APPLICATION OF COPULA AND VAR IN RISK APPRAISAL FOR CUSTOMER DEMAND IN LUBRICANT OIL WHOLESALE BUSINESS

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Introduction

The sales data of Lampang Lube Oil Company was used in the study. The company is a distributor of PTT lubricants in Lampang and northern Thailand retailing and wholesaling only for PTT lubricants trade mark. With the highly appreciation from PTT company, then this company got more discount rate than other competitors. No inventory shortage or highly customer's satisfaction is the strictly service policy for this company. Besides no inventory shortage, time to delivery is also set as short as possible. To acknowledge the customers demand, store display and salesman are applied. Industrial lubricants grade for the industrial sector are also included in the company business.

In practice, forecasting of customer demand in supply chain is very difficult, and in some cases, it couldn't be predicted due to unstable demand of goods or services. This will cause the bullwise effect in the supply chain. Therefore, the accuracy or the risk of forecasting techniques has to study and interpret. Risk is the ability to measure and accomplish the purpose of the task successfully under decisions, budgets, deadlines, time frames, and technical constraints, such as project planning as a series of activities to do certain event in the future using limited resources to proceed for success under limited time frames. This is a future action plan and risk can happen at any time due to uncertainty and limitation of resources of projects. Project administrators must manage their project risks to reduce problems and make the projects successful as targeted effectively and efficiently. In financial problem, many researchers adopted the Copola function technique for investment risk analysis. This Copola function has been studied since 1940 by Hoeffding (1940) and developed continuously since postwar by Frechet (1951). However, according to the study of Sklar (1959, 1973), Copula is a cointegration function of distributed random variables, which present a constant copula pattern on the interval of [0, 1]. That means we can tell the relationship between random variables without considering the marginal distribution. In various studies associated with Copula function, the Copula appears in a variety of applications. It is said that Copula is a model created when the relationship is not independent among the factors that are important to portfolio of investment. It was also found that Copula can help create the diversification of the risk in portfolio of investment (Kole et al., 2007). For risk appraisal, Value-at-Risk (VaR) was introduced by Guildimann (1980) who the lead researcher of J.P.Morgan investment bank. VaR was applied to manage the investment risk within the organization. VaR refers to the maximum loss resulting from investing in securities for a period of time. This is a measure of the amount of risk that could be incurred by holding securities at a certain time and at a specified level of confidence. In terms of finance, it can be said that VaR is the most popular measure of risk because VaR measures using the amount of money, such as baht and US dollars, which is easy to understand and measurable. A value of VaR is the maximum expected loss within a certain time period (usually a number of days) with a certain level of statistical confidence (% of confidence level). The higher the VaR, the riskier it is. However, this also means that it is not likely to damage more than that. The convenience of VaR in interpretation makes it possible for financial institutions and regulators of the world's financial institutions, such as the Basel Supervisory Board of Switzerland, the US central bank or financial institutions, often sets limits on VaR for risk mitigation. If each trading day of securities or financial instruments calculate the VaR of the whole group to be within the limit, it is considered safe. It means that in that day, if the money invested results in severe damage or the worst case scenario, it is still not over the ceiling.

From our study, application of Copula method and VaR are most in the financial engineering; however still cannot find for forecasting risk appraisal. Thus, to apply Copula and VaR for forecasting risk appraisal is a new challenge. This research aims to propose a method to identify the forecast risk value using the Copula method and VaR in order to identify the risk of forecast violation by using the best predictive methods in the selected methods to forecast customer demand. ANN, ARIMA, SETAR and LSTAR methods were used to forecast.

