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The Flexible Application of Real Options for Subcontractor in the Soft Drink Manufacturing Industry

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Abstract In the soft drink industry, especially small and medium enterprises in Japan, there is a possibility of conversion from a labor-intensive industry to a capital-intensive. The demand for soft drinks may not be satisfied in the summer because the supply is too low to meet the demand. To address this situation, this paper proposes 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 the Bermudan option: to employ additional workers to elevate efficiency in summer and laying off in winter, this attitude is repeated each year. The other is the American option: to replace equipment to increase machine ability throughout the year. Results in ROA show that the highest improvement is gained if the two options are in a symbiotic relationship. Soft drink producers should search for replacing equipment, using the employees repeatedly. A temporary decision is not equal to an infinite decision.

Keywords Real options approach, seasonal autoregressive integrated moving average, soft drink, uncertain demand

I. Introduction

In recent years, food sanitation as food hygiene standards has attracted interest in 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 is 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

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establishing, implementing and maintaining prerequisite programmes (PRP) to assist in controlling food safety hazards.

Investment in food sanitation was said not to be profitable. However, some food plants in Japan are facing a situation where retailers are suspended unless they meet FSSC 22000 or equivalent certification. Because the number of plants to be certified is limited, the plants get the opportunity to increase sales if they receive FSSC 22000 certification. This trend is expected to fall by 2020.

In the soft drink industry, especially small and medium enterprises (SME) in Japan, there is a possibility of converting from a labor-intensive industry to a capital-intensive. Soft drink producers intrinsically manage their plants in consideration not only of the food sanitation, but also upgrade to increase the capacity. If the investment for the upgrade is accompanied with food sanitation, it is easy to recover the investment made. However, this irreversible investment is critical of sunk costs if soft drink producers cannot fully recover the expenditures. The investment decision-making depends on expectations about uncertain future demand and profits. Sales of soft drinks have been affected by seasonal fluctuation in Japan. For example, based on statistical results of both 2013 and 2014 in Japan, monthly production indicators of soft drinks are enhanced in summer, and lowered in winter (Food marketing research and information center, 2015).

Then, we found a case study where the demand in the summer can be often too high for production capacity. The producer has a plan to upgrade by means of investment for either plant (facility and equipment) modification or added temporary human resources in the summer. The former needs huge amount of investment at once and the latter needs small labor costs repeatedly. We assumed that the producer finds the condition for full substitution of the plant investment and labor costs.

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 uncertain. This investment contains not only upgrade, but also evaluation of food sanitation.

This paper proposes optimal investment for seasonal high demand that integrates uncertainty is based on the real options approach (ROA) and seasonal autoregressive integrated moving average (SARIMA) model. ROA is one of the tools for the producer concerned about irreversible investments under uncertainty, and is a right, not obligation. The producer can invest only when he sees that investment is valid by ROA. It means that the producer is not conducted right now and can be delayed for optimal conditions. The SARIMA model forecasts future values of a seasonal time series with a relationship between current and past situations (Box et al., 2016). The forecasting of future values by SARIMA is meaningful for ROA.

Our objective is to choose a way to take risks of uncertainty in demand, linking improvement of production capacity. Since the seasonal fluctuation of demand is a risk to the producer, the ROA of the financial theory is applied. However this literature is not sufficient. As for production capacity, 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 uncertainty of seasonal production (Coleman et al., 1964).

Our research question is to decide on what and when is optimal investment according to information from ROA. The existence of the managerial contribution can be examined, based on which applicability and effectiveness of ROA can be assessed. The questions considered in the study revolve around the following: (1) Conducting time series analysis for sales using the SARIMA model; (2) Applying models for forecasting with the SARIMA model combined with ROA; (3) Identifying correlation type of ROA and decision-making; (4) Interpreting the results within and out of ROA. This study used IHS global EViews (Version 8), Oracle Crystal Ball (Fusion Edition) and Microsoft Excel (Version 2010).

II. Literature Review

We present in this section fundamental concepts from two different areas: ROA and SARIMA.

1. ROA

The uncertainty of demand is the most annoying problem for soft drink producers (Kume and Fujiwara, 2016b). Soft drink producers often possess unaware options. Thus, even if the unconscious producers face on option opportunities, they are unlikely to take the opportunities. Soft drink producers using active search to find options will be much more likely to distinguish option opportunities from environmental noise than producers employing passive search (Barnett, 2005).

ROA is the most acceptable solution for the uncertainty, which is derived from a conceptual extension of financial option theory (Black and Scholes, 1973; Merton, 1973). The basic idea of ROA is to state that investment in improved value of commodity or real assets is possible through flexible decisions in the future (Myers, 1977). ROA enables us to take the option to delay, expand, shrink or abandon in the uncertainties. If ROA applies to flexible decision-making for investment with irreversibility to be equated with the sunk costs under uncertainties, the focus is on the value of information (Pindyck, 2008). It is the most important factor for options to choose what and when is the optimal timing. We quantify an option value, analyzed timing and investment behavior in soft drink industry.

