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Industrial Wastes to Wastes Disposal Management by Using Box Jenkins-ARIMA Models and Created Applications: Case Study of Four Waste Transport and Disposal Service Providers in Thailand

Supawut Sriploy *, Krittiya Lertpocasombut

Department of Civil Engineering, Thammasat University, Thailand

* Corresponding author: sriploy.it@gmail.com
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Abstract

The purpose of this study is to develop forecasting models for four kinds of wastes: AA waste (Absorbents, filtered waste), BB waste (Plastics), CC waste (Discarded organic chemicals) and DD waste (Sludge from treatment process). The output of forecast is performed on an Excel application for planning, implementation and assets control as well as physical facilities and financial investments. The waste forecasting models could be used to support the wastes disposal and transportation business of four service providers. The method selected uses Box-Jenkins method with data periods from January 2008 to December 2017 (120 series data). Using Minitab software to analyze the data and fit parameters for models generated, the best forecasting values were by ARIMA (2, 1, 0) or ARI (2,1) for Service Provider A, ARIMA (0, 0, 1) or MA (1) for Service Provider B, ARIMA (3, 2, 2) for Service Provider C and ARIMA (3, 0, 3) or ARMA (3, 3) for Service Provider D. The results of forecasting the wastes for the four service providers had RMSE of 467.61, 518.80, 1,691.16 and 1,102.80, respectively, which is lower than another research paper (11,551.77). Suitable forecasting models, Excel application can generate valuable forecasts for service providers to utilize their budget of cash, assets and facilities better.

Keywords: Investment; Minitab; Planning; Root Mean Square Error; Waste management

1. Introduction

The definition of industrial waste varies between countries, but it generally includes wastes generated in any processes of industry, manufacturing, trade or business. Also the composition of industrial wastes varies, depending on the industrial structure of a country or region. It consists of general rubbish, packaging, food waste, acids, alkalis, oils, solvents, resins, paints, mine spoils and sludge (Juhasz *et al*. 2004).The industrial wastes situation is an important environmental issues in Thailand since the lack of capacity to handle these wastes causes problems for the community and environment. These do not seem to be any plans or preventive measures to solve these issues for storing, transporting and disposing of wastes (Wardona, 2016). However if information technology and knowledge can be applied to solve these problems, not only will the industrial sectors and all stakeholders gain valued benefits, but also the government sector could plan, implement and control its investments to balance the industrial and public sectors. For supporting solutions, the government in Thailand would prefer the industrial sector to use data recording and Information Technology to plan and control in order to propel development following the concepts and directions issued by the government for problems by applying the Industrial Revolution 4.0 (Aderson, 1977; Chaisuntorn, 2016).

Industrial wastes or residual wastes, industrial disposal processes and key stakeholders are classified by Department of Industrial Work in Thailand (Phetyoung, 2011). There are three key parties: the Waste Generator which is an organization in any industrial sector which generates wastes, Wastes Transporter who is anyone engaged in transportation of regulated waste generated or disposed of within Thailand, and who must possess a valid Thailand waste transporter permit, and the Waste Processor who is anyone engaged in waste disposal processes that must comply with Factory Act, B.E. 2535 and Hazardous Substance Act, B.E. 2535. The wastes generation is divided into four kinds which are absorbents, filter materials (including oil filters not otherwise specified), wiping cloths, protective clothing contaminated by dangerous material (AA), plastics shavings and turnings (BB), Discarded organic chemicals consisting of or containing dangerous substances (CC), and Sludge from other treatment of industrial wastewater (DD). These wastes are handled by four registered waste transportation and disposal service providers who need to know data of the waste in advance from their customers in order to plan, implement, control and find solutions to support their businesses and other issues of concern to the environment to avoid with Department of Industrial Work and Thai regulations. Thus the researchers would like to apply a concept and model to forecast data of wastes from the industrial customers to support the transporters and waste processors. Data of wastes handled and company information of Service Providers A, B, C, and D were collected as time series data, so these data could be applied as time series forecasting tools to generate forecasting data. Additionally the purpose of using these data about assets, facilities and investment planning was for short term forecasting data (three months to twelve months or one year), so the well-known univariate (Roengpeerakul, 1999; Yodpayung, 2008; Yisarkul, 2012; Rangkakulnuwat, 2013) time series forecasting technique ARIMA (Autoregressive Integrated Moving Average) and Box-Jenkins method are used. This model is to provide a better forecasting tool in future for short term forecasting (Holton, 2017).