Literature Review

In this research, the risk assessment of customer demand in lubricant wholesaling business based on the customer demand in 10 products was studied. Theories and research related to forecasting by using ANN, ARIMA, SETAR, and LSTAR methods, as well as Copula and VaR to find the relationship of the data used to create data model were evaluated for the risk containing the following relevant details. For the delivery of raw materials, Ngniatedema et al. (2013) investigated the conditions leading to a reduction in production costs when the delivery time of the supplier for goods, raw materials, and the inventory level at the beginning of the production process are in a delay time frame. These factors are in a form that shows that it is in the best position to maximize the benefits. There are delivery of the supplier and the delivery of raw materials in a suitable frame enabling us to create a model that can lower production costs with better productivity, as well as increase customer service level at an adequate level of inventory. Forecasting may use the same conceptual approach but using different tools will produce different results. Talha and Olaf (2009) applied ARIMA method to forecast using different computer programs which resulted in different results. If the programs were more complete, it would have better forecasting results. In the studies related to the importance of timely delivery of goods or raw materials, the program can make the work more efficient, increase productivity, reduce violations, and inventory costs. In order to forecast, there are many important ways for businesses or the management of the stock market and its activities. Wilson and Sharda (1994) had the idea of the Artificial Neural Network from Artificial Intelligence (AI), which refers to a process of reasoning imitation with the ability to remember and apply from experience. For the study using the Artificial Neural Network on financial forecast, Carvalhal and Ribeiro (2007) found that the Artificial Neural Network was effective in forecasting. Jing Li (2011) tested the Self Threshold Autoregressive (SETAR) to forecast many models. Ana et al. (2015), Chan et al. (2015) used the SETAR method to forecast NYMEX oil prices, investment in the Tungsten Market, and other prices which are efficient in terms of forecasting. Kalbkhani et al. (2017) used Logistic Smooth Transition Autoregressive (LSTAR) to forecast stock prices, and also compared LSTAR with other methods. There are a variety of effective methods of forecasting. In this paper, we are interested in using different instruments, ANN, ARIMA, SETAR and LSTAR, to forecast customer demand. Each method has efficient and different operating concept in forecasting. Then we compare the results to find the best method with the least violation value. Olson and Wu (2010) stated that operations need to identify and categorize risks. They conducted a study on the review of research related to supply chain risk management to identify and categorize risks, case studies, and models for problem solving and specific attitudes of supply chain risk by classifying within the supply chain involving many risks such as an internal risk and the factors related to the organization such as an external risk. In the study of risk-related research, it is evident that risk is present in every activity. Manufacturers may be exposed to risk in the event that they have a relationship or may not be related to each other. If the risk can be reduced, it will benefit the company.

Copola, the statistical theory that Sklar (1959) first proposed, has been applied in various fields. Until later, Li (2000), director of Riskmetric's Credit Derivatives Group, succeeded in using the Copola method to describe the co-relation of the credit assets generated by group investment for determining the price of the Collateralized Debt Obligation (CDO) of credit assets. As a result of the successful implementation of Li (2000), the Copola method has been applied extensively by scholars and practitioners in financial management to measure the risk of investing in securities and determining the price of financial derivatives based on several factors (Khanthawit, 2010). Yingying et al. (2016) and Berger (2016) used the Coppola and VaR methods as a basis for finding correlation, analysing, and reducing the risk of data requirements for better reliability and estimation than older methods. It also stated that the *t*-Copula method could find the correlation value more effectively than the Gaussian Copula method. Copula method can find the relationship of various data sets with different data distributions by using VaR to evaluate risks and to identify possible violations of events. In this research, we applied VaR through the Copula model to identify the forecasting risk by applying the predictive violation to find the relationship and identify the risk.

Methodology

Risk appraisal with VaR through the Copula model includes the following steps.

1. Prepare the data in the form of growth rate. Convert customer demand data into chronologically-ordered time series of the 10 products and convert them into growth rate from the past three years before forecasting.

$$R_i = \frac{S_t - S_{t-1}}{S_{t-1}} \tag{1}$$

2. Forecast the growth rate of 10 products by using four methods: ANN, ARIMA, SETAR and LSTAR through the *R* Project for Statistical Computing (*R*). Forecast the customer demand by using ANN, ARIMA, SETAR and LSTAR methods.