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. Many studies present ROA using the binominal lattice method (e.g. Copeland and Antikarov, 2003; Mun, 2003; Kato and Zhou, 2010; Fujiwara, 2014). For the binominal lattice method, a four-step process is used (Copeland and Antikarov, 2003). Firstly, a standard NPV analysis of this project using discounted cash flow method (DCF) is estimated by the entire Free Cash Flow (FCF) over the life of the project. This analysis is based on present value (PV) without flexible options. Secondly, a binomial lattice combined uncertainties is built to drive the volatility of the market demand. Thirdly, the decision-making into the nodes of the event tree turns it out to a decision tree. The decision tree shows the payoffs from optimal decisions. Fourthly, valuation of the payoffs in the decision tree is conducted by option value. ROA includes the PV plus the option value.

Monte-Carlo simulation 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 the 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 get stochastic model with frequency at each value, but binominal lattice method can get only one analytical answer. So, we propose new a method that combines the binomial lattice method and Monte-Carlo simulation. One of our contributions is to simulate the binomial lattice method repeatedly and show the stochastic model.

Computer software is used to determine the uncertainty and sensitivity of random variable from the simulation (de Neufville et al., 2006; Bhat and Kumar, 2008; Chan, 2011; Kume and Fujiwara, 2016a). Crystal Ball is one of the software and we use it for Monte-Carlo simulation (Bhat and Kumar, 2008; Chan, 2011; EPM information development team, 2012).

2. Options for Investment

The main option type is divided into three by exercise restriction: European, American, and Bermudan options. A European option is only exercised on maturity, and exercised nodes are at maturity nodes in binomial lattice. An American option is exercised once 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 option with dividends shall be exercised (Merton, 1973). A Bermudan option 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 options could be exercised at only one time, the Bermudan can be exercised more than twice within a decided frequency. The producer has a plan to upgrade by the investment for either plant modification or added temporary human resources in summer. The former is the American option and the latter is the Bermudan options. The producer can choose one option from the two symbiotic.

As for capacity management of a plant, it is a prerequisite for achieving optimal capacity in a production plant to provide opportunistic value based on current demand or on demand and supply forecasts using ROA (Rosqvist, 2010).

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 used to deal with seasonal data. In a seasonal time series $\{Z_t | \mathrm{t} = 1,2,\dots,\mathrm{k}\}$, SARIMA has two types of variations. The first is between consecutive observations, while the second is between pairs of corresponding observations belonging to consecutive seasons. The first is ARIMA $(\mathrm{p,d,q})$ models which can be constructed to depict the relation between consecutive non-seasonal observation values. The second is ARIMA $(\mathrm{P,D,Q})\mathrm{s}$ models which can be formed to show the relationship between corresponding observation values of consecutive seasons. SARIMA$(\mathrm{p,d,q})(\mathrm{P,D,Q})\mathrm{s}$ can be depicted if:

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

where k 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, 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 independently distributed as a normal random variable with $\mu = 0$ and σ^2 (Bouzerdoum et al., 2013).

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

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

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

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

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

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

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

Equation (5) is the seasonal MA (SMA) operator of order Q. $(1 - B)^d$ and $(1 - B^s)^D$ are the consecutive non-seasonal dth differencing and the seasonal Dth differencing at s number of lags, respectively.

One of our contributions is to combine seasonal change and ROA. As for ROA, it seems that SARIMA is rarely used for forecasting future sales. The interval of ROA is targeted 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. Evaluation of SARIMA

For fitting a SARIMA model to the data, procedures should involve the next four steps: first is to identify the variables of SARIMA $(p, d, q)(P, D, Q)s$; 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 is to forecast future values based on the known data with confidence interval (Box et al., 2016). Box and Jenkins (1976) proposed to use the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to identify the order of the ARIMA model. 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 criteria of transformation lambda, the Bayesian information criterion (BIC) and the corrected AIC (AICc), the procedure for selecting the model is predominantly based on AIC. Theil's U and Durbin-Watson are also used (Oracle, 2009). The Theil's U is accuracy measure that compares the forecast 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 value influences the next value. The value can be any value between 0 and 4, shows slow-moving, none, or fast-moving autocorrelation. If the value is less than 1, the statistical model has an increase in one period followed by 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 followed by a decrease in the previous one. Tracking signal method is also used and is one of the measurements used for evaluating a difference between actual demands and forecast one.

The analysis and presentation of ARIMA (p, d, q) results are more complex, when p and q are increased. Our study 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 AIC that are one of the goodness-of-fit tests based on the seasonal adjustment rules. The software Crystal Ball is one of these softwares and worked on Excel. To validate the forecasting models, tracking signal is calculated. 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.

