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Indicators of Environmental and Economic Problems Priority Arising from Energy Use in Food Manufacturing Sector in Realizing Sustainable Development Policy under Thai Environmental Law Framework

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ABSTRACT

This research was conducted to examine the true benefit of energy consumption within the scope of energy cost, as well as model a forecasting tool for energy cost in food manufacturing industry. It was limited to the analysis of true benefit of the consumption, energy cost, forward-and-backward relationship, and prediction of future energy cost during the next 10 years ranging from 2021 to 2030, and 20 years ranging from 2021 to 2040. The analysis was made possible via an application of ARIMAX model optimizing the input-output table of Thailand. As for the result, it reveals that the product of tobacco is found with the highest true value of benefit. While candy and sweets, sugar, breweries, corn, distilled spirit, slaughtering, milled rice, coffee and tea, and canned meat are respectively detected. In taking forward-and-backward relationship into account, a close monitoring is required for the sector of canned meat and milled rice, respectively. Since the developed model is confirmed for its validity, an optimization of RMSE, MAE, and MAPE measurement for 10 years (2021-2030) and 20 years (2021-2040) prediction of energy cost would result in the following outcomes; (1) a gradual increase of 41.86 percent is estimated for the energy cost by 2030 compared to 2021 per illustration in Model 1, and (2) energy cost is calculated at a steadily increased 70.79% by 2040 in comparison with 2021 per presentation in Model 2.

Keywords: Economic Problem, Environmental Law, Sustainability, Food Manufacturing Sector, Energy Cost
JEL Classifications: P28, Q42, Q43, Q47, Q48

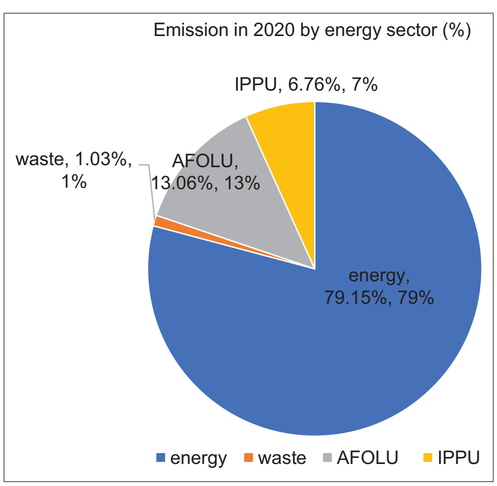
1. INTRODUCTION

Global warming is one of many global concerns contributing negative effect and challenges to the world. Since mid-century to date, a rise of average temperature has been observed by the Intergovernmental Panel on Climate Change or known as IPCC (The World Bank: Energy Use (Kg of Oil Equivalent Per Capita) Home Page, 2021; Office of the National Economic and Social Development Council: NESDC, 2021; National Statistic Office Ministry of Information and Communication Technology, 2021). Human activities are among many key causes sparking tenses in greenhouse gas (GHG) effect (NESDC, 2021). During 21st century (2001-2100), an increase of 1.1 up to 6.4 degree Celsius of average temperature surface is estimated to happen. In most cases, developed country Annex 1 group has the ability to reduce such a challenge (Department of Alternative Energy Development and Efficiency, 2021; Thailand greenhouse gas management organization (public organization), 2021). Unfortunately, it is not the case for developing countries, including Thailand and most countries in ASEAN community, in coping and dealing with the issue (NESDC, 2021; United Nations Framework Convention on Climate Change, UNFCCC, Bonn, Germany, 2016).

Thailand has rapidly and continuously developed proper economic system while GHG emission is found to increase day by day at the same time (NESDC, 2021; Pollution Control Department Ministry of Natural Resources and Environment. Enhancement and Conservation of National Environmental Quality Act, B.E. 2535, 2021); Pollution Control Department Ministry of Natural Resources and Environment. Navigation of Thai Waterways Act, B.E. 2546, 2021; Pollution Control Department Ministry of Natural Resources and Environment. Principle 4: In order to achieve sustainable development, environmental protection shall constitute an integral part of the development process and cannot be considered in isolation from it, 2021). The data retrieved from the Office of Natural Resources and Environmental Policy and Planning presents the release of real GHG emission at 379.61 $MtCO_2e$ in 2020 (Pollution Control Department Ministry of Natural Resources and Environment. Principle 4: In order to achieve sustainable development, environmental protection shall constitute an integral part of the development process and cannot be considered in isolation from it, 2021). The energy consumption sector was found as the major contributor to this emission discharging about 272.49 $MtCO_2e$ or 75.15 percent of entire greenhouse gas in Thailand. In comparison to the year 2000, the emission growth is progressed more than 65% as illustration in Figure 1 (Department of Alternative Energy Development and Efficiency, 2021; Thailand greenhouse gas management organization (public organization), 2021).