2.1 For ANN method using NNET time series model 1-3-1 network with 10 weights, select the method with least Akaike Information Criterion (AIC). The Akaike's Information Criterion (AIC) can be calculated as follows.

$$AIC = \log \hat{\sigma}^2 + 2\frac{p+q}{T} \tag{2}$$

when $\hat{\sigma}^2$ = estimated value of e_t variance

ANN is a mathematical model used to simulate complex systems with nonlinear components. ANN architecture consists of layers of neuron or node linked together. The first layer is the input layer, and the last layer is the output layer. Between the input and output layers, there may be a number of hidden layers. As ANN model has many forms, in training, input and expected output are installed into ANN. In order to study ANN, adjust w_{ij} weight of each layer to provide the predicted value which is close to the actual value as much as possible. The most common function used to measure the violation between actual and predicted values is the Mean Squared Violation. For the operation of BPNN, first, determine the initial weight and violation. Calculate the predictive value from input data. Calculate the violation based on the differences between the actual and predicted values. Then return the violation of output layer back to the other layers of ANN to re-adjust the w_{ij} weight to reduce the violation.

2.2 The ARIMA method includes three parameters: AR, I, and MA. This study forecasted by selecting the most appropriate method, the method which has the least value of AIC from Parameters 101, 102, 201 and 202. Forecasting by using Box-Jenkins method developed by Box and Jenkins (1976) is based on the ARIMA (Autoregressive Integrated Moving Average) model, which is a single-variable time series in the past until the present to predict future data covering the results that include seasonal time series, as well as processes or systems that are non-stationary. The analysing processes are as follows.

(1Identification

$$y_t = y_{t-1} + \varepsilon_t \tag{3}$$

(2Autoregressive Process

Autoregressive process) AR(p)) refers to AR system indicating time series data depends on the p level of the delay information of the past, which can be written in the equation as follows.

$$y_t = \delta_0 + \delta_1 y_{t-1} + \delta_2 y_{t-2} + \ldots + \delta_p y_{t-p} + e_t \tag{4}$$

(3Moving Average Process

Moving average process) MA(q)) is MA system indicating that the time series depends on the present violation as well as the violation of the q level of delay information in the past, which can be written in the equation as follows.

$$y_t = \tau_0 + e_t - \varphi_1 e_{t-1} - \varphi_2 e_{t-2} + \ldots + -\varphi_q e_{t-q} \tag{4}$$

In case of non-stationary data, ARIMA)*p*,*d*,*q* (model will be:

$$\Delta^d y_t = \delta_0 + \delta_1 \Delta^d y_{t-1} + \delta_2 \Delta^d y_{t-2} + \ldots + +\delta_p \Delta^d y_{t-p} + e_t - \varphi_1 e_{t-1} - \varphi_2 e_{t-2} + \ldots + -\varphi_q e_{t-q} \quad (6)$$

when Δ^d = Data Variance Rank

2.3 By using SETAR method, only j parameter is used, $j = 1$ or $j = 2$ based on equation)8). This study forecasted by using the most optimal method which has the least value of Akaike Information Criterion (AIC). Let y_t be a time series of interest which generates the observed data $(y, \ldots, y)$, with pre-sample values $(y, y, \ldots, y_{n-p+1})$. A two-regime self-exciting threshold autoregressive (SETAR) model of order p is written as

$$y_t = \left(\beta_1 + \sum_{j=1}^{p} \beta_{1j} y_{t-1} \right) 1(y_{t-1} > \gamma) + \left(\beta_2 + \sum_{j=1}^{p} \beta_{2j} y_{t-j} \right) 1(y_{t-1} \leq \gamma) + e_t \quad (7)$$

where $\hat{\beta}_{ij}$ denotes the least squares estimation of the coefficient and conditional on $\widehat{\gamma}$. By construction, the residual is at zero. The residual was not re-scaled since preliminary simulations showed little effect of rescaling. Let h denote the forecast horizon. The *h*-step ahead forecast, conditional on the last *p* observations of y_t, can be computed as follows.

$$\hat{y}_{t+h} = \left(\hat{\beta}_{10} + \sum_{j=1}^{p} \hat{\beta}_{1j} \hat{y}_{t+h-j} \right) 1(\hat{y}_{t+h-1} > \hat{\gamma}) + \left(\hat{\beta}_{20} + \sum_{j=1}^{p} \hat{\beta}_{2j} \hat{y}_{t+h-j} \right) 1(\hat{y}_{t+h-1} \leq \hat{\gamma}) \quad (8)$$

where $\hat{y}_t = y_t(t = n, n-1, \ldots, n-p+1)$.