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

Equation (6) is the formula for tracking signal, and its denominator is called as mean absolute deviation (MAD). Tracking signal is used as a ratio of the cumulative value 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 so as to identify any unexpected patterns as quickly as possible.

III. Problem Description

1. Soft Drink Plant

In this study, the problem description is based on the uncertainty of demand. The volume of demand includes other factors such as unit price, weather, trend and so on. The demand is strongly influenced by seasonal fluctuations. The demand for soft drinks may not be satisfied in summer because the supply is too low to meet the demand. It becomes an excess capacity when productive capacity is equal to meet 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 season. This is the dilemma for the producer. There are two alternative methods to meet the demand in summer, one is to employ additional workers to elevate efficiency in summer and layoffs in winter, this attitude is repeated each year. The other is to replace equipment to elevate machine ability throughout the year.

A case study is conducted in existent plant producing soft drinks for domestic demand only in Japan. The present year is end of 2014 and come to the start of 2015. Though sales are multiplied by volume and unit price, we assumed that the increase is only dependent on volume, not unit price. The sales of soft drinks from 2008 to 2014 are shown in Figure 1, based on both yearly and monthly 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 monthly sales are calculated as:

$$\mathbf{LN(sales\ in\ this\ month/sales\ in\ previous\ month)}$$

(a) Yearly sales (b)Monthly sales

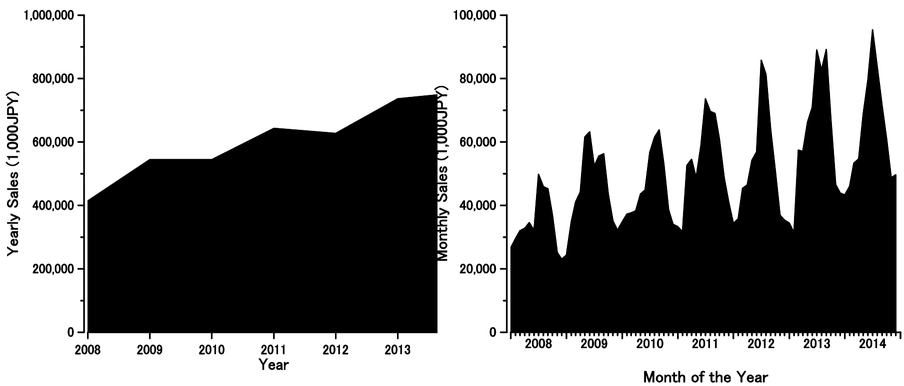

Figure 1 Soft drink sales in targeted plant based on yearly (a) and monthly (b)

and averaged historical monthly volatilities are shown in Table 1. Mean value (%) $\pm$ S.D. of yearly and monthly volatilities are 8.59 ± 11.43 and 0.73 ± 15.50, respectively.

Table 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

2. Calculating Free Cash Flow

Future sales are forecast by the 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 product sales only. Suppose that the available historical data on sales are only 84 monthly data equal to 7 years in Figure 1 (b). Using these historical data, we use Crystal Ball Predictor to choose the best fitting SARIMA model. Then, we incorporate SARIMA model in Excel spreadsheet. The forecasted sales for 60 months are taken into FCF model which is calculated as follows:

$$FCF_t = \text{EBIT}_t \times (1 - \text{Tax rate}) + \text{Depreciation}_t - \text{Investment expenditures}_t \quad (7)$$

Where, t is monthly period, EBIT is earning before interest and tax.

Suppose that historical monthly FCF turn out to be forecast yearly FCF based on each December. Fluctuation for working capitals is not considered. The accounting items are detailed in Table 2.

Table 2 Accounting items and assumptions

Accounting items	Assumptions
Sales	SARIMA model
EBIT	0.32% of Sales
Tax rate	40% of EBIT
Depreciation	Yearly 50 million JPY without option
	If American option is exercised, additional depreciation is yield within the year.
	If, however, Bermudan option is exercised, no additional depreciation is needed.
Investment expense	Option expense only

3. Investment Expenditures

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

Table 3 Two scenarios for investment

Scenario	Option type	Investment price (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/yearfor 5 years	1.18	100,000	Within year (June to October)
Facility and equipment	American option	50,000	1.18	100,000	5 years

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

4. ROA

4.1 Overall Approach

ROA can integrating demand uncertainty. ROA choose the outcome of multiple scenarios for option value. Basically, we make a reference to four step processes for valuing real options (Copeland and Antikarov, 2003). Some different points from original processes are to use Monte-Carlo simulation into binominal lattice method, resulting of more vivid decision-making.