With the information given, it implies that our world is gradually falling to a warmer state (Thailand greenhouse gas management organization (public organization), 2021). The later consequence due to climate change leads to various massive natural disasters, including floods, droughts, and many more. These events have a direct impact on consumers in relation to food security. Eventually, it causes economic growth to shrink (NESDC, 2021).

Figure 1: Ratios of greenhouse gas discharged in Thailand given by different sectors as of 2020



Thailand has made a number of drafting laying out plans and policies designed to improve manufacturing structure and business productivity. Unfortunately, energy plans and policies are observed incomplete and interrupted. Thailand needs energy input-output analysis (IOA) by acquiring most recent data and energy input-output information. In addition to this analysis, a forecasting model is required to predict greenhouse gas emission in energy consumption, and it must be fit and valid in order to manage and administer energy and environment for a better sustainability. Thus, this research is developed to explain the development of prediction model for optimal national use in energy sector. The research extends on ARIMA model integrating exogenous X variable. The analyses are systematically carried out in line with research methodology and statistical procedure in order to obtain research results with least residuals. The research also depicts no studies focusing on a forecasting model development with an integration of exogenous variables and the aforementioned model. Hence, this research is believed beneficial and practical for policy and plan formulation, and expected to benefit other countries as well.

2. MATERIALS AND METHODS

2.1. ARIMA Model

The model ARIMA comprises of three core components: Auto Regressive (AR), Integrated (I), and Moving Average (MA). These components can be explained and detailed out below (Zhang and Broadstock, 2016; Zhang and Xu, 2012).

1. Auto Regressive (AR) is composed of general characteristics of order p are as shown below

$$Y_t=\alpha+\beta_1 Y_{t-1}+\beta_2 Y_{t-2}+\ldots+\beta_p Y_{t-p}+\varepsilon_t \tag{1}$$

Where; $\beta_1 \ldots \beta_p$ are parameters; α is a content, ε_t is the random variable (white noise) (Yalta and Cakar, 2012)

2. Integrated (I) means to retrieve the difference of variables. Since the ARIMA is non-stationary, it is essential to define the differences of order p so that stationary data can be obtained from non-stationary data (Zhang and Lin, 2012; Lu, 2017)
3. Moving Average (MA) is to estimate the error term from forecasting by the differences in actual variables (Y Actual) with dependent variables (Y Forecast) or $\varepsilon_t=Y_{at}-Y_{ft}$ with prediction of needed variables in the future as formulated below (Xu et al., 2014; Ren et al., 2014).

$$Y_t=\delta+\varepsilon_t-y_1\varepsilon_{t-1}-y_2\varepsilon_{t-2}-\ldots-y_q\varepsilon_{t-q} \tag{2}$$

Where Moving Average of Order q or MA(q) by q indicates the last order of error value applied. The model development form of ARIMA can be explained as ARIMA (p,d,q). That is Order of AR=p, I=d, and MA=q, respectively.

2.2. ARIMAX Model

The ARIMAX Model is a newly-introduced model developed from ARIMA Model. When GHG emission is given to be dependent variable, various factors consisting of population, CO_2, CH_4, and

N_2O emission becomes independent variables (Dai et al., 2018; Liu, 2019). In fact, the ARIMAX model is expected to provide accurate and effective outcomes in the event of predicting future GHG emission due to following details (Ma, 2018).

2.2.1. Steps for modeling and forecasting

1. Analyze the data for stationary property by testing the Unit Root guided by Augment Dickey and Fuller theory

Stationary stochastic process also known as stationary in short is time series data which presents together mean or expected value, constant overtime, variance, and covariance (Qin et al., 2019). This type of data does not lie within time but distance or lag. By assuming Y_t as stochastic time series and stationary in the same time, three key properties must exist, and they can be expressed below (Dickey and Fuller, 1981; MacKinnon, 1991).