2.4. The LSTAR method uses one parameter, $p(p=1 \text{ or } p=2)$, in equation (9). This study forecasted by selecting the most appropriate method with the least AIC value. Smooth Transition Autoregressive model was developed by Teräsvirta and Anderson (1992), which is one of the models of Regime Switching, but is obviously different from the Markov Switching model that the STAR model has a transition variable, which is a variable that can collect data. Therefore, it is possible to identify the function used in any regime to describe the behavior of variables. However, the Markov Switching model cannot store variables that indicate a situation. Therefore, functions cannot be specified and changed. However, it is only possible to predict the probability of using any Regime to describe the variables being considered. Also, the probability of using a regime is constant at a certain value. Enders (1995) stated that the Smooth Transition Autoregressive model makes autoregressive parameters slow. To consider the Smooth Transition Autoregressive model, the Nonlinear Autoregressive Model (NLAR) has been adapted.

The value of y_{t-1} will lead to the use of the STAR model in general as follows.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_p y_{t-p} + \theta \lfloor \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} \rfloor + \varepsilon_t \quad (9)$$

when y_t is a dependent variable at certain time (t) y_{t-1} is a dependent variable time a $t-1; i = 1, \ldots, p$

α_0, β_0 is a stable value — α_n, β_n is an autoregressive coefficient $n = 1, \ldots, p$

θ is a transition function — ε_t is an violation value

STAR model has two changing functions: Logistic and Exponential. This study used Logistic (LSTAR) function.

3. Growth rate forecasting violation can be calculated by subtracting the actual value of growth rate with forecasting value, and the results will be the growth rate forecasting violation (e)

4. Estimation of growth rate forecasting violation rate of customer demand was conducted using the Copula't model with the *R* Project for Statistical Computing program (*R*)

4.1. Find ρ and v values starting from conversing growth rate forecasting violation of customer demand on each product (e), cumulative distribution function (CDF), to find ρ and v value using the 4 forecasting methods.
4.2. Model Copula't for CDF Estimation (CDF) using Copula't model with ρ and v value was conducted by forecasting 10,000 CDF data of the 10 products and converse them from the 4 forecasting methods back from Cumulative Distribution Function (CDF) value to growth rate forecasting violation of customer demand from the estimation with the Copula't model.

5. Evaluate the Value at Risk (VaR) using growth rate forecasting violation of customer demand growth with the Copula't model, where the violation value represents the volatility and volatility represents the risk of data. The VaR of each product can be calculated by using growth rate forecasting violation of customer demand with the Copula't model of all 10 products. Data were used to balance the importance of each product (equal to 0.1), and the data of 10 products were integrated into the total VaR of all products by sequencing the data in ascending order. Find the median of the growth rate forecast data of customer demand with the Copula't model based on the confidence level.

6. Risk appraisal of business by explaining the risk value showed that the risk value of data enabled entrepreneurs to know the risk of selling their products. The results of risk value will help entrepreneurs to make a decision to join or continue to do the business. It can also evaluate and compare with other businesses, and such risk value can be used to compare with other products or other business groups, including the loss or profit to entrepreneurs as well. In the past, the entrepreneurs normally evaluated by assessor or personal judgment, which made it unsure since it involved with different ideas. Through this method, the risk value will be used to reflect the truth without any prejudice or opinions enabling the entrepreneur to make the decision easier to join or continue the business.

Growth rate forecasting

After converting the growth rate data of customers, we forecasted the growth rate by using ANN, ARIMA, SETAR, and LSTAR methods. The data of growth rate forecasting violation of customer demand were identified for VaR through the Copula model to show the risk value for all 10 products and total risk value for all 10 products from all four methods. Then we compared the risk value of the customer demand from the four methods to find an appropriate forecasting method to determine the risk value.

Preparation for Forecasting

We prepared daily customer need data based on 10 products. The data were sorted by using time series data. Daily sales information was from January 2, 2013 to December 30, 2015, 594 cases in total.

Finding VaR

We started from the preparation of the growth rate data by gathering information on the customer demand and converted it to the form of growth rate. As the growth rate data of customer demand in each product was daily data, some of the products have low customer demand on a daily basis, resulting in a sharp drop of customer demand while some products have high customer demand, resulting in a significant increase in the growth rate data. After converting customer demand into the growth rate value of customer demand, the data were forecasted.

