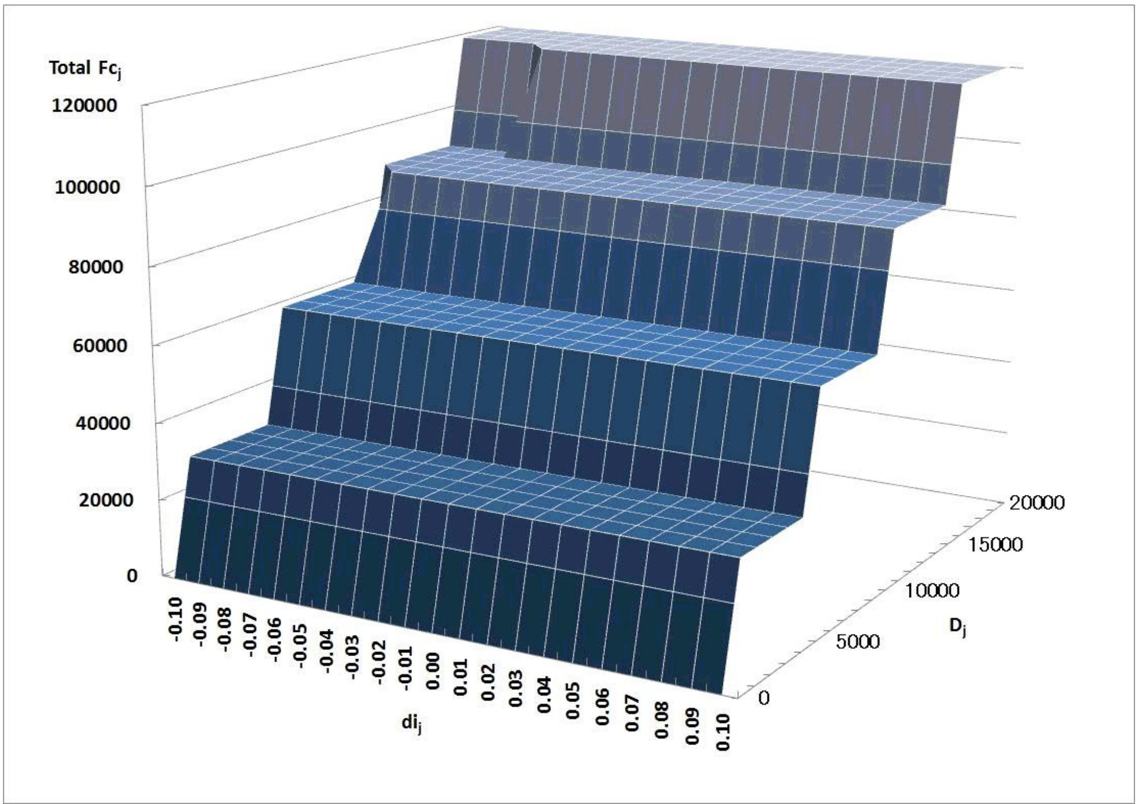
The main difference of second-stage is the exercise opportunity of put option within the previous surplus size of production by call option in first-stage.

6.5.2.1 Processing Cost

Sensitivity analysis of demand as a random variable D_j and call option as a decision variable di_j

to total fixed processing cost is shown as Figure 6-5. ROA can save the processing cost in some conditions. If total processing cost is same, it is benefit for supplier to produce more quantity using call option. For sensitivity analysis in first-stage, decision variable di_j can take only positive for call option. The total processing cost is regarded as a daily fixed cost proportional to the batch number. Then the total processing costs increases stepwise with demand by the multiple of $\mathrm{B_{max}}$ 5000. Naturally there is no impact of call option to $\mathrm{B_{max}}$.

For sensitivity analysis in second-stage, decision variable di_j can take positive and negative for call and put option respectively. For example, the unique exceptional cases are the areas including first: from -0.06 to -0.10 in di_j and 16,000 pieces in demand, and second: -0.10 in di_j and 11,000 pieces. These parts save the processing cost be means of the cancellation of last batch by exercising the put option. The boundaries or thresholds of put option exercise can be determined by benefits and cost of option exercise.



Total $\mathrm{Fc_j}$ (JPY): total processing costs

For first-stage, effective area is limited to positive $di_j(di_j > 0)$.

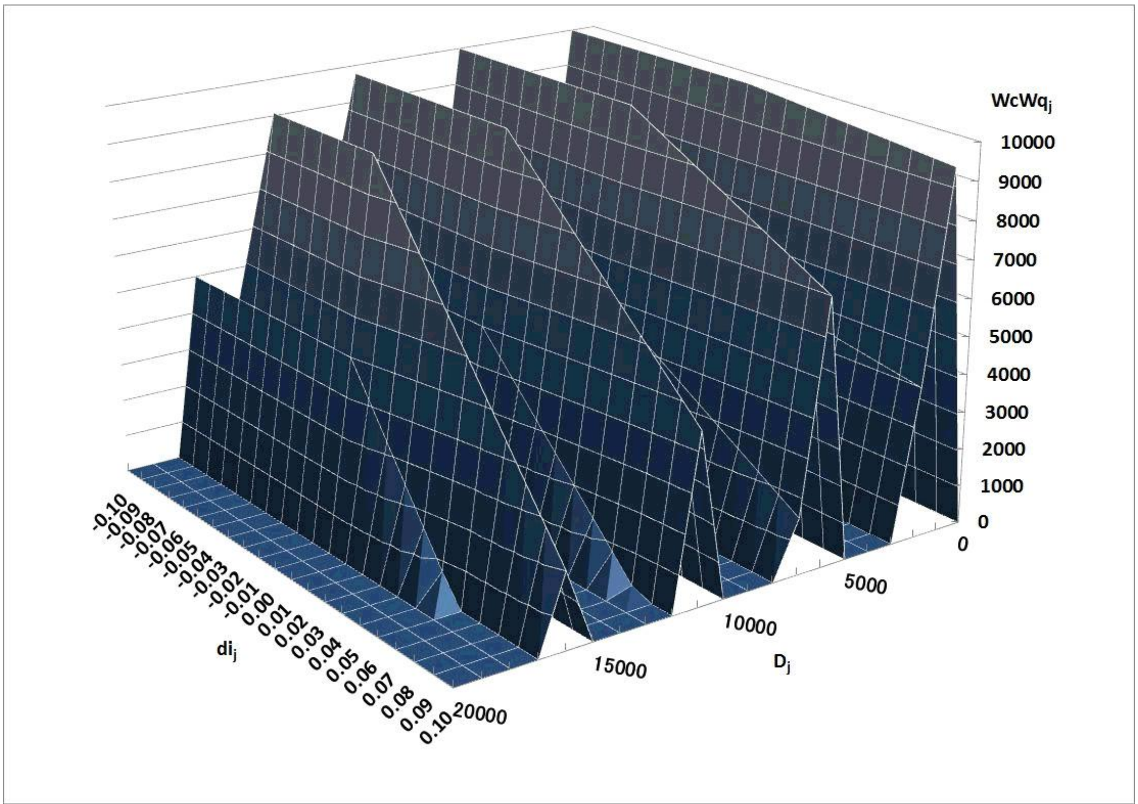
For second-stage, no such sign restriction is set about di_j.

Fig.6-5 Sensitivity analysis in total fixed processing costs

6.5.2.2 Waste Cost

The sensitivity analysis on two variables D_j and di_j to waste cost is shown as Figure 6-6. ROA can decrease the waste cost in some conditions. The waste cost is yielded from demand D_j as a random variable, less than the minimum necessary production volume B_{min} 3000 carton pieces, only in the last batch for abandonment. Thus, for both first- and second-stages, it is possible to find a cyclic behavior of this cost with batch number. However, a decision variable di_j, as call option and a differential increment ratio to D_j, can gradually reduce the cost with demand size D_j, because discarding comes only from last one batch at most 3000 carton pieces and can naturally be decreased with additional production even at given ratio di_j.

As related with above fixed processing cost, there are some areas of perfect losing the waste cost if demand D_j is around a little bigger than full batch demand size, 15000 or 20000, and if optional ratio di_j is around -0.1. Thus, for second-stage, if benefits of put option are bigger than exercise cost, both waste cost and processing cost can be removed perfectly.