4.2 Forecasting Standard NPV and Expanded NPV

Forecasting standard NPV without investment and expanded NPV (ENPV) when investment occurs are depicted in following Equation (8) and (9), respectively.

$$\mathrm{NPV}_j = \sum_{t=1}^{T} \left(\frac{V_{tj}}{(1+WACC)^{t/12}} \right) \tag{8}$$

$$\mathrm{ENPV}_{cj} = \sum_{t=1}^{T} \left(\frac{eVc_{tj}}{(1+WACC)^{t/12}} - \frac{\mathrm{Xc}_{kj}}{\left(1+r_f\right)^{t/12}} \right) \tag{9}$$

Where, V_t is monthly FCF_t at t period. j means jth simulation number, $(1+WACC)^{t/12}$ is a factor for V_t to convert from future value at period t to present value V_0, $(1+r_f)^{t/12}$ 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). eVc_t and Xc_t are asset value as monthly FCF_t with options, and investment expenditures 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, we can get Expected value for NPV (E[NPV]) and ENPV(E[ENPV]) as:

$$\mathrm{E[NPV]} \approx \frac{1}{J}\sum_{j=1}^{J} NPV_j \qquad (10)$$

$$\mathrm{E[ENPV]} \approx \frac{1}{J}\sum_{j=1}^{J} ENPV_{cj} \qquad (11)$$

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

4.3 Building a Binominal Lattice

The second step is to create 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. The FCF's volatility becomes the input volatility to the analysis. The other input parameters are based on the initial set of assumptions which can be obtained by risk-neutral probabilities to create binominal lattice.

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 the PV 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 equation (12) and (13), respectively.

$$u = e^{\sigma\sqrt{t}} \qquad (12)$$

$$d = \frac{1}{u} \qquad (13)$$

Where, σ is volatility, t is step period as 1 year. Using the logarithmic returns in FCF approach (Copeland and Antikarov, 2003; Mun, 2003), the volatility of j^{th} simulation is estimated as,

$$\text{averaged } LN(FCF\ in\ this\ year/FCF\ in\ previous\ year)$$

By definition, $u \geq 1$ and $0 < d \leq 1$ are settled. Each of these two alternatives has certain probabilities. The risk-neutral probability (p) to increase FCF is calculated with r_f , u and d as equation (14).

$$p = \frac{1 + r_f - d}{u - d} \qquad (14)$$

Where, r_f is 0.10%. The probability(q) to decrease d is given by equation (15).

$$q = 1 - p \qquad (15)$$

If V_0 is the PV of asset value as future FCF at period 0, at the next period 1, the asset value could either be $u \cdot V_0$ with a probability of p or $d \cdot V_0$ with a probability of $1 - p$. The V_0 included time value grows by repeating this step until maturity. 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 T in figure 2.

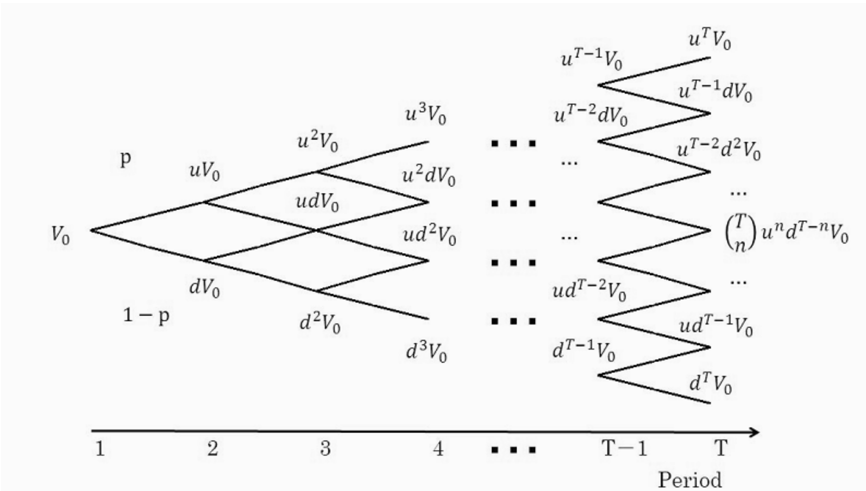

Figure 2 Asset values movement in binomial lattice model

4.4 Decision Tree

Consider a decision where food producers must either invest now or defer until the end of optimal period. Once made, the investment is irreversible. So, food producers expect the decision tree is positive regardless of degree and timing of investment. Decision tree can be 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 as follows;

$$f_{a(t)} = \begin{cases} max\left(ENPV_{aj}, NPV_j\right) & t = T \\ max\left(ENPV_{aj}, \frac{\left(p \cdot f_{au(t+1)} + (1-p) \cdot f_{ad(t+1)}\right)}{1+r_f}\right) & 0 \le t < T-1 \end{cases} \quad (16)$$

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 backwards starting from second last node and ending at the first nodes. Before the final node, this procedure is carried on until the first node is reached. Then, present value $f_{a(0)}$ is obtained. In this study, the American option is applied to Equation (16) without any limitation.