2. Materials and Methods

2.1 Literature Review

After reviewing and exploring papers applying Box-Jenkins and Autoregressive Integrated Moving Average (ARIMA), it was found that some papers could apply this method to solve their problem situations. Table 1 summarizes these papers (Authors, Methodologies, and Objectives and Findings.

2.2 Theoretical Framework

Before study the basic components of ARIMA and Box-Jenkins method, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) (Usombut, 2004) need to be considered. Autocorrelation is the correlation (ACF) of a signal with itself at different points in time, as shown in equation (1):

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \{\Sigma(X_t - \bar{X})(X_{t+k} - \bar{X})\} / \Sigma(X_t - \bar{X})^2 \qquad (1)$$

where X_t is observed data at t lag time, k is amount of lag period as k= 1, 2, 3, …, k, and $\bar{X}$ is average of data as $\bar{X} = \sum X_t / N$

Partial autocorrelation (PACF) is the partial correlation of a time series with its own lagged values, controlling the values of the time series at all shorter lags. It contrast with the autocorrelation function, which does not control other lag.

Formulation of this equation is shown in equation (2)

$$\emptyset_{kk} = \frac{\rho_k - \sum_{j-1}^{k-1} \emptyset_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \emptyset_{k-1,j}\rho_{k-j}} \qquad (2)$$

where $\emptyset_{kj} = \emptyset_{k-1,j} - \emptyset_{kk}\emptyset_{k-1,k-j}$, $j = 1,2,3,...,k-1$ for determining optimal selections of any p, q to Moving Average (MA), Autoregressive (AR) and Autoregressive Moving Average (ARMA) (Ibrahim, 1976; Ebenezer *et al.* 2013), Table 2 gives suggestions to forecasters.

Table 1: Selected research papers related to Box-Jenkins and Time Series methods

Author (s)	Methods	Objectives	Findings
Bin-Shan Lin, et al; 1986	Box-Jenkins, Regression and Exponential Methods	In this study a time-series model for predicting Louisiana's prisons population was developed using the iterative Box-Jenkins modeling methodology – identification, estimation, and diagnostic checking. This method was compared with results of Regression models and an exponential smoothing model. The results indicate that it is more accurate when compared with actual data.	The results indicate that it is more accurate when compared with actual data.
Usombut, 2004	Box-Jenkins Method	This study applied Box-Jenkins ARIMA method for forecasting broiler prices.	The best ARIMA model was (1, 1, 1) since there were minimum errors when compared with other methods.

The basics of ARIMA model and Box-Jenkins procedures (Song, 2014; Vicente et al. 1974) are ARIMA models consisting of three components: lagged values of the variable of interest (the AR component – parameter p), lagged values of the error term (the MA component – parameter q) and the degree of integration (the number of differences required to make a series stationary – parameter d). AR (p) model can be written as equations (3) and (4):

$$X_t = \delta + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots, \emptyset_p X_{t-p} + \mu_t \quad (3)$$

$$X_t = \delta + \sum_{i=1}^{p} \emptyset_i X_{t-i} + \mu_t = \delta + \sum_{i=1}^{p} \emptyset_i L^i X_{t-i} + \mu_t \quad (4)$$

where X_t is observed data at time t, δ is constant moving average, $\emptyset_1, \emptyset_2, \emptyset_3, \ldots, \emptyset_p$ are coefficients of p moving average terms, and μ_t is random error at time t., and L^i is lag operator.

MA (q) can be written as equations (5) and (6):

$$X_t = \mu + \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} \ldots, \theta_q \mu_{t-q} + \mu_t \quad (5)$$

$$X_t = \mu + \sum_{i=1}^{q} \theta \mu_{t-1} + \mu_t = \mu + \mu + \theta(L)\mu_t \quad (6)$$

where X_t is observed data at time t, μ is constant moving average, $\theta_1, \theta_2, \theta_3, \ldots, \theta_q$ are coefficients of q moving average terms, μ_t is random error at time t, μ_{t-1}, μ_{t-2}, μ_{t-3}, …, μ_{t-q} are coefficients of q moving average terms and $L(t)=1+\theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q$.