WcWq_j(JPY): waste costs

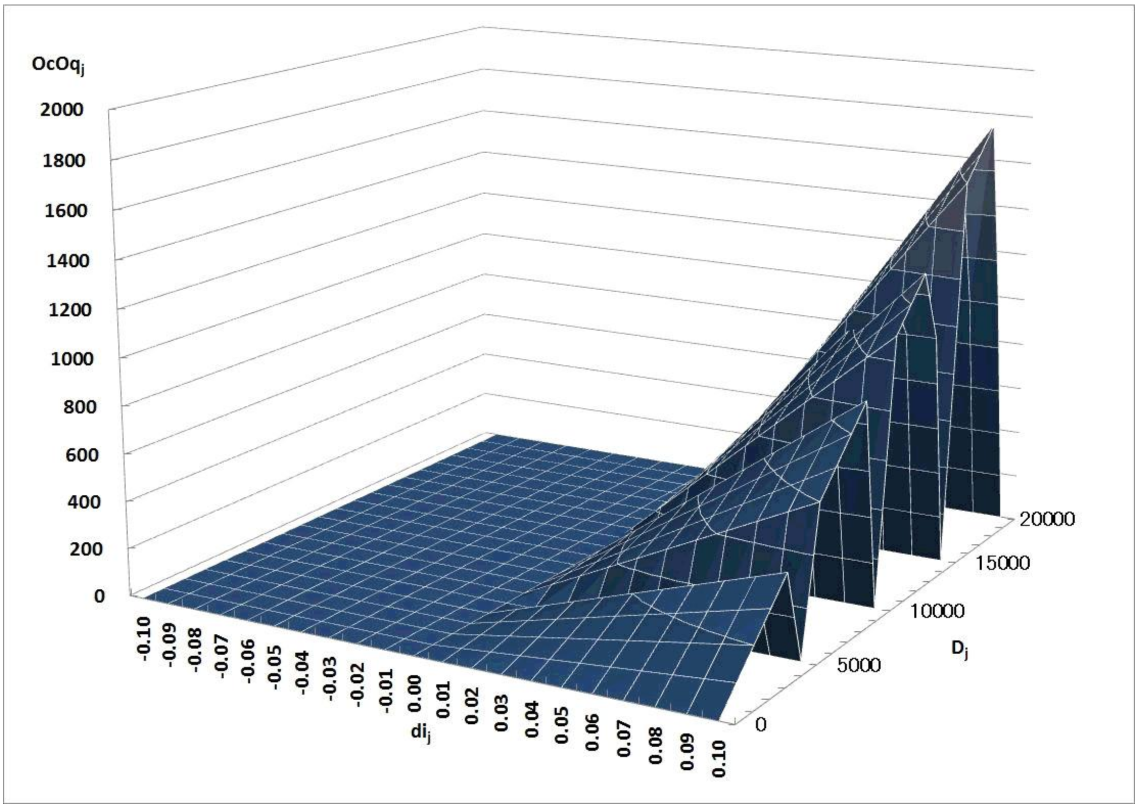
For first-stage, effective area is limited to positive $di_j(di_j > 0)$.

For second-stage, no such sign restriction is set about di_j.

Fig.6-6 Sensitivity analysis in waste cost

6.5.2.3 Option Exercise Cost

Here is the sensitivity analysis on option exercising cost of these both parameters like Figure 6-7. For first-stage, only positive di_j is treated as the call option. It is assumed that the supplier should pay the buyer the compensation fee for the additional inventory cost increased by call option within contract range of di_j previously agreed. From the definition of decision variable di_j, given the same value, if the conditional variable demand D_j expands, the option exercise cost: option exercise cost per piece (storage unit cost) times option exercise quantity (extra produced units), can sharply increase except full batch B_{max} demand points. According to the slope in cyclic trend curves, if the option price is constant, its more exercising to save waste is reasonable than to improve the operational increase rate.



$OcOq_j$ (JPY): option exercise cost

For first-stage, effective area is limited to positive $di_j(di_j > 0)$.

For second-stage, no such sign restriction is set about di_j.

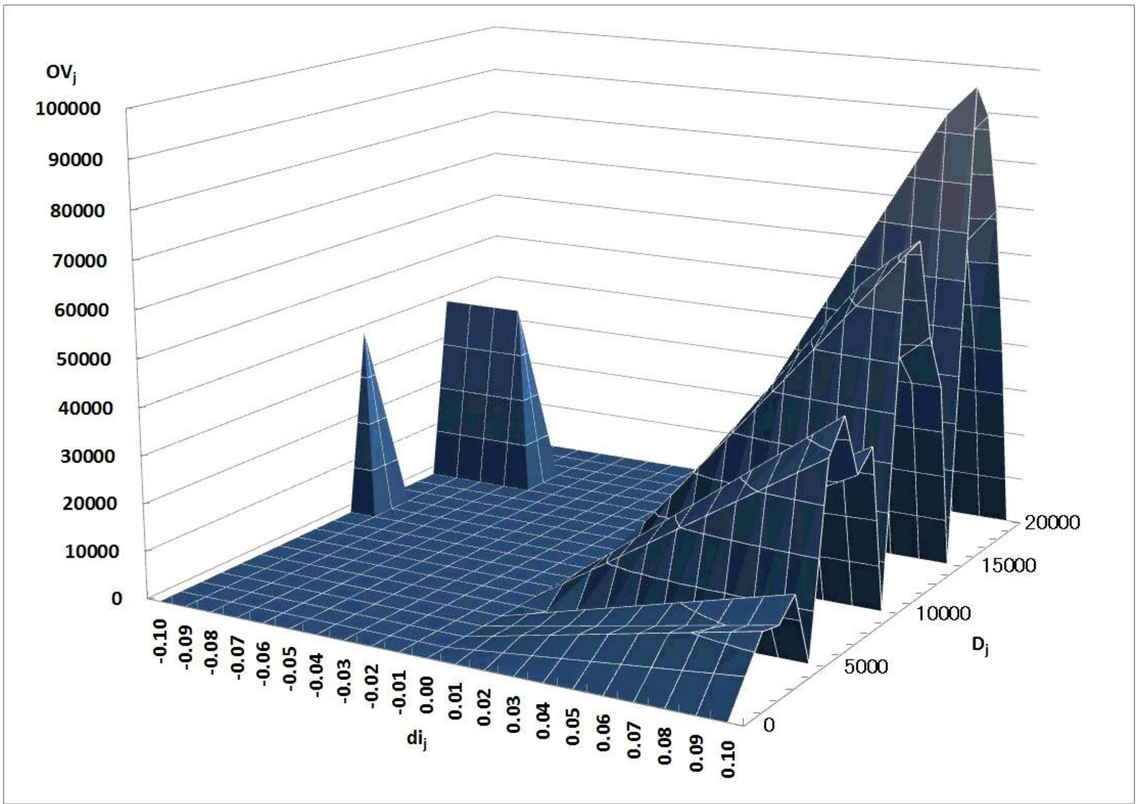
Fig.6-7 Sensitivity analysis in option exercise cost

6.5.2.4 Option Value

Sensitivity analysis of option value has mainly two effects as saving of waste and economy of scale shown in Figure 6-8. ROA can increase the OV in some conditions. The saving of waste is understood as the changing figure of waste cost from square to triangle in above Figure 6-6. The lost parts of that figure are oppositely added here. The other positive effect is come from the increase of tank utilization rate by more production improvement than minimum necessary level in the last batch. The increase ratio di_j to demand D_j is considered as call option here and provides accelerating influences on both saving of waste and economy of scale because of limiting the change only to the last batch. These benefits reflect the flexibility of operational production as real options.

For second-stage, there are two peak-areas in negative di_j or put option exercise as following, first area: from -0.06 to -0.10 in di_j and 16,000 pieces in demand D_j, and second area: -0.10 in di_j and 11,000 pieces in D_j. These areas correspond to above discussions. One of main effects of this put option is to remove the waste and the fixed batch processing costs without any option exercise cost, because the put does not increase but reduce the option exercise cost as inventory shown as Figure 6-7.

From the assumption, exercise cost is necessary from only the call but the put option, because of supplier's payback to buyer for additional inventory from surplus production discussed already. Since it removes both waste and one batch processing, put option can improve profits by reducing production. So, it is necessary to consider the integer treatment of full batch production and the risk management of demand forecasting, call and put options. Next, results of profits can be a guideline to decide the optimal option exercise di_j, depending on a conditional and random variable demand D_j.



OV (JPY): option values

For first-stage, effective area is limited to positive $di_j(di_j > 0)$.

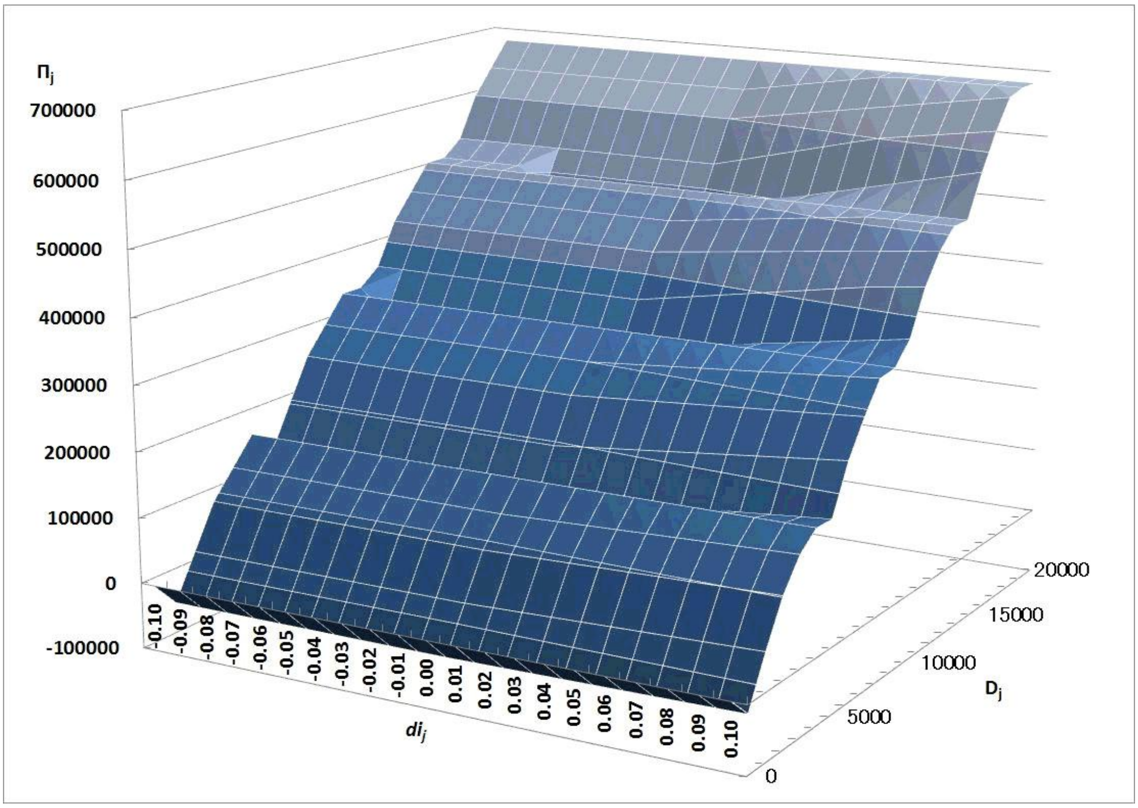
For second-stage, no such sign restriction is set about di_j.