$$EY_t=EY_{t+k}=\mu \tag{3}$$

$$VAR(Y_t)=E(Y_{t-\mu})^2=E(Y_{t-k-\mu})^2=\sigma^2 \tag{4}$$

$$E(Y_{t-\mu})(Y_{t+k-\mu})=\gamma k \tag{5}$$

Upon observing equation (3), (4), and (5), γ_k is seen as covariance between Y_t and Y_{t+k}, where distance exists between two values of Y. However, probability distribution remains unchanged but not expected value and constant variance due to ε_t lacks of property of white noise (Johansen and Juselius, 1990; Johansen, 1995). Under this phenomenon, autocorrelation is detected with high correlations or higher order autoregressive process. Therefore, a test of augmented Dickey Fuller (ADF) form is required (Enders, 2010; Harvey, 1989). This requirement is due to its addition of lagged variables at a higher level so that autocorrelation of residual, heteroskedasticity, and multicollinearity, can be eliminated as per discussion below (Sims, 1980).

$$\Delta Y_t = \delta_1 Y_t + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \tag{6}$$

$$\Delta Y_t = \alpha_1 + \delta_1 Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \tag{7}$$

$$\Delta Y_t = \alpha_1 + \alpha_2 T + \delta Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \tag{8}$$

With the above equations, the p value is explained to be lagged value of first difference variable, and that can be tested by using Unit Root testing with the Augmented Dickey Fuller method. The later equation can be written as follows (Byrne, 2009; Sutthichaimethee, 2018).

$$\Delta Y_t = \alpha_1 + \alpha_2 T + \delta Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \tag{9}$$

The equation (9) lays out a fact that three key issues are considered, particularly autocorrelation of ε_t is set to experience White Noise. When a tau-statistic of the co-efficient δ is found in the absolute term, more critical values are expected to list in the ADF table. However, this expectation fails to hold in core hypotheses. Yet, this fact implies that time series variables are stationary explaining ΔY_t Integrated Number d is represented by $\Delta Y_{t\sim}$ I(d) (Sutthichaimethee, 2016; 2017).

2. Analyze all the stationary data at the same level both dependent variables and independent variables (at level of 1st moment and/or 2nd moment only) for the long-term relationship or examine co-integration when variables of the model are relevant in the long term but the same level (Sutthichaimethee and Ariyasajjakorn, 2017). In order to ensure the best model in property, Vector Error-Correction model (ECM) must be applied (Sutthichaimethee and Ariyasajjakorn, 2018)

As for this research, the co-integrated relationship is presented based on the Full Information Maximum Likelihood (FIML) Approach as introduced by Johansen and Juselius (1990) due to the followings.

3. The model is applicable to apply with two variables or more
4. Number of co-integrated vectors can be examined without a need of variables specification whether they are exogenous or endogenous.

According to Johansen and Juselius method, it lies within the form of Multivariate Co-integration by denoting to Vector Autoregressive (VAR) Model, and that can be exchanged below (Sutthichaimethee and Ariyasajjakorn, 2017; Sutthichaimethee and Dockthaisong, 2018)

$$\Delta X_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta X_t, \Delta X_{t-1} - \Pi X_{t-k} + u \tag{10}$$

From Johansen and Juselius approach point of view, it is interested to seek Co-integrating Vectors of variables X_t in VAR Model. It is also essential to get the right Lag to activate the VAR Model by considering the Likelihood Ratio Test of Sims (1980) or the Minimum Final Prediction Error Test Akaike approach. The test is composed with the following stages (Sutthichaimethee and Kubaha, 2018).

- Prepare a needed equation for testing based on Vector Autoregressive Model (VAR)
- Conduct the test to obtain numbers of Lag fitting for the above equation
- Compute Co-integrating Vectors between model variables and retrieve a metric π rank, in which it is independent of π equal to Rows or Columns
- Apply two statistical testing tools to obtain numbers of Co-integrating Vectors (r) inside the model, and they can Trace Test and Maximum Eigenvalue Test, for instance. The both tools often function simultaneously to determine result accuracy (Sutthichaimethee et al., 2019)
- Estimating the Best Model: True impact of independent variables on dependent variable must be detected. This impact can be observed tau-statistic values with different significance level of 5%, 10%, and 15%
- Testing the Best Model for three core issues as follows
- Autocorrelation is tested by deploying Lagrangian Multiplier Test or known as LM test (Valipour et al., 2019; Pacheco, 2013).

The LM Test can be taken when lagged dependent variables in an equation become independent variables. In fact, the LM test can be used to detect Error Terms in relation to autocorrelation in high level. The following equation presents the test's method

$$Y_t=\alpha_0+\alpha_1 X_t+\beta_1 U_{t-1}+\beta_2 U_{t-2}+\ldots+\beta_p U_{t-p} \tag{11}$$

Process the equation $Y_t=\alpha_1 X_t+U_t$ to obtain Residual; major hypothesis can be $H_1:\beta_1=\beta_2=\ldots=\beta_p=0$ and the statistical test is expressed as $nR^2\sim\chi^2 p$, while F-Test$=\frac{n-k}{m}\times\frac{R^2}{(1-R^2)}$

If χ^2_p and $F_{m,n-k}$ – Test statistic is found greater than critical χ^2 value and F critical value at a selected level of significance, it means that the major hypothesis is rejected, and at least one β has a value difference from 0, presenting autocorrelation problem in the model (Sutthichaimethee, 2017).