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

$$f_{bk(t)} = \begin{cases} max\left(ENPV_{bkj}, NPV_j\right) & t = \frac{T}{M} \\ \frac{\left(p \cdot f_{bku(t+1)} + (1-p) \cdot f_{bkd(t+1)}\right)}{1+r_f} & 0 \le t \neq \frac{T}{M} \end{cases} \quad (17)$$

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;

$$f_{b(0)} = \sum_{k=1}^{5} f_{bk(0)} \tag{18}$$

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

4.5 Valuation to ROA

Payoff is calculated 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.

$$\text{Option Value}_c(\text{JPY}) = \max\left(f_{c(0)} - V_0, 0\right) \tag{19}$$

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;

$$\text{Improvement}_c(\%) = \frac{Option\ Value_c}{PV} \times 100 \tag{20}$$

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

We also test the effect of combination of symbiotic options between American and Bermudan options. Assume that American and Bermudan options are in a symbiotic relationship, and until exercising the American option, soft drink producer has a right to exercise Bermudan options every year. All of possible type is shown in Table 6. The option value of symbiotic options by adding the effect of independent the American and the Bermudan is calculated as;

$$\text{Option Value}_{\text{ab}}(\text{JPY}) = \max\left(f_{a(0)} - V_0 + f_{b(0)} - V_0, 0\right) \tag{21}$$

The option value of symbiotic options is evaluated as improvement and calculated as following;

$$\text{Improvement}_{ab}(\%) = \frac{Option\ Value_{ab}}{PV} \times 100 \tag{22}$$

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

Table 6 Possible combination of symbiotic 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

In the following sections, after the range of ROA, comparison between independent American and Bermudan options is tested. For five years using the finite annuity method (Luenberger 2009), we forecast two finite values; one is for the Bermudan option, the other is for American option. We assume that sales are repeated from sixth to tenth year in the same sales condition of fifth year without any option. The American option can be exercised and depreciated at sixth year as maturity. After seventh year, the American can't exercise. The Bermudan options pay investment expenditures every year if invested, though the American option cannot pay further. For the sake of brief calculation, we use finite annuity method for seventh to tenth year, and is calculated on December $(\mathrm{t} = 72)$ of sixth year. Finite improvements for American option and Bermudan options are calculated as follows;

$$\text{Improvement}_{Fa}(\%) = \frac{f_{Fa(t)}}{f_{F(t)}} \times 100 = \left(\frac{f_{a(6)} + \frac{f_{a(7)}}{WACC} \cdot \frac{1}{1+WACC}}{f_{(6)} + \frac{f_{(7)}}{WACC} \cdot \frac{1}{1+WACC}} \right) \times 100 \quad (23)$$

$$\text{Improvement}_{Fb}(\%) = \frac{f_{Fb(t)}}{f_{F(t)}} \times 100 = \left(\frac{f_{b(6)} + \frac{f_{b(7)}}{WACC} \cdot \frac{1}{1+WACC}}{f_{(6)} + \frac{f_{(7)}}{WACC} \cdot \frac{1}{1+WACC}} \right) \times 100 \quad (24)$$

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).

$$\mathrm{E}\left[\frac{f_{Fa(t)}}{f_{F(t)}} \times 100\right] \approx \frac{1}{J}\sum_{j=1}^{J}\left(\frac{f_{Fa(t)j}}{f_{F(t)j}}\right) \times 100 \quad (25)$$

$$\mathrm{E}\left[\frac{f_{Fb(t)}}{f_{F(t)}} \times 100\right] \approx \frac{1}{J}\sum_{j=1}^{J}\left(\frac{f_{Fb(t)}}{f_{F(t)}}\right) \times 100 \qquad (26)$$

IV. Results

1. Forecast Sales

The graph shown in Figure 3 illustrates 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 forecasts are based on SARIMA (2, 1, 2) (1, 0, 1)12 model as the best fitting line in the 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 cyclic movements with the highest and the lowest in summer and winter of each year, respectively. The difference between the highest mean value and the lowest in same year is biggest in 2015 and gradually decreased. This tendency will continue after 5 years by forecasting data.

We assume that forecasted monthly sales after 2020 are always the same as the results of 2019. SARIMA (2, 1, 2) (1, 0, 1)12 model statistics is shown in Table 3. We obtain confident and lowest value 17.84 for AIC of this model. Value of Theil's U is 0.7589; this figure shows the forecast model is the same as the supposed one. Value of Durbin-Watson is 2.13, this result is close to 2, and means that this model rarely have no over- and under- moving average. SARIMA (2, 1, 2) (1, 0, 1)12 model coefficients are also depicted in Table 4. As the coefficient of variables has small standard error, this model has good harmony with seasonality. Averaged forecast monthly volatilities from 2015 to 2019 are shown in Table 5. It is reasonable to assume that the sales have a stochastic process.