Fig.6-8 Sensitivity analysis in option value

6.5.2.5 Profits

Thus, from above discussion, sensitivity analyses on profits of both demand D_j and expand ratio of demand di_j as call option are shown in Figure 6-9. Equations 6-23, 6-24, 6-25, and 6-26 can explain this aggregate result. ROA can increase the profit in some conditions. Unless supplier has option, given the demand D_j is less than minimum necessary pieces $\mathrm{B}_{\mathrm{min}}$, the profit can be negative by subtracting fixed processing, variable and waste costs from small sales. So, there are cyclical declining stage after every a multiple of 5000 maximum pieces as $\mathrm{B}_{\mathrm{max}}$. But these declining phases are loosening with increase of demand D_j and its optional increase ratio di_j, even if that option needs exercise cost. Every cyclical peak of profits corresponds to each full batch demand with call option except for $di_j = 0.00$. After recovering the negative slop, by exercising call option as increase production ratio di_j at given demand condition D_j, the slope of profit recovering phase from waste damage is steeper than any other phases, because the net effects to profit are come from both the reduction of waste and the improvement of operational utilization rate even subtracting exercise cost.

For second-stage, the character of this figure is almost the same with that of first-stage except for the exercise condition of put option. Then, in addition to declining from waste, steep recovery due to waste reduction, improvement of operation utilization, and radical recovery with expanding demand by call option as discussed in first-stage, there are new contributions from both elimination of waste and processing cost by put option. The upper limit of put exercise range is constrained by previous exercise of call option in first-stage. This figure is useful as a guideline to select di_j as call or put option at facing conditional or random variable demand D_j for optimizing the profits within given restrictions.



Π_j (JPY): profits

For first-stage, effective area is limited to positive $di_j (di_j > 0)$.

For second-stage, no such sign restriction is set about di_j.

Fig.6-9 Sensitivity analysis in profits

6.6 Effectiveness Proof of Options by Factual Demand Data

6.6.1 Conditions of Performance Comparison in the Multi-stage Demand

This section summarizes the effect of options to waste reduction by applying multi-stage of factual demand data. To test for waste reduction, comparison targets can be classified by following three cases as Base case without options, Simple call option case, and Chooser (call or put) option case. Actual data of demand of 729 working days are given by a supplier in Toyohashi city, Japan. Exercise of both options is formulated by above series of equations. For example, put option exercise can be decided for preventing both waste and shortage after previous call option exercise.

6.6.2 Results in Factual Data Application

First is a Base case without options. Unless there are any options based on the demand data, each size frequency of last batches is consisted of the minimum necessary pieces with waste ($B_{lastj} < \mathrm{B}_{\min}$) 56.9%, the middle range pieces without waste ($\mathrm{B}_{\max} > B_{lastj} \geq \mathrm{B}_{\min}$) 43.0%, and the maximum pieces without waste ($B_{lastj} = \mathrm{B_{max}}$) 0.1% shown as Figures 6-10. Thus, the average frequency of last batch including waste is more than half regardless of the demand as pieces.

Secondly, it is possible for simple call option case to reduce the last batch frequency have waste from 56.9% to 34.6% by 22.3%, and increase the frequency of operational utilization improved ratio from 0% to 99.9% (43.0%+22.3%+34.6%) shown as Figures 6-9. That is, exercising call option can be expected to increase the operational utilization ratio anyway regardless of existence of waste. Thus, even only call option exercise contributes to hedge against downside risk and to take upside chances. In other words, the reluctance to exercise call option means opportunity loss, if possible in this condition.

Thirdly, chooser (call or put) option case, in two-stage cycle, can select also put option within previous call option exercise range. By exercising put option with frequency 12.8%, this type can decrease the frequency with waste to just 26.6% instead of probable 21.8% (34.6%−12.8%), compared with 34.6% of simple call option case. The reason of this too small reduction may come from order demand change into sometimes much smaller last batch demand, since order system is adjusted into two stage cycle in more detail from one broader cycle. And frequency range of without waste by call becomes to 60.6% (41.5%+19.1%). This frequency range allows not only exclude waste but also improve operational utilization ratio with option exercise cost. On the other hand, put option does not charge any exercise cost, because of unnecessary storage cost payment to client.

Among above three, this final system's flexibility is highest. But it is further needed to calculate expected profits by considering each probability and exercise cost at their facing conditions for more general forecasting and simulation.

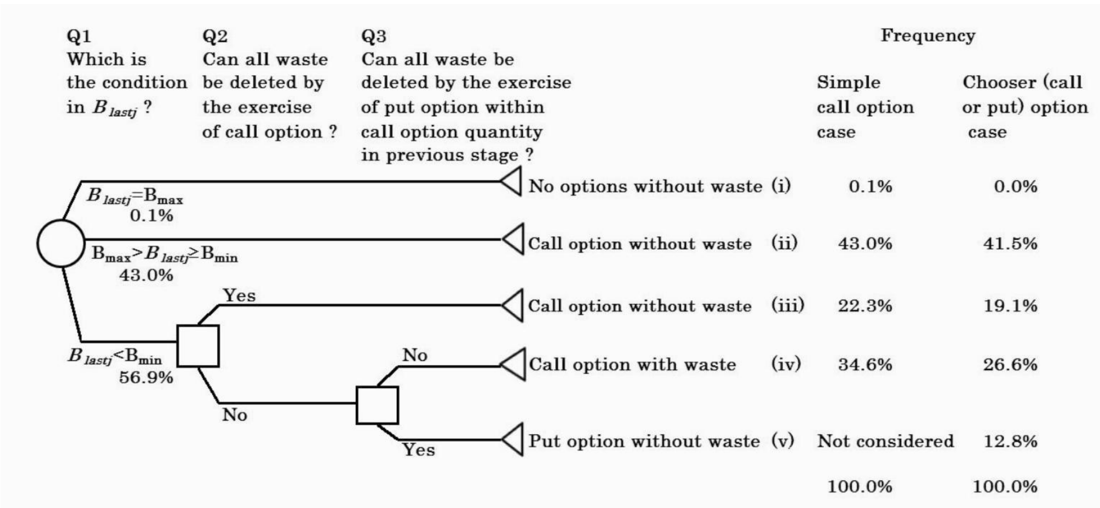


Fig.6-10 Decision tree and frequency with call and put options

6.7 Conclusion

This chapter's contribution is, as theory building, how some flexible before and behind shift of demand timing can enhance productivity and reduce waste based on agreement with both buyer and supplier. Valuable option opportunities for supplier are expected to exist in more variable daily demand. ROA predicts that higher OV can be gain even if supplier in ready-to-drink industry with uncertain demand has such technological constraints as informational feedback system, batch size, semi-fixed operating cost, and waste cost. ROA in daily supply chain shows the specific values of call and put options to uncertain demand of last batch, and then make a proof of concept, 'Virtual Inventory' by timing option in a case study of real demand data, resulting in improvement of production efficiency and waste reduction.

The definition of ROA here is the flexible production change ratio di_j to uncertain demand D_j to deal with control of last batch demand between minimum and maximum capacity for waste reduction and operational efficiency improvement. Then positive and negative selections of di_j means call and put options respectively. Sensitivity analysis of dependent variables to decision variable di_j and random and conditional variable D_j got following findings or implications as:

In first-stage, call option cannot be exercised for no chance if last batch demand just meets at maximum batch capacity, can be exercised for improvement of operational utilization rate if last batch demand is larger than minimum necessary capacity, and can be exercised for the improvement of that ration and the reduction of waste otherwise. And in second-stage, not only call in the above each condition but also put option can be exercised for removal of waste and processing of last batch within previous call option size of demand volume. Thus, it is shown that each optimal decision can be classified according to last batch demand level by using past practical demand data.