- Heteroskedasticity is tested by applying ARCH Test. The ARCH Testing is taken to examine Heteroskedasticity in time series data. When the Residual is observed, lagged variables of the residual is evaluated by accounting F and nR^2 value with Chi-Square distribution. If the χ^2_p statistical test value is greater than critical value of χ^2_p at a chosen significance level, that means the hypothesis is rejected due to the presence of Heteroskedasticity problem (Sutthichaimethee, 2018)
- Multicollinearity is tested by deploying correlation test as to check on responses from the Correlogram value in comparison to Chi-square value (Sutthichaimethee, 2016).

2.3. Measurement of the Forecasting Performance

Accuracy checking is assessed to see prediction capability. This forecasting accuracy is evaluated by comparing three different evaluation statistics, namely Root Mean Square Error (RMSE), Mean Absolute (MAE), and Mean Absolute Percentage Error (MAPE). These statistics are written as follows (Enders, 2010; Harvey, 1989):

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}(F_i - A_i)^2 / n} \tag{12}$$

$$\text{MAE} = \sum_{i=1}^{n}\left|F_i - A_i\right| / n \tag{13}$$

$$\text{MAPE} = \sum_{i=1}^{n}\left|\left(F_i - A_i\right) / A_i\right| / n \times 100 \tag{14}$$

From the above equations, F_i and A_i are the forecasted value and actual value, respectively, while n is the total number of forecasting. As for this research, it aims to retrieve results with the least error, and that reason accounts models with MAPE values of less than 30%.

The expansion of the GHG emission model developed in this research is made possible with the use of the ARIMAX model as per illustration below (Sutthichaimethee, 2018).

$$\Delta\ln(GHG)_t = \alpha + \sum_{i=1}^{n}\beta_{1i}\Delta\ln(GHG)_{t-i} + \sum_{i=1}^{n}\beta_{2i}\Delta\ln Population_{t-i} + \sum_{i=1}^{n}\beta_{3i}\Delta\ln(Tech)_{t-i} + \sum_{i=1}^{n}\beta_{4i}\Delta\ln(CO_2)_{t-i} + \sum_{i=1}^{n}\beta_{5i}\Delta\ln(CH_4)_{t-i} + \sum_{i=1}^{n}\beta_{5i}\Delta\ln(N_2O)_{t-i} + \sum_{i=1}^{m}\beta_{6i}MA + \beta_7 ECM + \varepsilon_t$$

Where GHG_t represents greenhouse gas at time *t*, GHG_{t-i} denotes dependent variables in the duration *t–i*, $Population_{t-i}$ expresses of population number, $Tech_{t-i}$ denotes technology, $(CO_2)_{t-i}$ in the duration *t–i*, refers to Carbon Dioxide, $(CH_4)_{t-1}$ represents Methane in the duration *t–i*, $(N_2O)_{t-i}$ signifies Nitrous oxide in the duration *t–i*, *ECM* embodies Error Correction Model, MA_i refers to Moving Average at time *i*, ε_t signifies residual at time *I*, Δ refers to first difference operator, and ln is explained as natural logarithm.

3. EMPIRICAL ANALYSIS

3.1. Indicator Analysis Findings on Environmental and Economic Problems Priority Arising from Energy Use Cost in Food Manufacturing Sector

The results of the real benefit, energy costs, Forward Linkage and Backward Linkage are classified by each category of the production. This research can be summarized as following:

Table 1 lists the top ten food manufacturing sectors in terms of Forward Linkage, Backward Linkage real benefit, and energy cost. In this study, "Forward Linkage" presents the relationships among each production line. It can show where input are sent from. It also signifies that the higher level of the forward linkage, the higher relationships among the involved sectors. real benefit is the revenue for a sector, minus the environmental costs. The average real benefit was 0.96. If the real benefit for a given industry is lower than the average, it can be considered to represent a loss, while values higher than the average represent profit. Besides, Table 1 has further explained the analysis outcome by highlighting key features as follows:

3.1.1. Highlights from the findings include the following

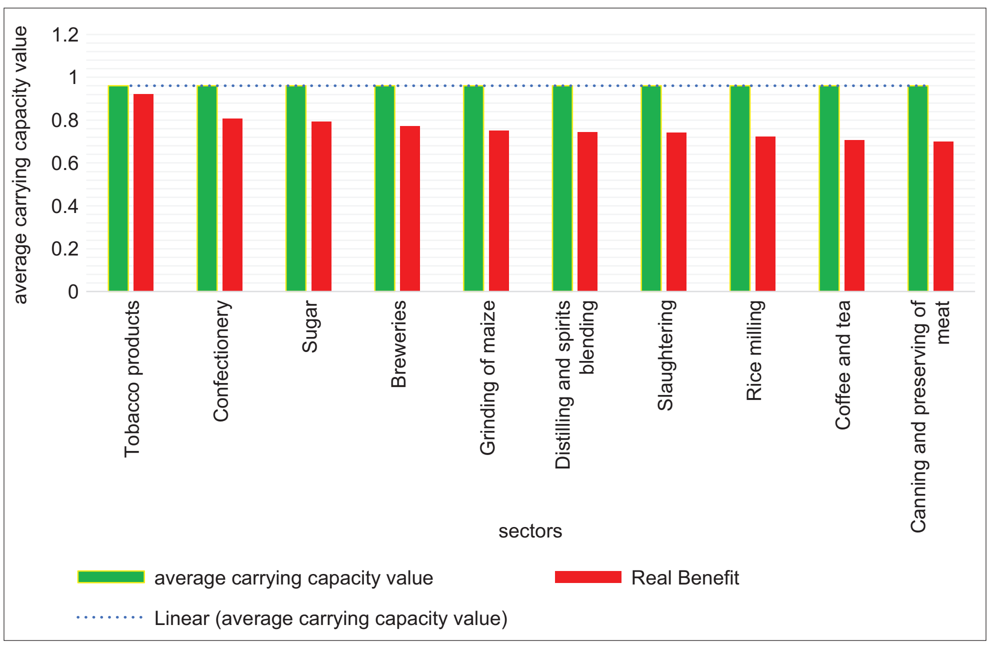
1. The highest real benefit in the Food manufacturing sectors was tobacco products, while the lowest real benefit was canning and preserving of meat. The lowest real benefit could signify loss in profit (Figure 2)
2. The highest Forward Linkage in the food manufacturing sectors was for canning and preserving of meat, while the lowest Forward Linkage was rice milling
3. The highest Backward Linkage in the food manufacturing sectors was for ice, while the lowest Forward Linkage was canning and preserving of meat.

Analyzing the indicator of environmental impacts from the food manufacturing sectors of Thailand. The average carrying capacity value for energy cost was 0.071, if the cost for a particular industry

Table 1: Indicator of environmental and economic problems priority arising from the use of energy cost in food manufacturing sectors

Forward linkage		Backward linkage		Real benefit		Energy cost	
Value	**Sectors**	**Value**	**Sectors**	**Value**	**Sectors**	**Value**	**Sectors**
0.7855	Canning and preserving of meat	0.6576	Ice	0.9212	Tobacco products	0.4893	Ice
0.7607	Monosodium glutamate g	0.6117	Monosodium glutamate	0.8053	Confectionery	0.1569	Monosodium glutamate
0.7292	Tapioca milling	0.5119	Tapioca milling	0.7931	Sugar	0.1444	Tapioca milling
0.7213	Coconut and palm oil	0.3958	Coconut and palm oil	0.7712	Breweries	0.1436	Coconut and palm oil
0.6853	Noodles and similar products	0.3796	Dairy products	0.7490	Grinding of maize	0.1297	Noodles and similar products
0.6827	Coffee and tea	0.3664	Animal oil, animal fat, vegetable oil and by-products	0.7433	Distilling and spirits blending	0.1207	Confectionery
0.6460	Slaughtering	0.3231	Canning and preservation of fish and other sea foods	0.7413	Slaughtering	0.1184	Canning and preserving of meat
0.6392	Grinding of maize	0.3098	Canning and preservation of fruit and vegetables	0.7219	Rice milling	0.1173	Sugar
0.6332	Confectionery	0.3025	Grinding of maize	0.7065	Coffee and tea	0.1138	Canning and preservation of fruit and vegetables
0.6308	Rice milling	0.3019	Canning and preserving of meat	0.6996	Canning and preserving of meat	0.1107	Canning and preservation of fish and other sea foods

Figure 2: Real benefit



is lower than the average carrying capacity value, there is further capacity for production. environmental cost values that are higher than the average carrying capacity value signify that there is no further capacity for production.