The ARMA (p, q) can be written as:

$$X_t = \delta + \emptyset_1 X_{t-1} + \cdots \emptyset_p X_{t-p} + \theta_1 \mu_{t-1} + \cdots + \theta_q \mu_{t-q} \quad (7)$$

where X_t is observed data at time t, μ is constant moving average, $\emptyset_1,\emptyset_2,\emptyset_3,\ldots,\emptyset_p$ are coefficients of p moving average terms, and μ_t is random error at time t, $\theta_1,\theta_2,\theta_3,\ldots,\theta_q$ are coefficients of q moving average terms, μ_t is random error at time t, and $\mu_{t-1}, \mu_{t-2}, \mu_{t-3},\ldots, \mu_{t-q}$ are coefficients of q moving average terms. This class of models can be extended to non-stationary series as Autoregressive Integrated Moving Average (ARIMA) models by allowing the differencing of the data series. There are many ARIMA and general non – seasonal models known as ARIMA (p, d, q) (p is the number of autoregressive, d is the number of differences and q is the number of moving average). However, the general seasonal model is known as ±ARIMA (p, d, q) (P, D, Q) s, where s is the number of periods per season. In the ARIMA model, the random disturbance term has the following notation.

$$E(\varepsilon t)=0, E(\varepsilon t,\varepsilon s)=0 \tag{8}$$

Estimation of parameters (ARMA (p, q)) (Taesombut, 1996; Mookda, 2006; Ungpansattawong, 2012) in any model is by maximum likelihood function $L(\emptyset,\theta,\delta, \sigma_u^2 \mid X_t, t=1,2,3,\ldots,N)$ and values of parameters $\emptyset,\theta,\delta$ are calculated in minimum square of summation of error terms. Notations are:

$$\text{Min } \sum_{t=1}^{n} \varepsilon_t^2 , \varepsilon_t = X_t - \widehat{\theta_1}X_{t-1} - \widehat{\theta_2}X_{t-2} - \cdots - \widehat{\theta_q}X_{t-q} \tag{9}$$

$$\mu_t = \widehat{\emptyset_1}X_{t-1} + \widehat{\emptyset_2}X_{t-2} + \cdots \widehat{\emptyset_p}X_{t-p} + \hat{\theta}_1\mu_{t-1} + \hat{\theta}_2\mu_{t-2} \cdots + \hat{\theta}_q\mu_{t-q} \tag{10}$$

when estimating parameter of $\emptyset,\theta,\delta$, estimation of equation (11) can be made.

$$\hat{\sigma}_{\mu}{}^2 = \frac{\sum_{t=1}^{N} \varepsilon_t^2}{N} \tag{11}$$

Let $\hat{\beta}$ be representative of any parameters and test of statistics is t as

$$t_{\hat{\beta}} = \frac{\hat{\beta}}{SE(\hat{\beta})} \tag{12}$$

where $SE(\hat{\beta})$ is standard deviation of t $(\hat{\beta})$ and degree of freedom is number of N – number of estimated parameters.

Diagnostic Chec king of models (ARMA (p, q)) (Ilbrahim, 1976; Lorchirachoonkul, 2005; Hepsen, 2011; Aiste *et al*. 2016) can find which model is suitable for forecasting by considering random error values μ_t without internal correlation, $Q \sim \chi^2$ lead to the notation:

$$Q(k) = \frac{[(N-d)(n-d)+2]}{\sum_{j=1}^{k} \frac{r_j}{((N-d)-j)}} \tag{13}$$

where Q is test statistics without correlation, standard deviation is μ_t, and degree of freedom is Q = k – number of parameters. k is a period of lag, N is amount of observed time series data, d is differences of orders in time series data and r_j is correlation of lag j. All forecasting techniques would have errors, and the levels of error would depend on error terms from each of the forecasting techniques.

$$e_t = Z_t - \widehat{Z_{t-1}} \tag{14}$$

$$E(e_t(l)) = o \tag{15}$$

$$V(e_t(l)) = \sigma^2 \frac{\sigma^2}{t-1} \tag{16}$$

There were two kinds of error measurement methods to apply for this paper (equations (17) and (18)).

1.Mean Square Error (MSE)

$$MSE = \left(\frac{\sum_{t=1}^{t} e_i^2}{t}\right) \tag{17}$$

2.Root Mean Square Error (RMSE) or Standard Error (SE)