In soft drink industry, some short shelf-life soft drinks need daily order production system 'without any inventory' at supplier side. However, if buyer can agree to provide supplier some flexibility to change daily uncertain production volume, supplier can improve operational utilization ratio, reduce waste, and remove waste and processing of one batch itself. This is a 'Virtual Inventory' system without any physical stock place but just timing flexibility. Ultimate style will be integer planning of only full batch tanks. Thus, even at daily repeated order-production system, 'Virtual Inventory' system serves as a buffer between demand and supply by some timing flexibility. 'Virtual Inventory' enables supplier to enhance productivity, escape waste, and control demand at once.

Although practical demand data validated our system, more general model is needed to expand the improvement of parameter measurement and innovative scenario. For example, some stochastic processes as theory testing can produce simulation models for real options. Then, 'Virtual Inventory' system with flexible timing can be analyzed by simulation based on multi-repeated transactions. The extension of this model is left for next chapter.

Chapter 7 Effects of the Exercisable Duration and Quantity in Multi-stages

7.1 Abstract

In response to the daily repeated supply chain of soft drink under uncertain demand, ROA is applied to a flexible production amount. A supplier can exercise call and put options in order to modulate between the demands and the efficiency of a supplier's productive capacity. First test is to examine the impact on the OV between the three-stage cycle and the multi-stage for a one-year duration using Monte-Carlo simulation. The comparison shows that the options with multi-stage can increase the value. The reason is that the former options are only optimized within each of three short stages during one year, while the latter options are totally optimized in one year. Next as to options with multi-stage, we examine the impact of the ratio of the exercisable option quantity to the demand carton pieces on the OV. The OV can be gradually increased in proportion to a larger ratio, but the growth ratio is gradually reduced. This study shows that options can yield OV to a longer stage and larger exercised quantity.

7.2 Introduction

7.2.1 Volume Flexibility over Periods

As shown in chapter 6, ROA is one of the tools for coordinating between batch size and costs. If the order volume to a given batch size is somewhat small, it has the opportunity to exercise the call option to enlarge the order. But if the volume in batch size is too small to produce, it might have the opportunity to exercise the put option to stop the production. Some works of ROA in the supply chain are discussed in terms of volume flexibility and relation between supplier and buyer (Kume and Fujiwara 2016a, 2016b).

In this chapter, it will be shown that ROA can modulate the volume flexibility not only in one stage but also over the stages. The former is the option to expand for the call or option to shrink for the put, and the latter is the timing option. The timing option seeks the optimal timing for the investment, where the waiting turns out to be better than investing immediately. The timing option plays an important role in many fields, such as biotech start-ups (Fujiwara 2011), environmental policy in a country (Nishide and Ohyama 2009), positron emission tomography (Pertile et al. 2009), and pumped hydropower storage (Fertig et al. 2014). As chapter 2 is referred, ROA can be evaluated by Monte-Carlo simulation.

7.2.2 Monte-Carlo Simulation

Monte-Carlo simulation is a simulation of stochastic natural phenomena, which utilizes random numbers in artificial processes (Allen 2011; Glasserman 2003; Chang et al. 2013; Schneider and Kirkpatrick 2006; Wright 2002). Whereas a binomial tree and finite difference are impracticable for purposes of valuing options with more than three uncertain factors, Monte-Carlo simulation is appropriated, because this type of technique is recommended for high-dimensionality or stochastic parameter problems (Lazo et al. 2009).

A feature of Monte-Carlo simulation is the calculation method of obtaining an approximate solution by performing several times simulations using random numbers. Even if the problem is hard to solve analytically, it is possible to obtain a solution approximately by sufficiently repeating the large number of simulations. Discrete event simulation is one type of a more general form of statistical simulation called Monte-Carlo simulation (Allen 2011).

Monte-Carlo simulation applied to a real options approach for commodity is studied such as in the investment integrity and value for power-plants with carbon-capture (Lorenzo et al. 2012) and power generation with renewable energy (Pereira et al. 2014).

When it comes to Crystal Ball, Monte-Carlo simulations using Crystal Ball are observed in many studies, such as greenhouse gas emission inventory (Monni et al. 2004), propagation of distributions (Gonzalez et al. 2005), information system project performance (Yang and Tian 2012), electric power plant construction (Madlener and Stoverink 2012), and airport construction (Martins et al. 2014). Within the supply chain problem, choosing between single and multiple sourcing is studied (Costantino and Pellegrino 2010). There are, however, very few studies on Monte-Carlo simulations about supply chain except for such cases.

7.2.3 Research Questions

There are two research questions. The first is how long and how much flexible before and behind shift of demand timing can enhance productivity based on agreement with both buyer and supplier. The second is how much options' upper limit is more suitable for supplier's cost effectiveness. The objectives of this study stand for a second step as practical simulations after theory building in chapter 6.

It is unique for this study in regard to the following two points. First, timing option can play as a 'virtual inventory' function in the supply chain. Second, the timing option cannot only postpone but also quicken for the optimal timing. General studies of the timing option consider only deferment. However, soft drink production in repeated uncertain demand will find also front-loading because of repeated inventory as a sort of irreversible investment under uncertainty.

7.3 Problem Description

7.3.1 Model Building

Model building is based on reaffirmation of the information of supply chain in chapter 6.4. From the supplier's viewpoint, it is considered as a general framework of daily repeated multi-stage supply contracts between one supplier and one buyer. The supplier gets orders from the buyer and produces the ordered soft drinks and delivers them to the buyer. Figure 6-2 again shows an illustration of informational feedback between buyer and supplier with respect to production from first-stage to fourth-stage in multi-stage. Even after fourth-stage, this informational and physical chain can last infinity as going concerns.

Typical formulation batches are explicitly considered to be the volume of the last batch and coped with options with respect to the condition of $B_{last\,j}$ in Figure 6-4. A supplier should consider not only exercising options but also preventing shortage for the buyer. The ROA on inventory in the supply chain is also regarded as a sort of timing decision to invest immediately or not. The decision making is clarified by the systematic decision tree. The ROA has the virtual inventory function by a possibility of bringing forward or postponing the order. Thus, the associated flexibility has a positive economic value when uncertainty exists in the last batch.

7.3.2 Mathematical Model

To evaluate OV, Equation 6-21 is used for mathematical model according to the conditions of $B_{last\,j}$ and di_j. Since OV_j is changed by D_j, it is hard to determine the general effect of exercised options on OV only at one stage. If the supplier exercises call option to increase production, demand in the near future, can be expected to decrease by the amount of the exercise of options and not be same with no options. To avoid this contradiction, we put the premise that the same amount of production per year (N=366). In order to evaluate the averaged OV at one stage, averaged OV is given by the following Equation 7-1.

$$\text{Dairy Averaged OV} = \frac{1}{366}\sum_{j=1}^{366}\left(\mathrm{ENPV_j} - \mathrm{NPV_j}\right) \qquad (7-1)$$

In this same situation, averaged di is given by the following Equation 7-2.

$$\text{Averaged } di = \frac{1}{366}\sum_{j=1}^{366} di_{\mathrm{j}} \qquad (7-2)$$

7.3.3 Monte-Carlo Simulation Model

7.3.3.1 Independent Variables

The definition of probability density function applied to each random variable can be made based on historical data in this study. D_j is taken as independent variable, because demand has the greatest influence on both buyer's safety stock and supplier's production in the supply chain.

The cumulative distribution function of a discrete random variable is the sum of unit step functions $u(d)$ located at each value of D, and weighted by each of the corresponding probability mass function values.

$$F_D(d) = \sum_{j}^{\infty} p_D(d_j) u(d - d_j) \qquad (7-3)$$

The probability density function of a discrete random variable is given by Equation 7-4, in terms of the Dirac delta function $\delta(d)$ (Guimaraes 2009).

$$f_D(d) = \frac{dF_D(d)}{dD} = \sum_{j}^{\infty} P_D(d_j)\delta(d - d_j) \qquad (7-4)$$

where

$F_D(d)$– Cumulative distribution function of D_j

$f_D(d)$– Probability density function of D_j

d_j – Discrete random variable of d_j, $1 > d_j > 0$ and $\sum_{j=1}^{\infty} d_j = 1$

Monte-Carlo simulation can use the assumed demand. Commercial Crystal Ball software running on the spreadsheet can offer probability distributions that can be used as independent variables: random variable and the probability density function.

7.3.3.2 Decision Variable

Notation di_j is chosen, because it is the index that allows the supplier to change the production volume as flexibility. Supplier depends directly on the di_j, and reduces the uncertainty in $B_{last\,j}$. In this paper, di_j is only affected on the condition of $B_{last\,j}$, since di_j is changed to escape from the worst condition of $B_{last\,j}$.

7.3.3.3 Implementations and Results

Monte-Carlo simulation results in repeated-calculated values, which are represented by probability frequency distributions. However, there are weaknesses, and that number of simulations becomes enormous if results need to get a high accuracy. In this study, the number is 10,000 times.

7.3.3.4 Analysis and Decision

After all simulations are performed, statistical data are prepared for the ROA. Then, all information obtained is analyzed for guiding the supplier's action. Table 7-1 shows options with the possibility in the annual stage by the following three cases.

7.4 Case Study

Here are three cases.

7.4.1 Case 1: No Options

The case with no option is the base case and does not have a right to exercise options all over the stage. The supplier produces the soft drink relative to just the demand in each stage and may yield the waste without the supplier's will. The profits in one stage are always given by Equation 6-1.