3.1.2. Highlights from the findings include the following

The food manufacturing sectors with the highest environmental cost in terms of energy cost was Ice. The cost indicator was above the average carrying capacity value, signifying that this sector does not have capacity for further production (Figure 3).

3.2. Formation of Analysis Modeling with the ARIMAX Model

The results of the Forecasting model of energy costs is classified by each category of the production. This research can be summarized as following:

1. Unit root test: with the augmented Dickey-Fuller test is shown in Table 2

Table 2: The ADF Test Statistic at level of all variables has a variable unit root component or non stationary i.e. the value

calculated from the ADF, all lower than the critical value. From the table at the significance level of 1%, 5% and 10%, so that it must be to qualify as Stationary by the difference moment. This research found that all variables Stationary at the first differencing included energy consumption (EC), population (Population), technology (Tech), and GDP per capita (GDP). The value of the test based on the "Tau-test" is greater than the all "Tau-critical" at the first difference, results in Table 3.

2. Result of the co-integration test

The result in Table 4 brings all variables are stationary at the first difference to test co-integration by using the method of "Jansen Juselius" shown in Table 3.

Table 3 as the results, "co-integration test" showed that model is a co-integration because of the Trace Test is 178.28, which is higher than the critical value at significance level of 1% and 5%, the Maximum Eigen value test at 127.75 which is higher than the critical value significance level of 1% and 5%.

3. The result of ARIMAX model

Figure 3: Energy cost

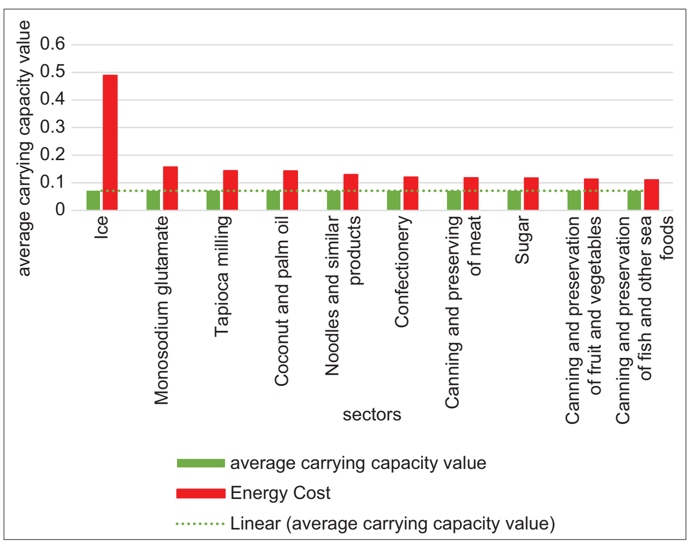


Table 2: Unit root test at level

Variables	Lag	ADF test	MacKinnon Critical Value			Status
			1%	5%	10%	
In(*EC*)	1	–2.71	–4.31	–3.45	–3.25	I(0)
In(*Population*)	1	–2.47	–4.31	–3.45	–3.25	I(0)
In(*Tech*)	1	–3.08	–4.31	–3.45	–3.25	I(0)
In(*GDP*)	1	–2.74	–4.31	–3.45	–3.25	I(0)

1. ARIMAX Model 1 (2,1,1)

$$\Delta In(EC)_t = -0.031 + 2.61\Delta In(EC)^{*}_{t-1} + 2.95\Delta In(EC)^{*}_{t-2} + 4.16\Delta In(Population)^{**}_{t-1} - 7.12\ \Delta In(Tech)^{**}_{t-1} + 5.78\Delta In(GDP)^{**}_{t-2} + 2.02\ MA^{*}_{1} + 5.23ECM^{***}$$

Where ** is significance α = 0.01, * is significance α = 0.05, R-squared is 0.95, Adjusted R-squared is 0.93, Durbin-Watson stat is 2.02, F-statistic is 154.75 (Probability is 0.00), ARCH-test is 43.05 (Probability is 0.11), LM – test is 1.63 (Probability is 0.10) and response test (χ^2>critical) is significance.

2. ARIMAX Model 1 (2,1,2)

$$\Delta In(EC)_t = -0.073 + 4.12\Delta In(EC)^{**}_{t-1} + 3.78\Delta In(EC)^{**}_{t-2} + 6.53\Delta In(Population)^{**}_{t-1} - 6.97\ \Delta In(Tech)^{**}_{t-1} + 5.05\Delta In(GDP)^{**}_{t-1} + 2.12\ MA^{*}_{1+2}.78MA^{**}_{1+2}.10ECM^{*}$$

Where ** is significance α = 0.01, * is significance α = 0.05, R-squared is 0.92, Adjusted R-squared is 0.89, Durbin-Watson stat is 2.17, F-statistic is 165.05 (Probability is 0.00), ARCH-test is 33.05 (Probability is 0.12), LM – test is 2.71 (Probability is 0.11) and response test (χ^2>critical) is significance.