$$RMSE = \sqrt{MSE} \tag{18}$$

Box-Jenkins procedure (Yisarkul, 2012) is procedure for applying ARIMA models to time-series analysis, forecasting and control was proposed by Box and Jenkins (1976) (Yisarkul, 2012) and popularized the use of ARIMA models through the following three steps. First of all is identification, the step involves determining the order of the model required to capture the dynamic features of the data. Graphical procedures are used (plotting the autocorrelation function (ACF) and partial ACF (PACF) of the time series) to decide which (if any) AR or MA component should be used in the model. To achieve this, first ARIMA needs to be stationary, that is, it should have a constant mean, variance and autocorrelation through time. Since the data are non-stationary, the series has to be transformed to induce stationary data. Second is estimation, this step involves estimating the parameters of the models specified in the model identification step. Computational algorithms (least squares or another technique, known as maximum likelihood) are used to arrive at coefficients which best fit the selected ARIMA model. The last is diagnostic check, this step is to test whether the model specified and estimated is adequate. Box and Jenkins suggest two methods: over fitting and residual diagnostics. Over fitting involves deliberately fitting a larger model than that required to capture the dynamics of data as identified in step 1; any extra terms added to the ARIMA model would be insignificant. Residual diagnostics implies checking the residuals. The residuals should be white noise (or independent when their distributions are normal) drawing from a fixed distribution with a constant mean, variance and not correlated with each other. After reviewing a summary of Box-Jenkins procedure in other textbooks and research papers (Bin-Shan et al. 1986; Usombut, 2004; Ebenezer *et al*. 2013), steps to proceed with this method were similar to research paper (Yisarkul, 2012).

2.3 Disposal and Recovery Methods

In this study, we are interested in the characteristics of four types of wastes handled by four service providers as shown in Table 3.

2.4 Factual Data of Case Study

Service Providers A, B, C and D are waste transportation and disposal service companies. At present they serve the four kinds of wastes by providing wastes transportation, waste processing and waste container service to waste producers. However each service provider has different assets, services and facilities as shown in Table 4 and each of service providers who has to apply their recovery and disposal method to fit to kinds of wastes which were already allowed by Department of Industrial Work in Thailand are shown in Table 5.

Table 2: Suggestions to select p and q parameters in AR, MA, and ARMA Models

Properties of the ACF and PACF of MA, AR and ARMA Series			
Process	MA (q)	AR (p)	ARMA (p, q)
Autocorrelation function (ACF)	Cuts off	Infinite. Tails off. Dominated by damped Exponentials and Cosine waves.	Infinite. Tails off. Dominated by damped Exponentials and Cosine waves.
Partial Autocorrelation function (PACF)	Infinite. Tails off. Dominated by damped Exponentials and Cosine waves.	Cuts off	Infinite. Tails off. Dominated by damped Exponentials and Cosine waves.

Table 3: Summary of characteristics of four wastes to service providers

Kinds and Status of Wastes		Company A		Service Providers	
Name	**Appearance**	**Physical**	**Chemical**	**Physical**	**Chemical**
AA	White solid	8.75% Moisture	0.09% Chloride content	8.75% Moisture	0.09% Chloride content
BB	White Plastic	65% Moisture	0.04% Chloride content	65% Moisture	0.04% Chloride content
CC	Grey liquid	93% Moisture	Cadmium, Zinc, Thallium, Manganese, Sodium, Potassium and Mercury	93% Moisture	Cadmium, Zinc, Thallium, Manganese, Sodium, Potassium and Mercury
DD	White sludge	61% Moisture	Arsenic, Chromium, Copper, Nickel, Sodium, Potassium and Zinc	61% Moisture	Arsenic, Chromium, Copper, Nickel, Sodium, Potassium and Zinc

Table 4: Summary of owners of service assets and facilities

Service Provider	Name	Owner of transportation?	Owner of facilities and equipment	Had service for selling and / or renting waste containers?
A	AA	Yes	Yes	Yes
B	BB	Yes	No	No
C	CC	No	Yes	Yes
D	DD	Yes	No	No

Note: Yes means that service providers have the assets, and facilities to service their customers, and No means that service providers do not have the assets and facilities, so they use outsourcing services from other companies.

Table 5: Summary of recovery and disposal methods to four kinds for wastes

Service Provider	Name	Recovery and Disposal Methods
A	AA	Fuel blending
B	BB	Secure landfill of stabilized and solidified wastes
C	CC	Co-incineration in cement kiln
D	DD	Sanitary landfill

2.5 Applications

There are two main phases of model development and application in Figure 1. Details of how to proceed are:

1st phase is divided into 2 steps. First step is to identify, estimate and check suitable models. After finished first step, then we are to select the optimal forecasting techniques and define parameters to generate forecasting data on next.

2nd phase is divided into four parts of system developments to build created applications to their service providers.

Management in Service Providers A, B, C and D could use these forecasted data to plan, implement and control their assets and facilities. However for some assets and facilities which they do not own themselves, they would purchase the service from other providers with a purchasing contract agreement to gain best prices and services.