7.4.2 Case 2: Options with Three Stage Intervals

The case, which has options with three stage (or day) intervals, has a right to exercise options in the first two stages. The last stage must meet the same number with the gap between demand and production within three stages. In other words, the effect of options is adjusted in each third stage and not carried over to the next fourth stage. This case repeats the stage of these three patterns until it meets the number of annual stages (N=366). Moreover, the supplier can exercise only call option to increase the production in first stage. Put option to decrease the production should be exercised, only after call option is exercised in the previous stage and within the quantity of exercised call. By virtue of this constraint, the buyer can avoid that the production volumes of two successive stages become negative. With three stages, there is a possibility that supplier exercises call option in the first stage, call or put in the second stage, and no options in the third stage.

The profits in each stage of the first two are always given by Equation 6-9 because of options, and the profits of the last one are given by Equation 6-22 because of no options. The profits components with their respective costs are also meaningful.

7.4.3 Case 3: Options with Multi-stages

The case, which has options with multi-stages, can exercise options during all the stages except the last stage. The last stage must meet the gap number between demand and production as the case 2. In other word, the effect of options is continued and carried over to the next stage with multi-stages. In the same way as case 2, the supplier can exercise call option to increase the production in the first stage. From the second stage to last stage, there is a possibility that the supplier exercises the call or put, but put option has a restriction to exercise like case 2.

The profits in each stage (except for the last stage) are always given by Equation 6-22 because of options, and the profits of the last one are given by Equation 6-9 because of no options. The profits components with their respective costs are also meaningful.

Table 7-1 Options with the possibility in the annual stage by cases

Number of stage	Case 1: No options	Case 2: Options with three stages intervals	Case 3: Options with multi-stages
1	No option	Call option / No option	Call option / No option
2	No option	Call option / Put option / No option	Call option / Put option / No option
3	No option	No option (Just meet the production and demand in recent three stages)	Call option / Put option / No option
4	No option	Call option / Put option / No option	Call option / Put option / No option
5	No option	Call option / Put option / No option	Call option / Put option / No option
6	No option	No option (Just meet the production and demand in recent three stages)	Call option / Put option / No option
...	...	...	...
N(=366)	No option	No option (Just meet the production and demand in the annual stages)	No option (Just meet the production and demand in the annual stages)

7.5 Simulations

7.5.1 Experiment 1

There are two simulations according to the right of exercised options. First is experiment 1 which simulates dairy averaged OV and di, second is experiment 2 which simulates optimal di to set a value of upper limit.

The model in case of no options is given in Equation 6-1. This model is used in all stages of case 1, each third stage in case 2, and the final stage in case 3. The model in case of options is given in Equation 6-9. This model is always used in the first two stages of case 2, and all the stages except for final stage of case 3. When options are not exercised, di_j and Oq are considered to be zero.

First of all, option value and all account items are expressed as JPY per stage. Next, sales, direct material costs, processing cost, waste cost, and option cost are calculated for NPV and ENPV.

Values of option value and accounting items are summed up and divided by the number of the stages, because the annual number of production is equal in all three cases according to assumptions, but the production number of each stage is different between three cases because of options. Results are shown as 10,000 simulation trials of averaged annual value per stage. The number of stages in one year is 366.

The model parameters of averaged OV with Equation 7-1 are shown in Table 7-2. In particular, it is considered that direct material and processing costs show a clear idea of the volume flexibility. Costs of waste and exercised options are also considered. D_j is given as independent variable, while B_{last} , n, Oq , and Wq are dependent variables. Then D's change gives the uncertainty on the amount of the B_{last}.

Decision variable di_j is an indicator of suppliers' decision making and its range in the discrete is shown in Table 7-3.

Table 7-2 Model parameters for Monte-Carlo simulation

Symbols	Value	Description
$\mathrm{B_{max}}$	5,000	Maximum pieces of production in one batch (pieces/group)
$\mathrm{B_{min}}$	3,000	Minimum pieces of production in one batch (pieces/group)
R	60	Sales price (JPY/piece)
Vc	20	Direct material cost (JPY / piece)
Fc	30,000	Processing cost per batch (JPY / group)
Wc	5	Waste cost per piece (JPY/piece)
Oc	1	Option exercised cost (JPY / piece)

Table 7-3 Feature of decision variable for Monte-Carlo simulation

Symbols	Range of value	Type
di_j	$0.10 \geq di_j \geq -0.10$	Discrete (0.01)

The sample distribution of D_j is presented in Figure 7-1. The lognormal distribution is fitted with the values of the variable D_j, within a previously given range from historical data in practice. The detail of the distribution is shown in Table 7-4.

The averaged OV and its ratio of the option exercise quantity to the demand pieces (di) are compared between Case 2 and Case 3. After that, the comparison of values in composed accounting items is done.

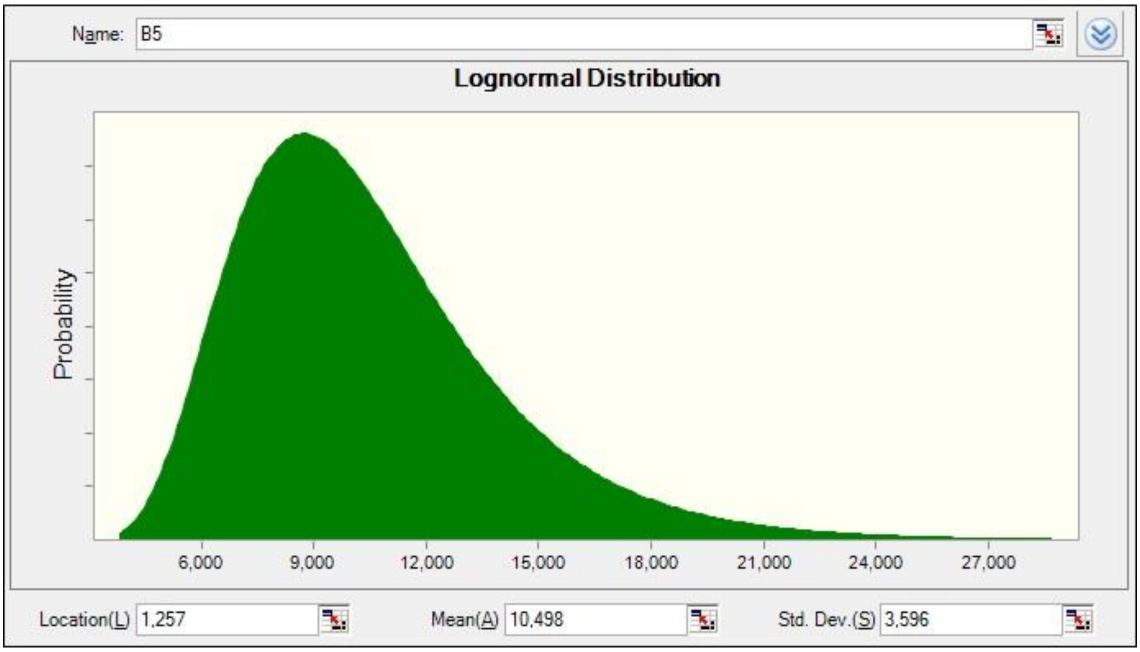


Fig.7-1. The probability distribution of D

Table 7-4 Feature of independent variable for Monte-Carlo simulation

Symbols	Range of value	Parameters
D_j	$40{,}000 \geq D_j \geq 1{,}000$	$\text{Location} = 1{,}257, \text{Mean} = 10{,}498, \text{S.D.} = 3{,}596$

7.5.2 Experiment 2

The previous experiment 1 is based on specific stage settings for Monte-Carlo simulation, as shown in Tables 7-2 and 7-3. According to Equation 6-21, it seems that larger di_j can get higher option value by increasing quantity of call option. However, it is not known what di_j is suitable for supplier's cost effectiveness. Since the Oc is always constant, the option value ratio to upper di is a good indicator of the efficiency. "Upper di" means not value of mean or median, but set value of upper limits.

The Monte-Carlo simulation is started in case of options with multi-stage only, which has several different upper di. The parameter values of upper di are assumed by 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, and 1.00 with the same discrete interval of 0.01. Each value of lower di also corresponds to -0.10, -0.20, -0.30, -0.40, -0.50, -0.60, -0.70, -0.80, -0.90, and -1.00. Therefore, as the upper di increases, the range of di that can be selected spreads. With these 10 groups (pair values of positive and negative signs), the option value, di, and the ratio of option value to upper di(OV/di) are compared as sensitivity measure. The other conditions are the same as in experiment 1.

7.6 Results

7.6.1 Results of Experiment 1

To show the validity of the proposed ROA, two steps in three cases is discussed together. First is the analysis of expected dairy averaged OV, and second is the values of di.

The behaviors of OV are shown in Figure 7-2, where there are two probability distributions of OV. They have each mean option value of 12,197 JPY/stage and 24,367 JPY/stage in the three stage intervals and in the multi-stages. The median option value with three-stage-intervals, with 9% probability of occurrence, is 12,203 JPY/stage, while the value in option within multi-stages, with 8% probability, is 24,365 JPY/stage. Thus it is seen that most option values in multi-stages are higher than in three-stage-intervals, because options can be continuously exercised in multi-stages.