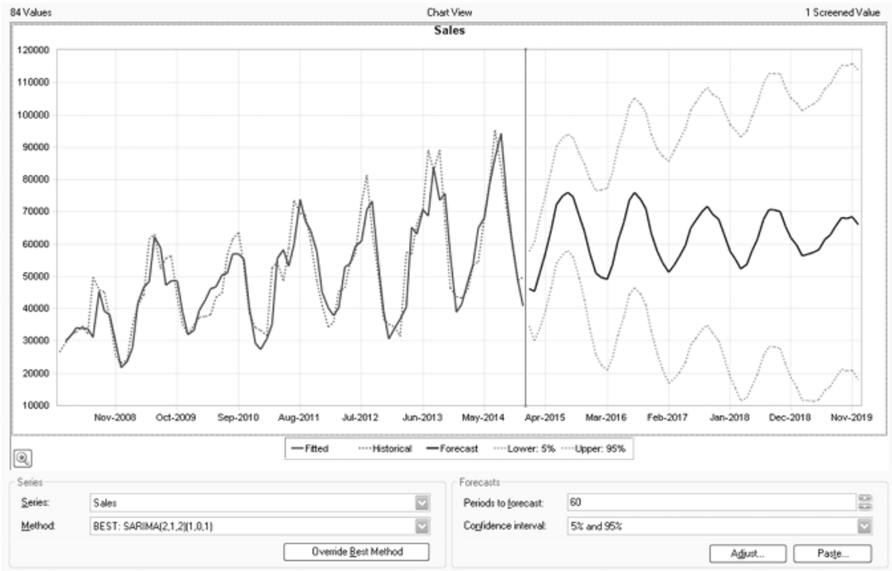

Figure 3 Monthly sales results from historical and forecasted data

Table 2 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 3 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 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 achieved by tracking signal at each period ranging 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.

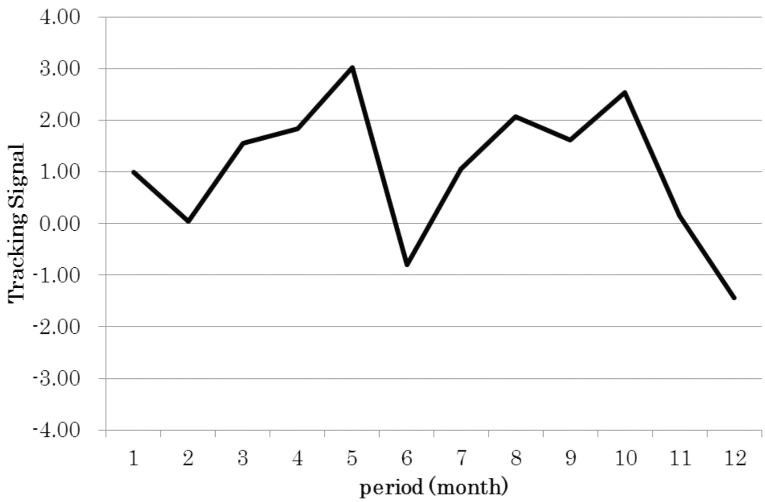

Figure 4 Tracking signal

2. PV

Figure 5 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 location of -2,509,428 and standard deviation of 24,728.