3.3. The Results of Forecasting Model

When the modeling ARIMAX Model 1 (2,1,1) and ARIMAX Model 2 (2,1,2), which is the best model that was used to predict 2 models. The first, 10 years forecast (year 2021-2030), the second, 20 years forecast (2021-2040) the forecast results shown in Figures 4 and 5.

The results forecasts found that the model 1 (year 2021-2030) energy cost volume increased steadily and average rising up to 41.86% in 2030, and the model 2 (year 2021-2040) energy cost volume increased steadily as well and average rising to 70.79% in 2040. However, that model 1 and model 2 were tested the effectiveness of the model compared with Actual value found that both models are highly effective with the low deviation can be used to decision making that shown in Table 5.

This study, the first of its kind in Thailand, creates the forecasting model of energy cost using ARIMAX model and from review of literature of many of sources such as Qin et al. (2019) constructed Autoregressive (AR) model and Long Short-Term Memory (LSTM) model in Python language based on the TensorFlow framework aimed at simulating and predicting the hydrological time series. As of their study's result, the feasibility of the models is captured for the prediction of the hydrological time series. Mosavi et al. (2018) revisited the existing literature and studies to illustrate the state of the art of Machine Learning (ML) models in flood prediction and to investigate the most suitable models. By taking ML models as a benchmark, hybridization, data decomposition,

Table 3: Co-integration test by Johansen Juselius

Variables	Hypothesized No. of CE(S)	Trace statistic test	MacKinnon critical value		Max-Eigen statistic test	MacKinnon critical value		Status
			1%	5%		1%	5%	
ΔIn(*EC*), ΔIn(*Population*), ΔIn(*Tech*), ΔIn(*GDP*)	None**	178.25	21.16	15.41	127.75	17.78	15.21	I(1)
	At Most 1**	70.05	4.75	3.25	78.03	4.75	3.25	I(1)

Figure 4: Forecasting from ARIMAX model 1 (2,1,1)

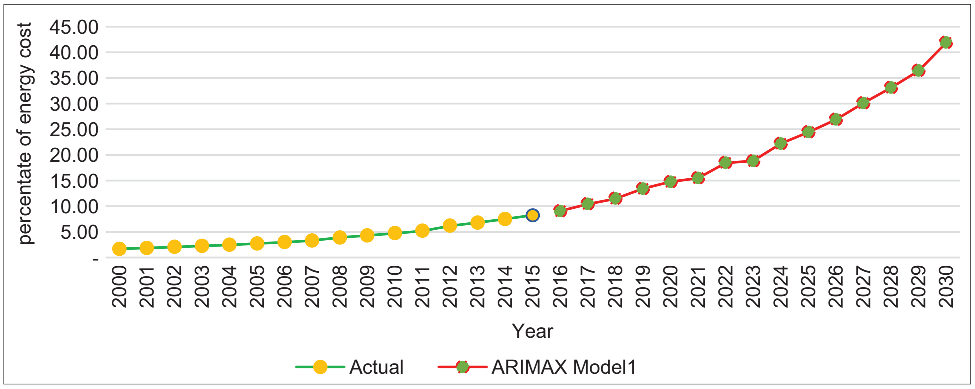


Figure 5: Forecasting from ARIMAX model 2 (2,1,2)