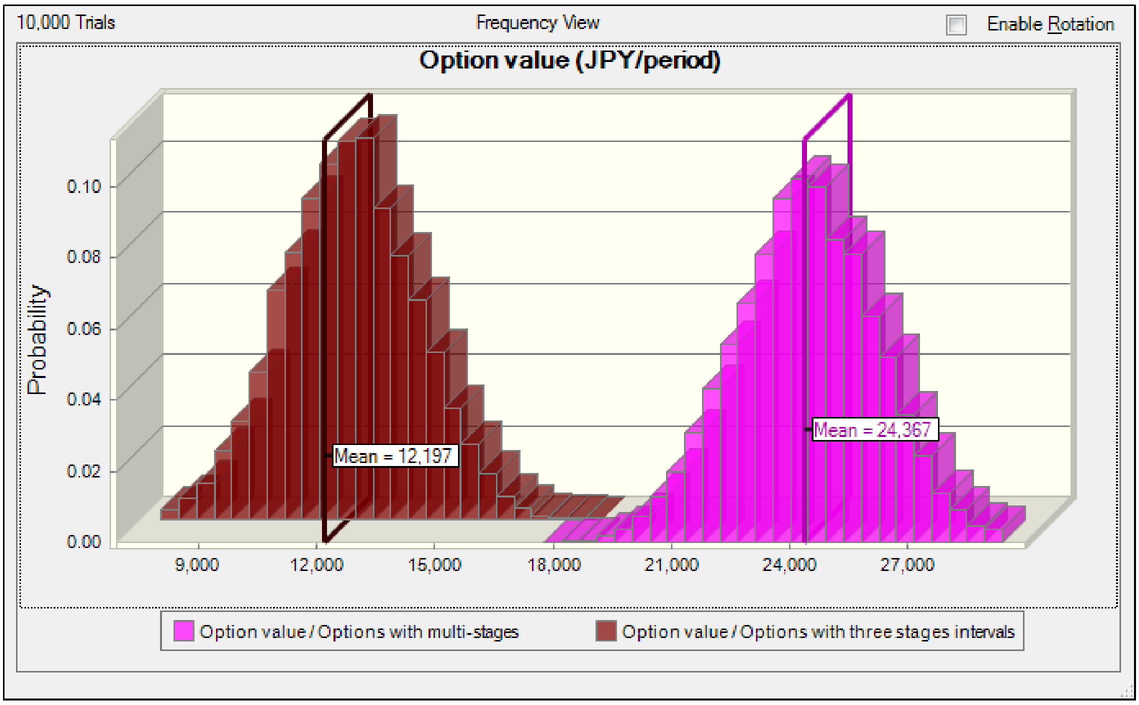


Fig.7-2 The results of OV

Figure 7-3 shows the results of the expected dairy averaged di, which means the ratio of the option exercise quantity to the demand pieces per stage. As can be seen, the mean value of 0.07 in the case of options with multi-stage is higher than that of 0.03 within the case of options with three stages intervals. In Figure 7-3 options with multi-stages would generate much bigger OV based on di. While di can take negative as well as positive value, the distribution of di is biased to the positive side, suggesting that risk-hedge function can increase OV. However, even if one changes the production quantity of each stage using options, it is worth noting that total production volume must be the same with the demand.

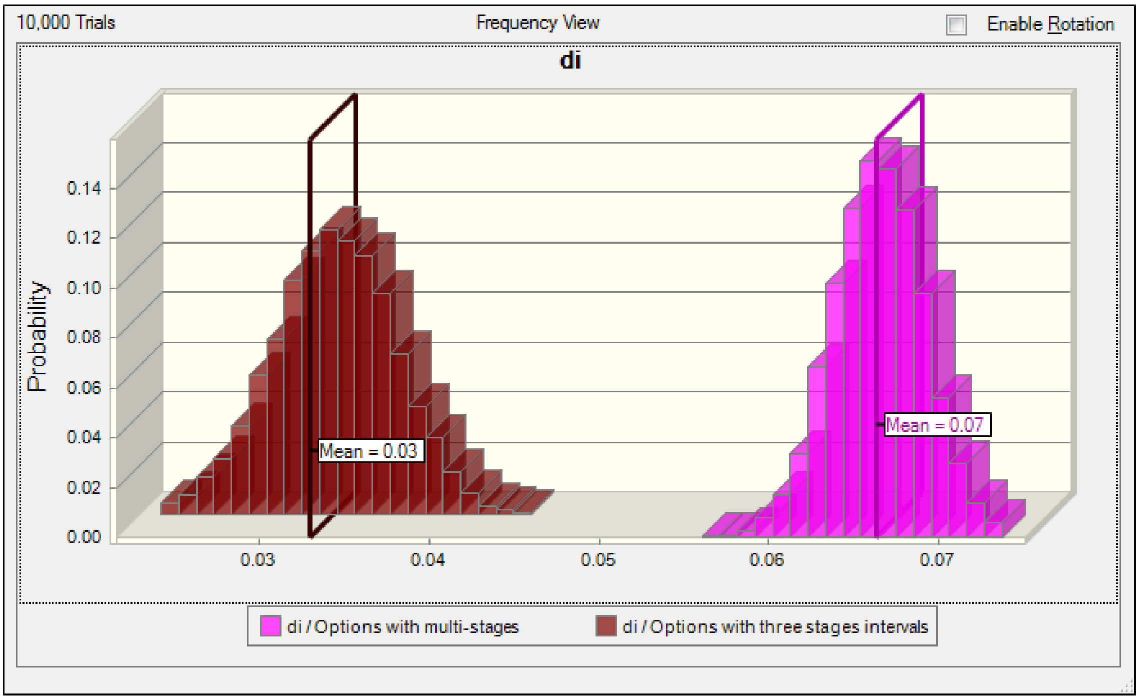


Fig.7-3. The results of *di*

To further examine the distribution of the OV variability, the statistical measurements (mean, median, standard deviation (S.D.), skewness, kurtosis, minimum, and maximum) of the accounting items are calculated. From Table 7-5, the values of mean, median, S.D., skewness, kurtosis, minimum and maximum of the sales are all the same among three cases. This means that total production volume is equal with the demand even if the options change the partial sales in some stages of annual period.

However, a significant discrepancy exists between the option value between the three stage intervals (Case 2) and the multi-stages (Case 3). Both S.D. values of options are within a narrow range between 1,688 and 1,794, whereas both minimum and maximum option values with three stage intervals are much less than those of options with multi-stages. Given that the magnitude of difference between minimum and maximum represents the distribution in a potential, it is better for a supplier to exercise options with multi-stage.

Each value of the mean, median, S.D., skewness, kurtosis, minimum, and maximum is similar in profits, direct material costs, processing cost, and waste cost. The expected profits are all positive (ranging from 319,478 to 343,845) and the kurtosis varies between 3.00 and 3.03. The highest value of profits is provided with case 3, following case 2 and case 1. On the contrary with respect to direct material costs, processing cost and waste cost, the highest value is obtained in case 1, following case 2 and case 3 subsequently. It is natural that case 3 gets the highest profits because of same sales and cheapest costs within three cases. Additionally options are only optimized for each three short stage of one year in Case 2, while options are continually optimized for whole one year in Case 3. Case 3 has more opportunity to exercise options to flexibly minimize the costs under the facing condition.

Even though more option exercise cost is paid in case 3 (mean of 809 JPY/stage) than in case 2 (mean of 625 JPY/stage), case 3 has higher profits and option value.

Table 7-5 Results of accounting items for Monte-Carlo simulation

	Number of Case	Mean	Median	S. D.	Skewness	Kurtosis	Minimum	Maximum
Option value	Case2	12,197	12,203	1,688	-0.0187	2.94	5,929	18,350
(JPY/piece)	Case3	24,367	24,365	1,794	0.0107	2.98	18,006	31,989
Profits	Case1	319,478	319,427	6,604	0.0479	3.03	295,193	346,676
(JPY/piece)	Case2	331,675	331,604	6,597	0.0495	3.03	305,929	356,914
	Case3	343,845	343,804	6,615	0.0474	3.00	319,960	366,871
Sales	Case1	629,858	629,796	11,154	0.0472	3.00	591,115	670,439
(JPY/piece)	Case2	629,858	629,796	11,154	0.0472	3.00	591,115	670,439
	Case3	629,858	629,796	11,154	0.0472	3.00	591,115	670,439
Direct material costs	Case1	227,856	227,823	3,827	0.0353	2.97	213,931	241,890
(JPY/piece)	Case2	218,846	218,816	3,716	0.0327	2.98	205,946	231,543
	Case3	214,261	214,231	3,624	0.0403	2.99	201,623	227,650
Processing cost	Case1	78,049	78,033	1,181	0.0272	2.98	73,525	82,459
(JPY/piece)	Case2	76,490	76,475	1,161	0.0189	2.95	72,295	80,410
	Case3	69,868	69,836	1,062	0.0336	3.02	65,820	74,016
Waste cost	Case1	4,476	4,477	257	0.0331	3.02	3,612	5,546
(JPY/piece)	Case2	2,223	2,223	179	0.0064	3.00	1,493	2,980
	Case3	1,076	1,074	114	0.1137	2.99	671	1,538
option exercised cost	Case2	625	625	19	0.0210	3.00	554	700
(JPY/piece)	Case3	809	808	20	0.0307	2.95	742	881

7.6.2 Results of Experiment 2

The previous experiment 1 shows that the multi-stage system can get the highest OV in three cases while a range of di_j from -0.1 to 0.1. Next the objective of experiment 2 is what upper di_j is suitable for supplier's cost effectiveness between 0.1 and 1.0.