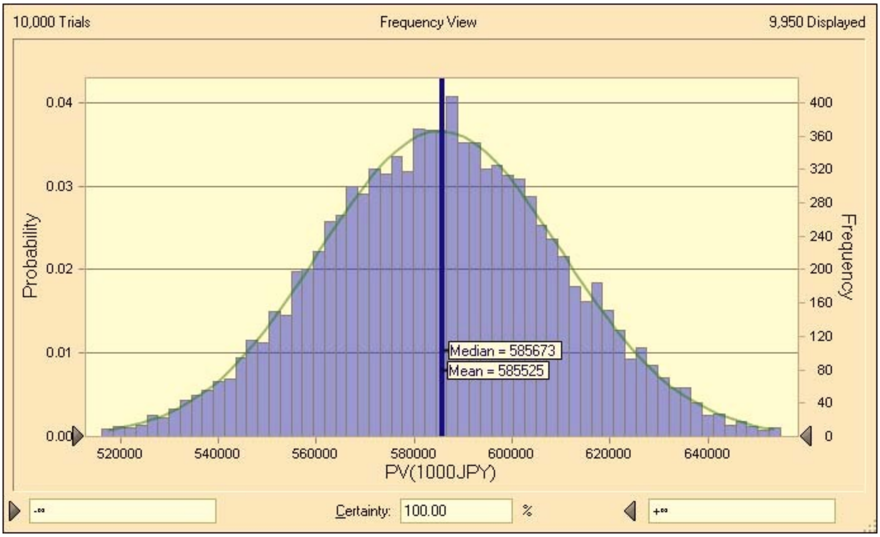

Figure 5 Probability distribution of PV for NPV

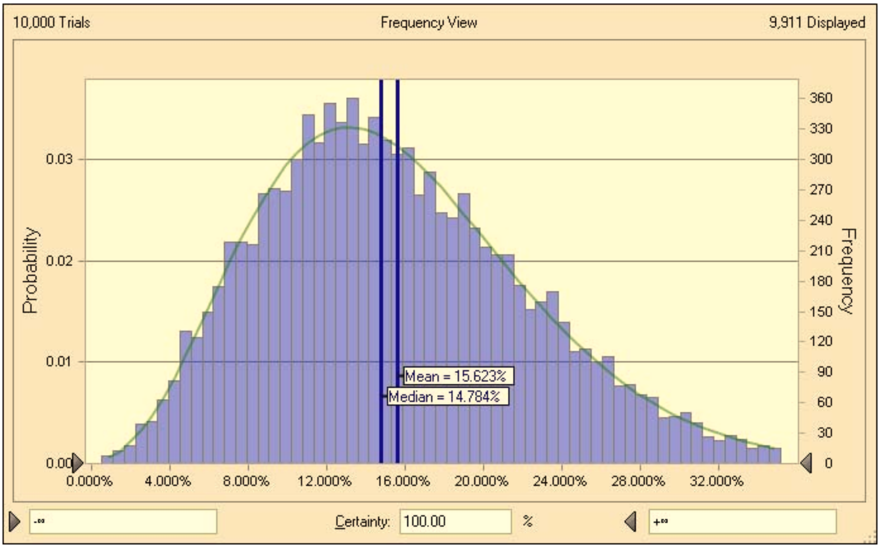

Figure 6 Probability distribution of volatility

3. Volatility

Volatility σ is changed by each simulation, and the result of probability distribution of σ is shown in Figure 6. 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.

4. Improvements of American and/or Bermudan Options by ROA

Figure 7 indicates that improvement effects with a comparison of independent American option, Bermudan options, and symbiotic options. The result shows that the mean value of the Bermudan options (0.860%) has an advantage over the American option (0.478%). It is seen that over 35% of simulations American option do not exercise. But, the highest improvement is gained if the two options are symbiotic,choosing between American and Bermudan options. By using symbiotic options, lower risk is averted and higher opportunity is gained.

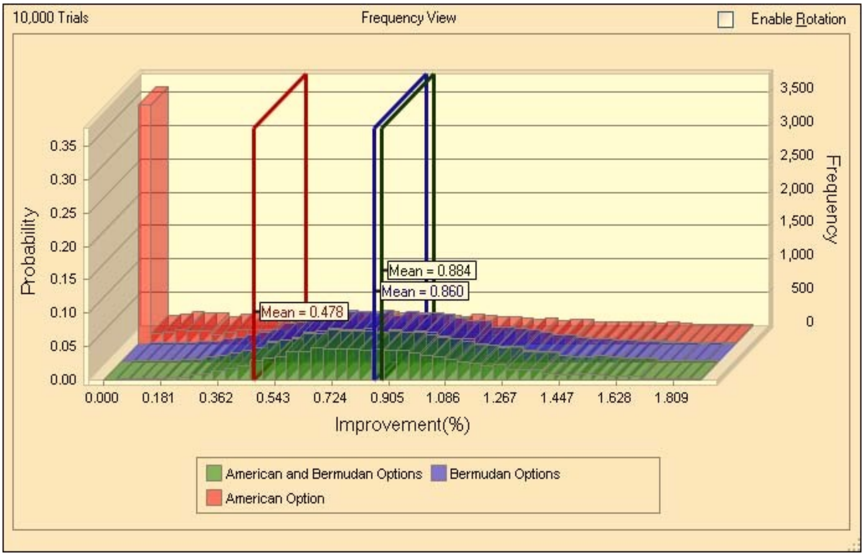

Figure 7 Probability distribution of American and/or Bermudan options by ROA

5. Timing for Exercising American Option in Symbiotic Options

Figure 8 shows the timing for exercising the American option in symbiotic options. The result shows that only 1,692 out of 10,000 times the American option is exercised on the basis of choosing the most profitable decision-making. High opportunity for the American option lays in first period, following very low opportunities in second, third and fourth period and no opportunity in fifth period. If no American option is exercised in first period, the results imply that the Bermudan options can be exercised for the rest of periods.