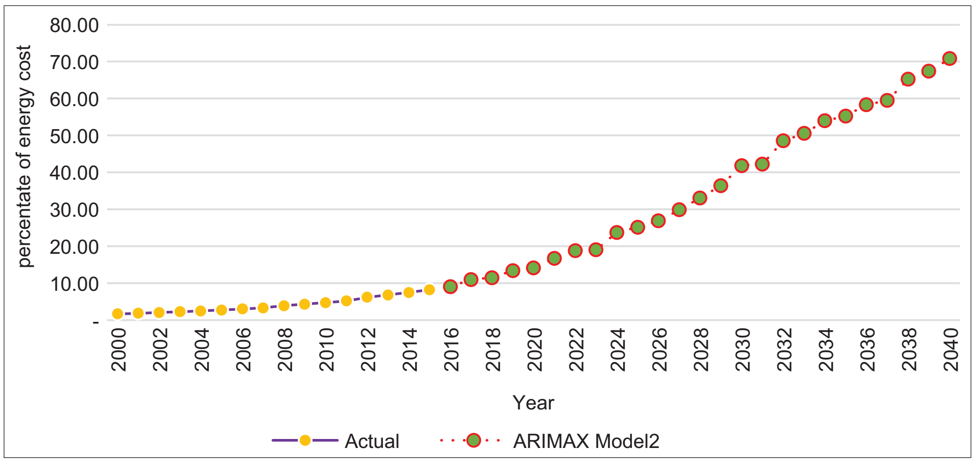


Table 4: Unit root test at the first difference

Variables	Lag	ADF test	MacKinnon critical value			Status
			1%	5%	10%	
In(*EC*)	1	–4.37	–4.31	–3.45	–3.25	I(1)
In(*Population*)	1	–5.57	–4.31	–3.45	–3.25	I(1)
In(*Tech*)	1	–4.75	–4.31	–3.45	–3.25	I(1)
In(*GDP*)	1	–6.47	–4.31	–3.45	–3.25	I(1)

Table 5: The performance monitoring of forecasting model

Forecast of energy cost	RMSE	MAE	MAPE
Model 1: ARIMAX Model (2,1,1) (2021-2030)	0.013	0.040	1.05
Model 2: ARIMAX Model (2,1,2) (2021-2040)	0.058	0.077	1.02

algorithm ensemble, and model optimization are found as the most effective strategies in improving the quality of the flood prediction models. While Lohani et al. (2014) proposed Peak Percent Threshold Statistic (PPTS) as a new model performance criterion to examine the performance of a flood forecasting model using hourly rainfall and discharge data as a sample. They also compared the result of the proposed model with artificial neural networks (ANN), Self-Organizing Map (SOM) based ANN model and subtractive clustering-based Takagi Sugeno fuzzy model (SC-T-S fuzzy model). As of their analysis, the SC-T-S fuzzy model is shown with reasonably accurate forecast coupled with sufficient lead-time. To Shrestha et al. (2013) examined the quality of precipitation forecasts from four Numerical Weather Prediction (NWP) models, namely ACCESS-G 80 km resolution, ACCESS-R 37.5 km, ACCESS-A 12 km, and ACCESS-VT 5 km, based on the Australian Community Climate Earth-System Simulator (ACCESS). As part of their findings, it presents that the systematic biases in rainfall forecasts has to be removed before using the rainfall forecasts for streamflow forecasting. Jabbari et al. (2020) deployed a numerical weather prediction and a rainfall-runoff model to assess the precipitation and flood forecast for the Imjin River (South and North Korea). As a result, they no result, they notice that the Weather Research and Forecasting (WRF) model underestimates precipitation in point and catchment assessment. However, there has not been any study done at all. Therefore, this study is a guide for the studying and applying in other countries in the future.

4. CONCLUSION AND DISCUSSION

In conclusion, this research indicates that tobacco products come with the highest value of true benefit. Whereas confectionery, sugar, breweries, maize, distilled spirit, slaughtering, milled rice, coffee and tea, and preserved meat, are found respectively. By taking the relationship value of forward-and-backward linkage into account, preserved meat and milled rice segments are shown with a need of close control and administration, respectively. This research also predicts energy cost in 10 years (2021-2030) and 20 years (2021-2040) by measuring RMSE, MAE, and MAPE. The prediction results can be summarized as per presentation in two sub-models; Model 1 and Model 2 have been estimated with a gradual rise in energy cost by 41.86% and 70.79%, respectively. This research has made an assurance of sustainable development through policy making and planning by carefully controlling specified sectors suggested by this research finding. Some sectors have been observed with higher energy cost, yet they are lower in real benefit. The sectors cover various fields across consumer production lines, including ice, monosodium glutamate, milled tapioca, palm oil and coconut, noodles and similar products, preserved food in meat, fruits, vegetables, fish and other sea foods. In the meanwhile, some sectors have also found with high value of forward-and-backward connection. This finding signifies an urgency alarm for the government and policy makers to take a serious caution and control over these sectors. In relation to the prediction of energy cost in both terms, 10 years (2021-2030) and 20 years (2021-2040), this research indicates that Thailand has witnessed an increment in rates making it experience in higher energy cost as per confirmation by this study. This phenomenon implies an impact on economy and society, especially environmental damage due to higher predicted ratio than Thailand's carrying capacity to handle. With this effect, it spreads a rise of greenhouse gas worldwide. Nevertheless, findings from this research can be used as a noble guideline for effective and efficient national policy and planning, enabling Thailand and other countries in application to achieve sustainable development.

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