Figure 7-4 shows the OVs with different upper di_j. As a result, when di_j increases, the OV also tends to be increased. The OV is measured by the order of upper di_j from 1.0 to 0.1 with 0.1 increments. The expected OVs (JPY/stage) with different upper di_j from 0.1 to 1.0 ranges from 24370 to 34068. Except 0.5 and 0.6 of the upper di_j the range of expected option value is almost monotonously increasing with the upper di_j. However, the increase rate of option value is gradually diminishing. It is due to that batch affordance to exercise options is fixed.

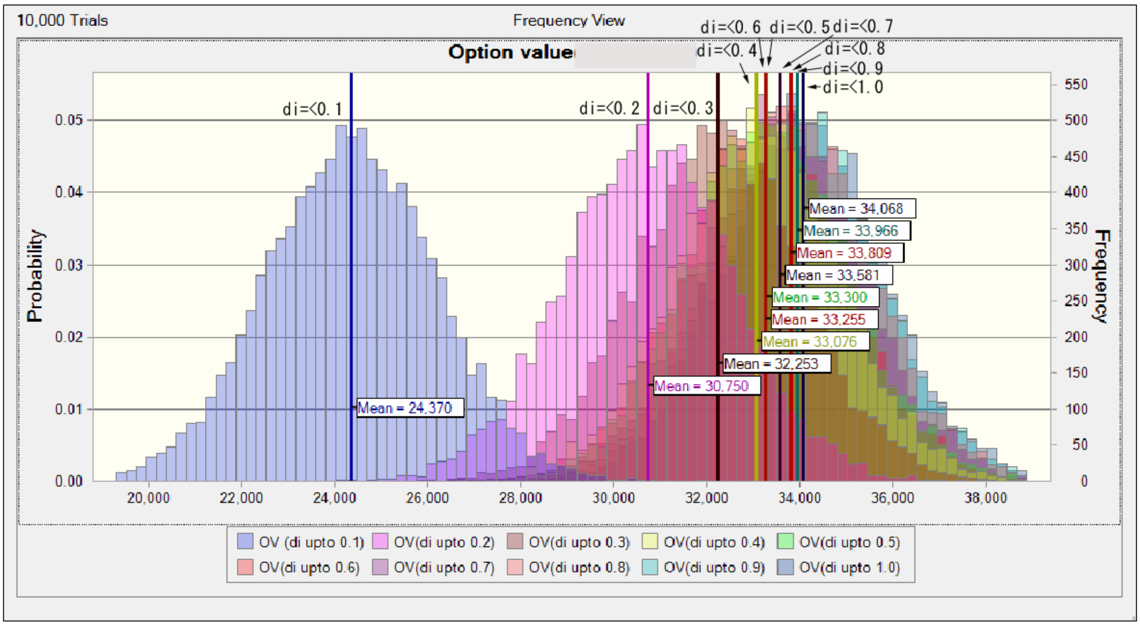


Fig.7-4 The results of OV with different di ranges

To illustrate further numerical results on di_j as decision variable, behavior of di_j with regard to previous OV is shown in Figure 7-5. The di_j is measured by the order of upper di_j from 1.0 to 0.1 with 0.1 increment. The expected di_j with different upper di_j from 0.1 to 1.0 ranges from 0.066 to 0.372.

The value of di_j becomes large, as the upper limit of di_j is large. In many cases, however, the options are not exercised up to an upper di_j. Actual exercised value of di_j increases, if the upper di_j becomes larger. If upper di_j is smaller, kurtosis is relatively bigger, and *vice versa*. As the same with OV, the increase rate of di_j diminishes gradually. When the optimal di_j becomes larger, other conditions except di_j can restrict an optimal di_j.

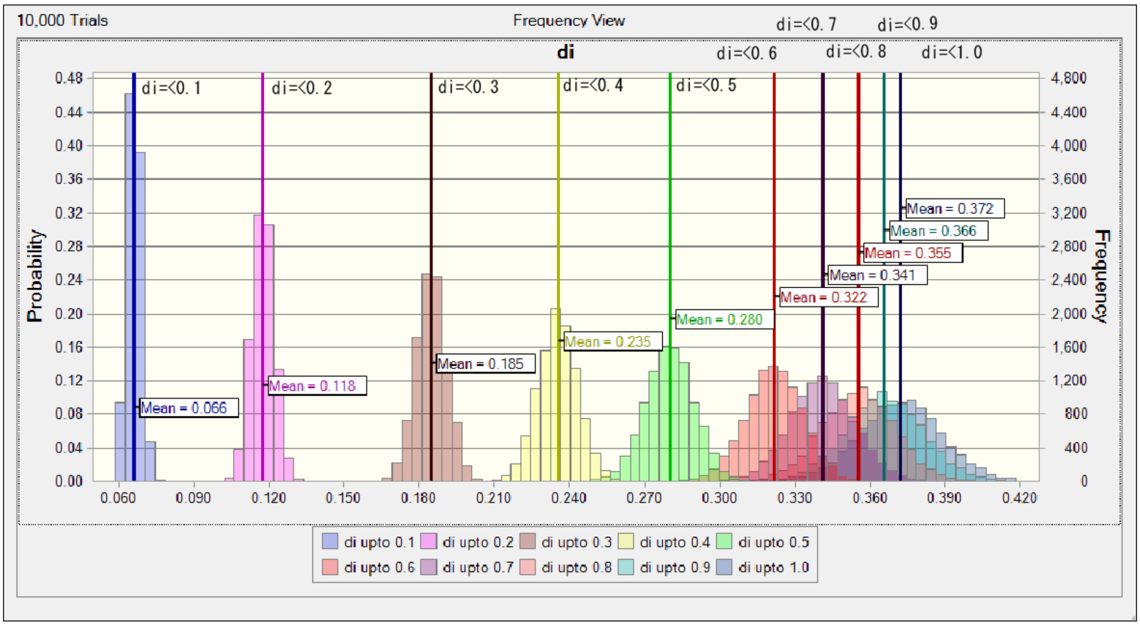


Fig.7-5 The results of mean of di with different di ranges

The di_j is measured by the order of upper di_j from 1.0 to 0.1 with 0.1 increment. With these 10 groups, the ratio of option value to upper di(OV/di) is compared, using the Monte-Carlo simulation in the multi-stage,

Figure 7-6 shows the values of OV/di with different di ranges. As upper di_j grows larger, the OV and actual di_j are also increased as shown in Figures 7-4 and 7-5, respectively. However, the ratio of OV/di is gradually decreased when upper di_j grew larger. It means that effect of exercised options is diluted by option cost (JPY/pieces).

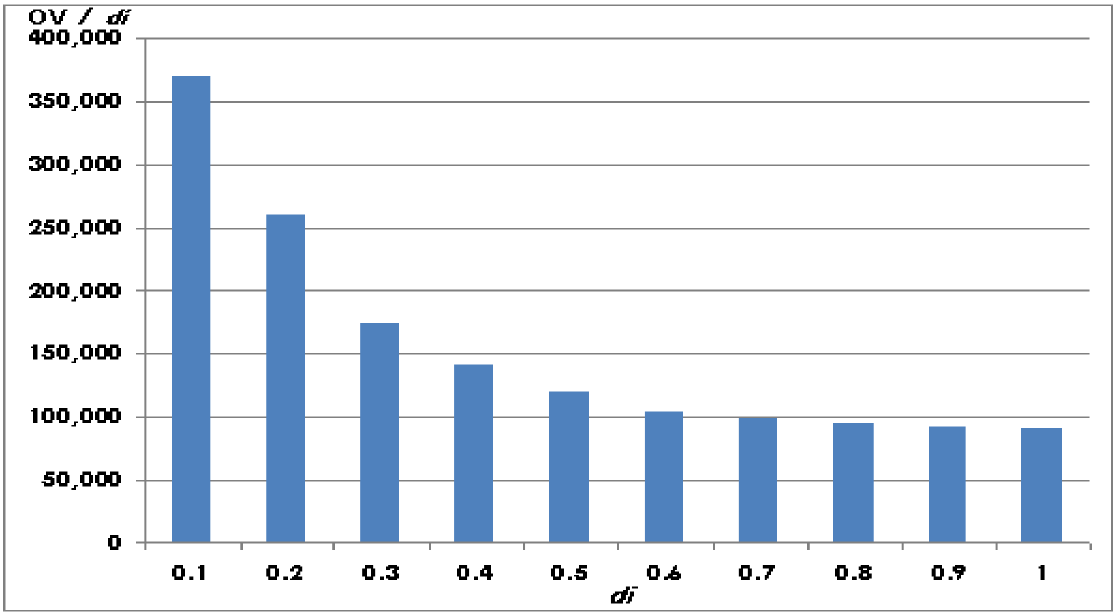


Fig.7-6 The results of OV/di with different di ranges

7.7 Conclusion

In supply chain of soft drinks, the use of real options has advantages over no options because of gaining positive option value in experiment 1. Moreover, the option value of case 3 is greater than that of case 2 by means of large options exercised quantity as di. The results show that continuous option-exercise opportunity yields a large option value. Call option is useful for not only the reducing the waste cost but also the utilization of processing cost by expanding production as possible as in the same batch. On the other hand, put option is effective in diminishing whole production in the last batch to prevent the waste and inefficient processing costs.