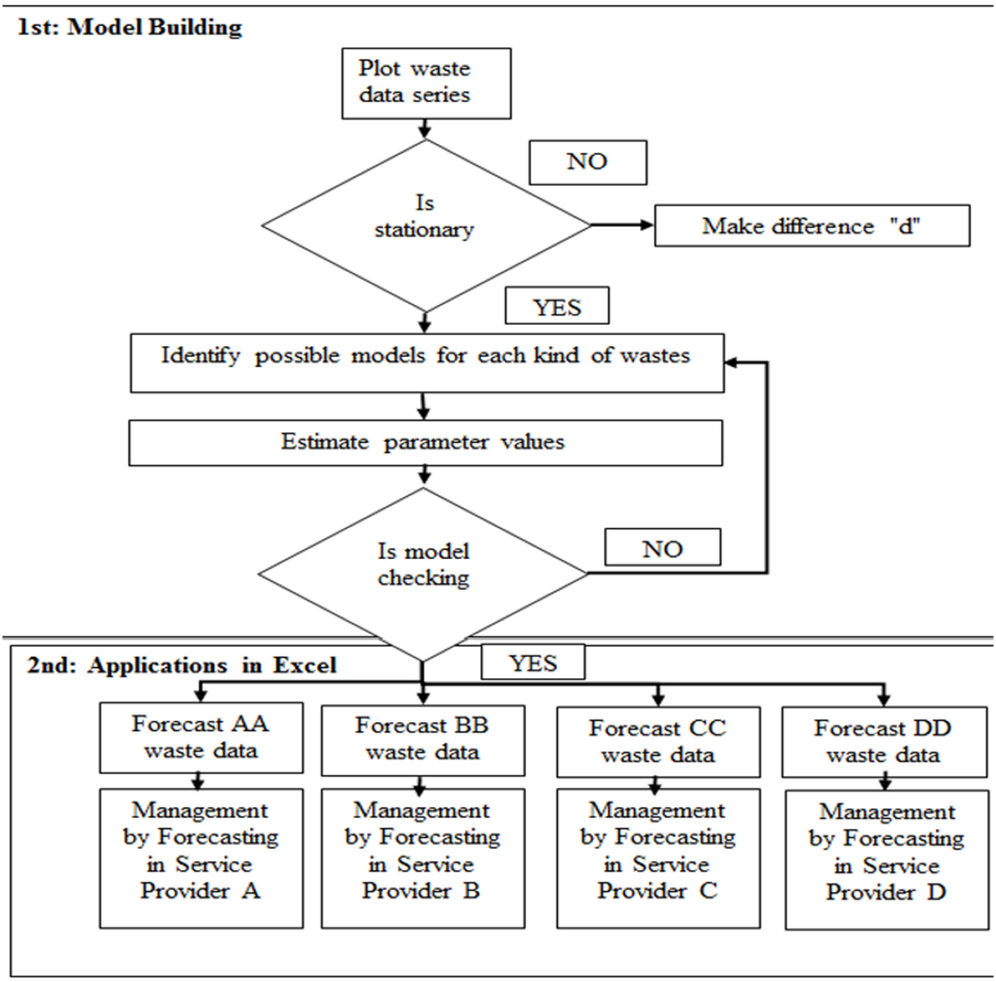

Figure 1: Steps on executions of study

3. Results and Discussions

The data were analyzed for four types of wastes, AA, BB, CC and DD wastes from January 2008 to December 2017 handled by Service Providers A, B, C, and D (120 data series). Data analysis used Minitab version 18 software (Wardona, 2016). After ran data with program, the results were shown in Table 6

Based on Table 6, ARIMA equations of each waste can be determined:

1. AA waste (ARIMA(2, 1, 0) or ARI(2,1)) :
$X_t = -0.70(X_{t-2} - X_{t-3}) + \mu_t$

2. BB waste (ARIMA(0, 0, 1) or MA(1)) :
$X_t = 0.27(X_{t-1}) + \mu_t$

3. CC waste (ARIMA(3, 2, 2)) :
$X_t = -0.52(X_{t-3} - X_{t-4}) + 0.88 (X_{t-1} - X_{t-2}) + \mu_t$

4. DD waste (ARIMA(3, 0, 3) or ARMA(3, 3)) :
$X_t = 0.85(X_{t-3} - X_{t-4}) +0.96 (X_{t-3} - X_{t-4})) + \mu_t$

The results of forecasting the four kinds of wastes at Service Providers A, B, C and D with ARIMA using Minitab software are shown in Table 7. Based on Table 8, the accuracy of these models is better than other research papers which are using different and similar forecasting models. Ebenezer and team (Ebenezer *et al*, 2013) used the ARIMA method to forecast only one type of solid waste data and its purpose was to forecast solid waste generation in Ghana. Aiste and team (Aiste *et al.*, 2016) studied many methods of time series forecasting techniques to forecast data of hazardous wastes generation in Lithuania. Their preferred choice was minimal RMSE of time series (HOLT's Winter method), but the RMSE data sets were higher than our models. These comparisons should ensure the performance of forecasting data that could be useable for the next processes.