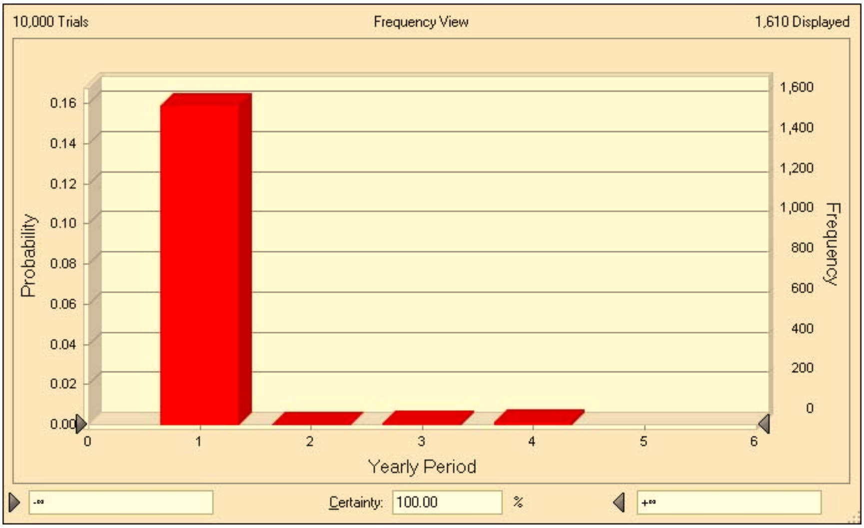

Figure 8 Timing for exercising American option in symbiotic options

6. Improvements of Independent American and Bermudan Options by Finite Annuity

Figure 9 shows probability distribution of independent American and Bermudan options by finite annuity. In opposition to prior results shown in Figure 8, there is higher mean improvement for the American option, with 5.979%, than the Bermudan option, with 0.366%. If the American option is exercised, the effect of investment is to be active until maturity. The depreciation and upgrade by the American option will yield in favor of FCF. If, on the other hand, the Bermudan option is exercised each year, upgrade by the Bermudan option will increase sales as the American option without depreciation. If sales are constant and the uncertain is cleared, it is possible to aim upside opportunity and avoid downside risk.

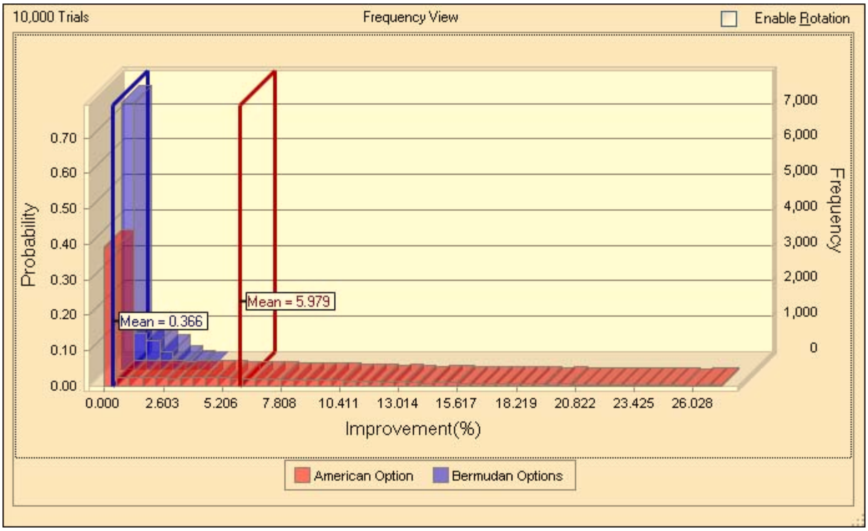

Figure 9 Probability distribution of both American and Bermudan options by finite annuity

V. Conclusion

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

We can decide on what and when is the investment according to information from ROA. Each simulation can show the condition according to the sales. With statistical information based on 10,000 simulations, most use the Bermudan options for five years, and 16% of the case are exercised by the American option. It means that producers would tend to invest in added temporary human resources rather than in plant modification. If, however, sales are constant and the uncertain is cleared after the duration of ROA, producers would tend to invest in plant modification rather than adding temporary human resources. Even if choosing the human resources by ROA, producers should not choose the Bermudan options again for infinity without ROA. A temporary decision is not continual and should be reviewed in the near future. Producers know that the plant modification has a potential advantage over added temporary human resources in the long term. But, in practice, there is uncertainty about sales. It is wise for the producers to have the symbiotic American and Bermudan options and seek for the opportunity for the American. ROA can help the producer do his right decision-making.

There is little possibility of forecast and reality in sales coinciding. When the volume of demand exceeds the production capacity of the producers' plant, it may be outsourced through original equipment manufacturer (OEM), instead of upgrades of the producers' plant. As seasonal fluctuations are similarly received by all soft drink plants, the premise of the contract becomes difficult. We would like to leave the option for OEM in future research.

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