Regarding the forecasting stage of customer demand in each of the four products, it started from forecasting the growth rate of customer demand in each product using the four methods: ANN, ARIMA, SETAR, and LSTAR through the R Project for Statistical Computing (*R*) to illustrate MAD, RMSE and MAPE values as shown in Table 1.

	Method	SUM e	MAD	RMSE	MAPE
Turbo	ANN	873.43	1.48	2.50	2.45
	ARIMA	1373.34	2.32	4.86	5.47
	SETAR	1034.03	1.75	3.60	2.95
	LSTAR	1128.59	1.91	3.35	4.38
Max1L	ANN	8403.32	14.19	40.44	12.37
	ARIMA	10030.82	16.94	43.92	25.75
	SETAR	8421.68	14.23	40.42	12.44
	LSTAR	8412.84	14.21	40.14	12.46
Max0.8L	ANN	6107.29	10.32	35.22	5.66
	ARIMA	7305.91	12.34	38.49	11.95
	SETAR	6535.66	11.04	35.59	6.55
	LSTAR	6399.57	10.81	34.87	8.33
Max2T	ANN	3826.80	6.46	20.82	9.91
	ARIMA	5557.48	9.39	37.26	14.94
	SETAR	4998.44	8.44	34.53	6.14
	LSTAR	3579.43	6.05	20.29	9.06
Commonrail	ANN	1662.94	2.81	7.40	3.58
	ARIMA	2362.71	3.99	10.88	7.80
	SETAR	1916.43	3.24	8.78	3.39
	LSTAR	1798.33	3.04	7.74	5.50
HLP	ANN	2479.77	4.19	9.12	5.53
	ARIMA	3215.00	5.43	10.43	10.68
	SETAR	2549.19	4.31	9.18	6.38
	LSTAR	2549.99	4.31	9.18	6.39
NGV	ANN	2462.62	4.16	9.09	9.64
	ARIMA	3099.11	5.23	11.60	7.30
	SETAR	2553.83	4.31	10.32	4.06
	LSTAR	2542.65	4.30	10.31	4.22
Plus	ANN	2035.49	3.44	10.84	2.80
	ARIMA	3492.36	5.90	15.37	11.23
	SETAR	2495.66	4.22	12.27	3.74
	LSTAR	2399.95	4.05	11.60	6.37
Premeir	ANN	1554.99	2.63	7.94	2.37
	ARIMA	2085.90	3.52	9.18	7.58
	SETAR	1631.46	2.76	8.14	2.72
	LSTAR	1644.07	2.78	8.15	2.75
Semi	ANN	1313.00	2.22	4.86	4.05
	ARIMA	3461.53	5.85	11.71	7.97
	SETAR	2671.11	4.51	9.97	3.93
	LSTAR	2671.29	4.51	9.98	3.94

Table 1: Growth rate forecasting violation of customer demand in each product from the four forecasting methods

From Table 1, e is the growth rate forecasting violation of customer demand which will be used for making the Copula't model from the four forecasting methods of 10 products.

Risk Identification Procedure

We identified the risk value of each customer demand in the four forecasting methods and received the total risk of customer demand by using VaR method through the Copula model.

Finding ρ and v values

We started from converting the growth rate forecasting violation of customer demand for each product (e) to the Cumulative Distribution Function (CDF). Then created Copula't using Method Spearman through the *R* Project for Statistical Computing (*R*) to find the ρ and ν values and values from the four forecasting methods.

ρ represents the relative value of each product between Product 1 and Product 10, which may be in the same or opposite direction, and the ν value is the Degree of Freedom = 5 to create a model for CDF estimation.

Modelling from Copula't for CDF value estimation

We estimated the CDF value from the Copula't model using ρ and ν values to estimate 10,000 data of CDF from 10 products. Then converted the data from the 4 methods from the Cumulative Distribution Function (CDF) to the growth rate forecasting violation value of customer demand by estimating the value of the Copula't model. This estimation will allow the data to be dispersed into normal distribution.