Table 6: Summary of fitted of ARIMA (p, d, q) parameter of models by Minitab software

	AA waste					BB waste				
Parameters	**ARIMA**	**Coef**	**SE Coef**	**T-Value**	**P-Value**	**ARIMA**	**Coef**	**SE Coef**	**T-Value**	**P-Value**
AR (p)	2	-0.70	0.14	-4.94	0.00	0				
I (d)	1					0				
MA (q)	0					1	0.27	0.09	3.02	0.00
	CC waste					**DD waste**				
Parameters	**ARIMA**	**Coef**	**SE Coef**	**T-Value**	**P-Value**	**ARIMA**	**Coef**	**SE Coef**	**T-Value**	**P-Value**
AR (p)	3	-0.52	0.09	-6.05	0.00	3	0.85	0.08	10.57	0.00
I (d)	2					0				
MA (q)	2	0.88	0.09	10.06	0.00	3	0.96	0.06	16.70	0.00

Table 7: Summary of fitted ARIMA (p, d, q) parameters of models by Minitab software

	AA waste (1,000 tons)			BB waste (1,000 tons)		
Period	**Forecast**	**Lower**	**Upper**	**Forecast**	**Lower**	**Upper**
Jan-18	5.21	4.29	6.13	5.28	4.27	6.30
Feb-18	3.89	2.87	4.90	5.25	4.20	6.31
Mar-18	6.56	5.54	7.58	5.25	4.20	6.31
Apr-18	6.12	4.94	7.29	5.25	4.20	6.31
May-18	4.50	3.19	5.81	5.25	4.20	6.31
Jun-18	5.67	4.35	7.00	5.25	4.20	6.31
Jul-18	6.22	4.83	7.60	5.25	4.20	6.31
Aug-18	5.13	3.64	6.63	5.25	4.20	6.31
Sep-18	5.34	3.81	6.87	5.25	4.20	6.31
Oct-18	6.01	4.44	7.59	5.25	4.20	6.31
Nov-18	5.54	3.89	7.19	5.25	4.20	6.31
Dec-18	5.34	3.64	7.04	5.25	4.20	6.31
	CC waste (1,000 tons)			**DD waste (1,000 tons)**		
Period	**Forecast**	**Lower**	**Upper**	**Forecast**	**Lower**	**Upper**
Jan-18	16.11	12.79	19.42	9.70	7.53	11.86
Feb-18	16.82	13.24	20.41	9.58	7.41	11.75
Mar-18	17.20	13.47	20.92	9.49	7.32	11.67
Apr-18	15.30	11.09	19.51	9.68	7.48	11.88
May-18	16.83	12.16	21.51	9.66	7.46	11.86
Jun-18	15.73	10.88	20.57	9.53	7.33	11.73
Jul-18	16.22	10.99	21.45	9.65	7.43	11.87
Aug-18	15.24	9.71	20.77	9.71	7.49	11.93
Sep-18	16.19	10.36	22.03	9.58	7.36	11.81
Oct-18	14.92	8.85	21.00	9.63	7.39	11.86
Nov-18	15.76	9.33	22.19	9.73	7.49	11.97
Dec-18	14.71	8.04	21.37	9.64	7.40	11.88

Table 8: Fitting ARIMA (p, d, q) parameters of models by using Minitab software for four types of waste

Types of Waste	ARIMA (p, d, q)	RMSE	RMSE (Ebenezer et al. 2013), (Aiste et al. 2016)
AA waste	ARIMA (2, 1, 0)	467.61	(11,551.77), (303,212)
BB waste	ARIMA (0, 0, 1)	518.80	(11,551.77), (303,212)
CC waste	ARIMA (3, 2, 2)	1,691.16	(11,551.77), (303,212)
DD waste	ARIMA (3, 0, 3)	1,102.80	(11,551.77), (303,212)

Table 9: Comparing between estimated total quantities of the types of four wastes generated annually and quantities reported by Industrial Waste Management Division (Industrial of Work in Thailand) since 2008 to 2017