ROA can influence on adjusting the amount of production not only simple call and put options at that stage but also timing option as virtual inventory between stages. Unfavorable condition in demand turns out to be more favorable by means of the ROA functions. Our contribution is to consider this options' effect as one of the timing options. Generally speaking, shortage in supply chain is not permitted. But if the call option is exercised in the previous stage, the supplier has an opportunity to exercise the put option at this stage within the range of exercised call option quantity. In this way, it may meet the demands with sequential two stages, and it is possible to avoid the risk of shortage. The put option plays an important role in timing option.

The range of exercised options in experiment 2 is spread each side 0.1 step by step and reached from -1.0 to 1.0, although the range of exercised options in experiment 1 is limited from -0.1 to 0.1. Using case 3, which is the most effective in experiment 1, we examine the most desirable range in exercised options. As a result, when the range of exercised options is widened, actual exercised options and option value are also increased gradually. However, efficiency of exercised options, which is evaluated by dividing the option value by the upper limit of the exercised options range, is reduced when the range is widened.

Since option value is always positive including option exercise cost, supplier should exercise options in the range as large as possible. In such an optimal condition for supplier, the uncertainty of production would increase to the buyer.

There is little possibility of reaching an agreement to exercise options such as a large range between the buyer and the supplier. The point that is difficult to reach the agreement is the limitation in this research.

Chapter 8 General Conclusion and Future Research

8.1 Abstract

This chapter discusses the general conclusion and future research that have discussed throughout the chapters, and uses these limitations to characterize challenging future research. This study is mainly divided into three parts: (1) potential capital investment for long term sales, (2) potential capital investment in seasonal high demand for medium term sales, and (3) possible investment in the optimal production for daily sales. This study is the first conducted from short-term to long-term problems in response to repeated uncertain demand. Especially combinations of ROA and either seasonal variation or daily uncertain production are novel examples to examine in supply chain area, regarding food waste and productivity.

When ROA is used in practice, it is considered that the parameter for stochastic model in the future sales in more accurate ways such as application of Bayes' rule, as well as the technical difficulties in interval between decision-making and exercise.

In the future research, it may be better to forecast the hybrid type model that applies to both ARIMA (SARIMA) and ARCH (GARCH).

8.2 General Conclusion

Demand forecasting prior to an actual demand is inevitable in supply chain. If there is a gap between them, friction against smoothing should be removed. However, the soft drink industry has been faced with technological and market uncertainties. The technological uncertainties, for example, arise from reasons as strengthen in food sanitation standard, wasteful use of resources, short expiration date, and innovation in containers. The market uncertainties are such as daily demand which is known just on the day starting production, sudden cancellation of production contract, and product life cycle. Because of these uncertainties, an improved cooperative supply chain between buyer and supplier is required in order to build out the productive system for commercial production.

This study is the first study to introduce ROA into different investments on a daily, monthly (seasonally) and yearly basis in a daily-repeated production.

The focus of this study is to determine the appropriate demand forecasting in yearly and monthly units, and to respond to them from supplier's (producer's contract with buyer) perspective by using ROA. The basic idea of ROA is to enable the investment for improved value of commodity or real assets through flexible decisions in the future. Here, real option is a right, but not an obligation, to exercise. In this study, ROA is applied to the matters, from not only long but also short terms, of concern about supply chain.

This study is mainly divided into three parts: (1) potential capital investment for long term sales, (2) potential capital investment in seasonal high demand for medium term sales, and (3) possible investment in the optimal production for daily sales.

First topic is potential capital investment for long-term sales. Annual demand is forecasted by ARIMA model which is one of the methods for time series analysis. ROA indicates when, how much sales and how to respond to demand in cases of demand increase and decrease. If sales of soft drink are favored, the supplier can exercise the option to expand (American call option) and expects increase in the sales. If the sales are unfavorable, the supplier can exercise the option to shrink (American put option) and expects decrease in the sales, sparing the cost. These options are evaluated by four-step process in binomial lattice only once. The option value becomes increased when flexible decision for irreversible investment is made under uncertainty.

Second is potential capital investment in seasonal high demand for medium term sales. The demand of soft drink may not be fulfilled in the summer because the supply is too low to meet the demand. In particular, there are several studies that combine only one season with ROA, but this study forecasts repeated seasonality with SARIMA and associates it with ROA. Monthly demand is forecasted by SARIMA model which depicts seasonal movements. Two alternative options are compared and evaluated, one is Bermudan call options to employ additional workers to increase efficiency in summer and dismiss in winter. This attitude is repeated each year. The other is American call option to replace equipment to improve machine capability throughout the year. These options are evaluated by four-step process in binomial lattice with 10,000 runs of Monte-Carlo simulation. Results show that employing additional workers has an advantage over replacing equipment under uncertainty. But, the highest improvement is gained if the two options happen to be alternatively exercised. It is wiser for the producer to forecast the sales, have the both American and Bermudan options and seek for the opportunity of the American call to the underlying assets with dividends. ROA can support the producer to make his right decision. The decision for investment is usually subject to time lags before it can be made. Under the independent American call option based on SARIMA model forecasting, signal of monthly sales prior to critical optimal investment timing is evaluated. Then it is observed to enable to provide robust signal of decision-making for option exercise.

Third and final is possible investment in optimal production for daily sales. In response to the daily repeated supply chain of soft drink under uncertain demand, ROA is applied to a flexible amount of production. Volume flexibility and ROA are combined with the concept of uncertainty. A supplier can exercise call and put options in order to modulate between the demands and the efficiency of her productive capacity. Sensitivity analysis can be used to find critical conditional and decision variables at a decision tree, with call and put options for flexibility of positive and negative daily production. This shows that it is effective to exercise options for repeated daily production. Adjusting the daily production amount by ROA not only improves productivity but also proposes a method to improve food loss problems Next, effects of the exercisable duration and quantity in the three-stage cycle are compared with more multi-stages. This study shows that options can yield more their value to options with a longer stage and larger exercisable quantity.

In conclusion, even if the target period is long or short-term, the results reveal that ROA is useful for the supply chain. The flexibility in ROA allows supplier to avoid downside risk and gain upside opportunity under uncertainty conditions. This study is the first endeavor, conducted from short-term to long-term problems in response to repeated uncertain demand. Especially combinations of ROA and either seasonal variation or daily uncertain production are novel examples to examine in supply chain area, regarding food waste and productivity.

8.3 Future Research

In this study, author picks up the supply chain of soft drink which is restricted to ready-to-drink or personal-packaged drink, and have not touched on other supply chain. For example, supply chain of milk is one of the supply chains that are similar to soft drink and has same daily manufacturing system, uses often same carton container which means short best-before date, and same accounting component just like soft drink. Moreover, with limitation to carton containers, market size of milk is about ten times that of soft drink. On the other hand, there are various severe regulations on milk and shortage of raw milk also occurs. With such constraints, author would like to study the validity and effectiveness of ROA using the milk supply chain. It may need game theory to analyze the competitive and partnership relationships between players in the supply chain.

Time series analyses used in this study are ARIMA and SARIMA models. They are nonlinear time series analysis and dominant tools to handle time series forecasting. These models have a prerequisite to obtain stationary process which shows constant mean and variance. It shows white noise in their equations. It is important to remember ARIMA and SARIMA are methods that the forecast variance remains constant because the models do not reflect recent changes nor incorporate new information. Contrary to ARIMA and SARIMA models, there are autoregressive conditional heteroskedasticity (ARCH) and general autoregressive conditional heteroskedasticity (GARCH) models. They are also methods in time series analysis, but have different prerequisite from ARIMA and SARIMA models. ARCH and GARCH models reflect recent changes or incorporate new information. If white noise cannot be predicted, it is worth to check the procedure of ARCH and GARCH models. Since white noise is obtained in both ARIMA and SARIMA models, it is not necessary that ARCH and GARCH models are evaluated in this study. In the future research, it may be better to forecast the hybrid type model that applies to both ARIMA (SARIMA) and ARCH (GARCH), which is influenced by the prerequisite.

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Publications and Conferences

1. Publications with peer review

(1)Katsunori Kume and Takao Fujiwara, Production flexibility of real options in daily supply chain, Global Journal of Flexible Systems Management, 17(249-264), 2016.

(2)Katsunori Kume and Takao Fujiwara, Effects of the exercisable duration and quantity of real options in multistage, Technology Transfer and Entrepreneurship, 3(107-118), 2016.

2. International conferences with peer review

(1)Katsunori Kume and Takao Fujiwara, Valuation on flexibility in daily balancing between supply and demand in fresh beverage business; Based on real options approach, Portland International Center for Management of Engineering and Technology (PICMET), 2326-2331, 2014.

(2)Katsunori Kume and Takao Fujiwara, Optimal investment in soft drink plant under seasonal demand using a real options approach, UTS Business and Glogift 2016 Joint Conference, 1-1, 2016.