Evaluation of VaR

The evaluation of VaR employs the growth rate forecasting violation of customer demand from the estimation with the Copula't model, where the violation value represents the volatility and volatility shows the risk of data using all 10 products, 10,000 data, $x_{1j}, x_{2j}, \ldots, x_{10j}$ and the total estimation of all products $\hat{x}_j$ when $j-1,\ldots,10000$ at 95% confidence level and 99%. Monte Carlo Simulation was used for data analysis.

Total VaR of all products

Simulation of total data relationship can be calculated by equation (10).

$$\sum_i x_{ij} \times w = \hat{x}_j \tag{10}$$

$x =$ Growth rate forecasting violation of customer demand from the estimation using Copula't model of each product

i = product 1 to10 j = data sequence 1 to10 ,000

w = 10/1 is weighting the importance of each product (equally)

$\hat{x}_j$ = Data of growth rate forecasting violation of customer demand from estimation with the Copula't model of all products, sequence *j*

Based on the data of growth rate forecasting violation of customer demand from the estimation of the Copula't model of the product from the four forecasting methods, VaR can be calculated by using $\hat{x}_j$ and by sorting in ascending order.

Find the median of $\hat{x}_j$ data by using ANN forecasting method based on the required confidence level.

Examples of ANN forecasting method are as follows.

95% Loss = 0.6102 95% Gain = 0.6100

99% Loss = 0.8789 99% Gain = 0.8770

The total VaR value of all products can be explained as follows.

95% Gain means that all 10 products have 5% chance to increase sales (0.6183) * 100 = 61.83 units, 100 + 61.83 = 161.83 units from the original sales 100 units.

99% Gain means all 10 products have a 1% chance to increase sales (0.8750) * 100 = 87.50 units, 100 + 187.50 = 187.50 units from the original 100 units.

95% Loss means all 10 products have a 5% chance of decreasing sales (0.6189) * 100 = 61.89 units, 100 - 61.89 = 38.1146 units from the original sales 100 units.
99% Loss means that all 10 products have a 1% chance of decreasing sales (0.8757) * 100 = 87.57 units, 100 - 87.57 = 12.4321 units from the original sales 100 units.
After knowing the VaR and total VaR values of all products from the four forecasting methods, an appropriate growth rate forecasting method, ARIMA, can be selected because if it is the high VaR, it can better predict the chance of losing or getting higher value with less violation.

Selecting appropriate VaR

Finding the right forecasting method for predicting the growth rate of customer demand can be conducted by focusing on VaR value, the highest among the four forecasting methods in each product. This is because if there is a high VaR value, if it is the high VaR, it can better predict the chance of losing or getting higher value with less violation. To select appropriate VaR, VaR values from the four methods were compared with the real value of the customer growth rate. If the real value of the customer growth rate is over the given VaR, this is considered a violation. Then the violations were gathered for consideration. The method with the least violation is considered the most appropriate because it has the highest reliability as shown in Table 2. Find an appropriate forecasting method of VaR for all products as illustrated in Table 2.

	%vaR	Growth Rate Values of Customer Demand Exceeding VaR Values				Least Violation Method
		ANN	ARIMA	SETAR	LSTAR	
Products	95%Gain	162	154	162	162	ARIMA
	99%Gain	135	130	135	135	
	95% Loss	43	28	53	43	
	99% Loss	1	1	2	1	
Violation (%)	95%Gain	27.27	25.93	27.27	27.27	
	99%Gain	22.73	21.89	22.73	22.73	
	95% Loss	7.24	4.71	8.92	7.24	
	99% Loss	0.17	0.17	0.34	0.17	

Table 2 Selection table for VaR of appropriate total products from the four forecasting methods

Table 2 shows that an appropriate forecasting method for VaR is ARIMA, which has less violation than other methods. When considering the percentage of violation, at VaR 95%, Loss 99%, the violation is not higher than confidence interval. In general, VaR method is only used to quantify negative VaR.

Conclusion and Recommendations

When considering the value of a product risk, including 10 products, the ARIMA methodology should be used to predict the growth rate of customer demand. It is possible that tomorrow there will be a 5% chance that the demand of all 10 products combined is reduced to no more than 65.70%, which is in line with customer demand looking back to the total data of all 10 products. With the VaR that will lower sales, entrepreneurs may have to increase their promotional prices to increase sales.

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