	Wastes (1,000Tons) - Our Study				Wastes (1,000Tons) - Department of Industrial Work, 2018			
Year	AA	BB	CC	DD	AA	BB	CC	DD
2008	51.41	60.78	257.04	115.65	154.22	547.02	771.12	1,040.84
2009	48.03	61.77	288.16	113.33	144.08	555.92	864.49	1,019.95
2010	51.24	62.54	307.44	118.81	153.72	562.85	922.32	1,069.32
2011	48.09	62.59	288.54	116.66	144.27	563.28	865.62	1,049.90
2012	39.48	62.76	296.10	110.37	118.44	564.88	888.30	993.29
2013	37.66	64.82	282.45	121.90	112.98	583.38	847.35	1,097.09
2014	39.45	63.47	197.25	118.39	118.35	571.22	591.75	1,065.47
2015	38.05	62.35	190.26	116.48	114.15	561.16	570.77	1,048.29
2016	41.61	63.79	208.07	118.33	124.84	574.14	624.20	1,064.98
2017	48.29	65.44	217.40	121.68	144.86	588.99	652.20	1,095.08

Based on Table 9, there are shown comparing figures of estimated total quantities of the four types of wastes generated annually and quantities reported as being treated which was reported by Industrial Waste Management Division in Department of Industrial Work in Thailand (Industrial Waste Management Division. 2018). Figures in Table 9, we found proportion between our estimated kinds of wastes by our study and the quantities reported by Industrial of Work as 25% of AA waste, 10% of BB waste, 25% of CC waste and 10% of DD waste. Next step is to proceed to Management by Forecasting for the four service providers. This step applies Excel application to support the concept of Management by Forecasting in version 2013. New template in Excel were created for Service Providers A, B, C and D after receiving the demand forecast from ARIMA model. Each service provider owned different assets and facilities and these of them had to use outsourcing to support their transportation or disposal processes. Details of four Excel applications for the four service providers are in Tables 10, 11, 12 and 13.

Table 10: Excel application template for supporting service provider A

		Transportation (Rounds)		Capacity		
Period	**Forecast**	**Lower**	**Upper**	**Transportation**	**Disposal**	
Jan-18	261	215	307	400	3,600	
Feb-18	195	144	246	400	3,600	
Mar-18	328	278	379	400	3,600	
Apr-18	306	248	365	400	3,600	
May-18	225	160	291	400	3,600	
Jun-18	284	218	350	400	3,600	
Jul-18	311	242	381	400	3,600	
Aug-18	257	182	332	400	3,600	
Sep-18	267	191	344	400	3,600	
Oct-18	301	223	380	400	3,600	
Nov-18	278	195	360	400	3,600	
Dec-18	267	182	352	400	3,600	
	Over Disposal Capacity (Ton)			**Over Storage areas (m3)**		
Period	**Forecast**	**Lower**	**Upper**	**Forecast**	**Lower**	**Upper**
Jan-18	1,610	693	2,527	677	292	1,062
Feb-18	285	-	1,302	120	-	547
Mar-18	2,958	1,940	3,975	1,243	815	1,670
Apr-18	2,518	1,344	3,692	1,058	565	1,551
May-18	898	-	2,207	378	-	928
Jun-18	2,072	747	3,398	871	314	1,427
Jul-18	2,619	1,233	4,004	1,100	518	1,682
Aug-18	1,535	39	3,030	645	17	1,273
Sep-18	1,739	206	3,273	731	87	1,375
Oct-18	2,415	843	3,987	1,015	355	1,675
Nov-18	1,943	294	3,592	817	124	1,509
Dec-18	1,739	38	3,439	731	16	1,445

Table 11: Excel application template for supporting service provider B

	Transportation (Rounds)			Capacity	
Period	**Forecast**	**Lower**	**Upper**	**Transportation**	**Disposal**
Jan-18	529	427	631	600	15,000
Feb-18	526	420	631	600	15,000
Mar-18	526	420	631	600	15,000
Apr-18	526	420	631	600	15,000
May-18	526	420	631	600	15,000
Jun-18	526	420	631	600	15,000
Jul-18	526	420	631	600	15,000
Aug-18	526	420	631	600	15,000
Sep-18	526	420	631	600	15,000
Oct-18	526	420	631	600	15,000
Nov-18	526	420	631	600	15,000
Dec-18	526	420	631	600	15,000
	Over Transportation (Rounds)				
Period	**Forecast**	**Lower**	**Upper**		
Jan-18	-	-	31		
Feb-18	-	-	31		
Mar-18	-	-	31		
Apr-18	-	-	31		
May-18	-	-	31		
Jun-18	-	-	31		
Jul-18	-	-	31		
Aug-18	-	-	31		
Sep-18	-	-	31		
Oct-18	-	-	31		
Nov-18	-	-	31		
Dec-18	-	-	31		

Table 12: Excel application template for supporting service provider C

	Transportation (Rounds)			Capacity	
Period	Forecast	Lower	Upper	Transportation	Disposal
Jan-18	806	640	972	1,200	20,000
Feb-18	842	662	1,021	1,200	20,000
Mar-18	860	674	1,047	1,200	20,000
Apr-18	765	555	976	1,200	20,000
May-18	842	608	1,076	1,200	20,000
Jun-18	787	545	1,029	1,200	20,000
Jul-18	812	550	1,073	1,200	20,000
Aug-18	762	486	1,039	1,200	20,000
Sep-18	810	518	1,102	1,200	20,000
Oct-18	747	443	1,050	1,200	20,000
Nov-18	788	467	1,110	1,200	20,000
Dec-18	736	403	1,069	1,200	20,000

	Over Disposal Capacity (Ton)			Over Storage areas (m3)		
Period	Forecast	Lower	Upper	Forecast	Lower	Upper
Jan-18	-	-	-	-	-	-
Feb-18	-	-	411	-	-	173
Mar-18	-	-	922	-	-	388
Apr-18	-	-	-	-	-	-
May-18	-	-	1,511	-	-	635
Jun-18	-	-	570	-	-	240
Jul-18	-	-	1,454	-	-	611
Aug-18	-	-	769	-	-	323
Sep-18	-	-	2,029	-	-	853
Oct-18	-	-	999	-	-	420
Nov-18	-	-	2,188	-	-	919
Dec-18	-	-	1,374	-	-	577

Table 13: Excel application template for supporting service provider D

	Transportation (Rounds)			Capacity	
Period	**Forecast**	**Lower**	**Upper**	**Transportation**	**Disposal**
Jan-18	970	754	1,186	800	15,000
Feb-18	958	741	1,175	800	15,000
Mar-18	950	733	1,167	800	15,000
Apr-18	968	748	1,188	800	15,000
May-18	967	746	1,187	800	15,000
Jun-18	953	733	1,174	800	15,000
Jul-18	965	743	1,188	800	15,000
Aug-18	972	749	1,194	800	15,000
Sep-18	959	736	1,181	800	15,000
Oct-18	963	740	1,187	800	15,000
Nov-18	974	750	1,198	800	15,000
Dec-18	965	740	1,189	800	15,000

	Over Transportation (Rounds)		
Period	**Forecast**	**Lower**	**Upper**
Jan-18	170	-	386
Feb-18	158	-	375
Mar-18	150	-	367
Apr-18	168	-	388
May-18	167	-	387
Jun-18	153	-	374
Jul-18	165	-	388
Aug-18	172	-	394
Sep-18	159	-	381
Oct-18	163	-	387
Nov-18	174	-	398
Dec-18	165	-	389

In Tables 10, 11, 12 and 13, Service Providers A and C lacked disposal capacity and storage areas to support the forecasted lower or upper demands while B and D had an issue over available transportation service to satisfy the forecasted upper demands. Thus solutions for Service Providers A and C would be to extend their disposal capacity and storage areas or find new service providers to serve their excess demands, and for Service Providers B and D subcontracted to invest in additional transportation services or find new transportation services that can obtain authorization to move or transfer extra wastes for them.

4. Conclusions

After studying and modifying data by Box-Jenkins Model with ARIMA (Autoregressive Integrated Moving Average), the four fitted ARIMA models could predict and generate forecast amounts of wastes (by Statistical software such as Minitab, SPSS, SAS and Eview etc;) for the four service providers to plan, implement and control their assets, facilities and investments in monthly or yearly plans with customized Excel applications. Recommendations of this study are (1) This forecasting model should be developed by someone who fully understands ARIMA and Box-Jenkins Model and is knowledgeable in time series in ARIMA and Box-Jenkins Model to create suitable models and has been experienced in this industry, (2) This Excel application could be developed by someone who understands all the key information from all stakeholders; however if a company could build a software application to support this, there would be benefits for other companies that have the same issues.and (3) Forecasting should consider other factors which would affect the amount of waste generated from their customers such as 3Rs (Reuse, Recycle and Reduce) and new technology productions or processes that could minimize their wastes.

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