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Article

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Guidelines for Increasing the Effectiveness of Thailand's Sustainable Development Policy based on Energy Consumption: Enriching the Path-GARCH Model

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ABSTRACT

The objective of this study is to develop a model for forecasting energy consumption and to increase the effectiveness of Thailand's sustainable development policy based on energy consumption by using the best model, the Path Analysis-Generalized Autoregressive Conditional Heteroscedasticity Model (Path-GARCH model). To improve the effectiveness of sustainability policies, the researcher has envisioned the final energy consumption over a 20-year period (AD 2023-2022) by defining a new scenario policy. Comparing the performance of the Path-GARCH model to other previous models, the Path-GARCH model was found to have the lowest mean absolute percentage error (MAPE) and root mean square error (RMSE) values. In addition, the study found that energy consumption continued to rise to 125,055 ktoe by 2042, with a growth rate of 115.05% between 2042 and 2023, which exceeded the carrying capacity limit of 90,000 ktoe. When a new scenario policy is implemented, however, the final energy consumption continues to rise to 74,091 ktoe (2042). Consequently, defining a new scenario policy is a crucial development guideline for enhancing the effectiveness of Thailand's sustainable development policy.

Keywords: Sustainability Policy, New Scenarios Policy, Energy Consumption, Forecasting, Carrying Capacity
JEL Classifications: P28, Q42, Q43, Q47, Q48

1. INTRODUCTION

From 1990 to the present, Thailand has established policies and development plans aimed at achieving sustainability (2021). To fulfill the policy of transforming Thailand into a new technology country and a new industrial nation, Thailand has collaborated with several nations around the world to foster economic, social, and environmental development for continuous and stable growth in the future. These development plans are divided into three distinct timeframes: Short term (1-5 years), medium term (1-10 years), and long term (>10 years) (1-20 years). Despite this development plan, Thailand's development in every sector, especially the economy, has accelerated dramatically, a phenomenon known as "leaps and bounds development." It seems that the country's income has continued to increase while its industrial structure has grown exponentially. Several factors have led to this result, for instance, the promotion of both domestic and international production for the advancement of technology and innovation to effectively support global change, as well as the encouragement of foreign investors to invest so as to increase Thailand's income and the amount of money flowing into the country.

In addition, the government is taking several measures to keep interest rates low. In other words, the government supports low tax rates, encourages the growth of foreign investors' investments, supports Thailand's export business and market share expansion, particularly in the European and Chinese markets, and encourages European, American, and Chinese tourists to visit Thailand and spend money. As a result, Thailand's economy continues to grow at a rate of 8.5% (in 2021/2020) (Office of the National Economic and Social Development Board, NESDB, 2022), fostering social growth as evidenced by the accelerated promotion of various fields such as education, sanitation, safety, and career development to ensure stability, etc. Consequently, Thailand's economy and social development have grown steadily in the past, as evidenced by the 3.1% increase in the social growth rate (2021-2020). (National Statistic Office Ministry of Information and Communication Technology, 2022).

Obviously, the abovementioned fact demonstrates Thailand's ability to develop economically and socially to achieve continuous growth, as well as the country's capacity to effectively implement policies to achieve predetermined objectives, propelling Thailand into a new type of industrialized nation known as Thailand 4.0. However, these developments depict that environmental degradation will intensify as the economy and society continue to expand. In a more straightforward sense, the ecosystem's condition has continued to deteriorate. In addition, it was determined that Thailand's total CO_2 emissions in 2021 increased by 5.1% compared to 2020 (Department of Alternative Energy Development and Efficiency, 2022). Clearly, the production of greenhouse gases such as methane (CH4), nitrous oxide (N20), hydrofluorocarbons (HFC), perfluorocarbons (PFC), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3) has risen. (Achawangkul, 2022; Thailand greenhouse gas management organization (public organization), 2022). Furthermore, the energy consumption rate is rising in tandem with the rate of growth in electricity consumption, which is 15.05 percent (2021/2020). As a result, the cost of energy consumption and electricity skyrockets, fueling even more inflation (NESDB, 2022; Department of Alternative Energy Development and Efficiency, 2022; Sutthichaimethee, 2017).

According to the results of Thailand's sustainable development plan, economic and social growth continued to increase. Nevertheless, the opposite direction has a negative impact on the environment, as evidenced by the continued rise in greenhouse gas emissions (Thailand greenhouse gas management organization [public organization], 2022; Sutthichaimethee and Kubaha, 2018). Therefore, Thailand must have short-, medium-, and long-term tools for policymaking and plans for sustainable development, particularly for the long term. Since no research has been able to model long-term energy consumption forecasting in the past, Thailand lacks the optimal model for long-term energy consumption forecasting. This study aims to address this deficiency by reviewing previous related research and designing a study to answer the question. The details are as follows:

2. LITERATURE REVIEW

The researcher selected the following specific studies regarding sustainable policy. In this literature review, it will explore on some studies pertaining the energy consumption forecasting. It is indeed necessary to examine what has been done on such a topic as to increase in the quality of the proposed model. In fact, there have been few stream studies exploring the total energy consumption. For instance, Zhao et al. (2016) started to estimate the electricity consumption of Inner Mongolia by deploying GM (1,1) optimized by MFO with Rolling Mechanism from 2010 to 2014. Their study results in the indication of which the model can improve the forecasting performance of annual electricity consumption significantly. Li and Li (2017) also initiated on a comparative study by using the ARIMA model, GM model, and ARIMA-GM model to forecast an energy consumption in Shandong of China from 2016 until 2020. Upon their analysis in the study, the prediction results showed that the energy demand of Shandong province between those years will increase at an average annual rate of 3.9%. In the same streamline, Xiong et al. (2014) proposed a novel GM (gray model) (1,1) model based on optimizing initial condition in accordance with new information priority principle to predict China's energy consumption and production from 2013 to 2017. The study indicated that China's energy consumption and production will keep increasing, while does the gap between them increase as well. Besides, Panklib et al. (2015) attempted to forecast an electricity consumption in Thailand by using an Artificial Neural Network and Multiple Linear Regression for the year 2010, 2015 and 2020. Based on their estimation from the study, it revealed that the electricity consumption of the country in 2010, 2015, and 2020, retrieved from the regression, will reach 160,136, 188,552, and 216,986 GWh, respectively. Whereas 155,917, 174,394, and 188,137 GWh were the results obtained from ANN model. Apparently, ANN integrated with genetic algorithm was also presented by Azadeh et al. (2007) to estimate the electricity consumption in Iranian agriculture sector in 2008. Based on their result of the study, it can be observed that the integrated GA and ANN dominate time series approach from the point of yielding less MAPE (Mean Absolute Percentage Error) error.

By incorporating values of socio-economic indicators and climatic conditions, Günay (2016) modelled the artificial neural networks with the use of predicted values of socio-economic indicators and climatic conditions to predict the annual gross electricity demand of Turkey in 2028. Upon the analysis is done, it produced a result of which the demand would become doubled accounting for 460 TW in 2018 compared to the year 2007-2013. While Dai et al. (2018) explored on the topic of energy consumption forecasting in China from 2018 until 2022 by adopting a model of Ensemble Empirical Mode Decomposition and Least Squares Support Vector Machine with the technology of Improved Shuffled Frog Leaping Algorithm. The study results revealed China's energy consumption to have a significant growth trend. Based on Wang and Li (2017), they tried to find whether China's coal consumption during 2016-

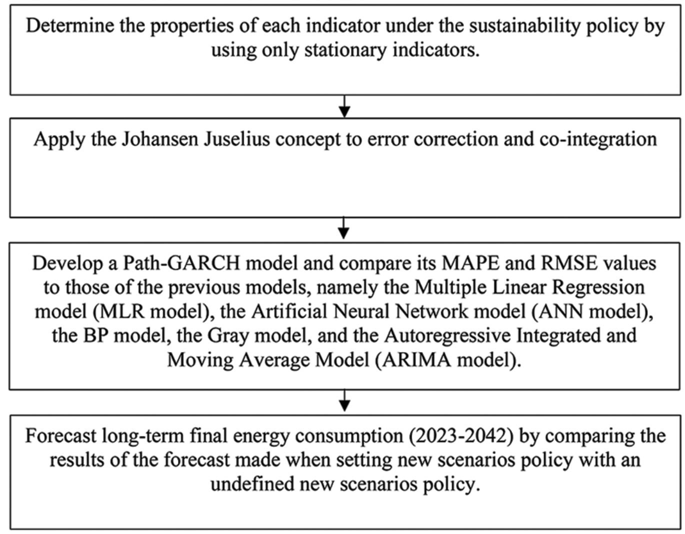
2020 would be higher or lower than the level of 2014. Here, they optimized a time series model with a comprehensive analysis of data reliability. According to the analysis, it indicated that the annual Chinese coal consumption during 2016-2020 will be lower than the level of 2014 given that the annual average GDP growth rate is <8.2% per year. Whereas Suganthi and Samuel (2016) developed econometric models as to study the influence of the socioeconomic variables on energy consumption in India for the year 2030 to 2031. The study found that the electricity demand depends on the GNP and electricity price, and the total energy requirement is found to be 22.944 × 1015 kJ.

In fact, Zou et al. (2017) analyzed the factors that contributed towards the changes in energy consumption in Tangshan city for 2007-2012 by applying logarithmic mean Divisia index. Their findings show that the technical effect plays a vital role in reducing energy consumption in most sectors. Another investigation of the impacts of urban land use on energy consumption in China from 2000 till 2010 done by done by Zhao et al. (2017). They used a panel data analysis with nighttime light (NTL) data estimation. With their study on sight, it has shown that an increase in the irregularity of urban land forms and the expansion of urban land will accelerate in energy consumption, and that indicates the relationship between urban growth and energy consumption. In the same focus of study, Tian et al. (2017) evaluated on the potential impacts of China's industrial structure on energy consumption by deploying a fuzzy multi-objective optimization model based on the input-output model for 2015 until 2020. As of their analysis, they drawn a conclusion of which the industrial structure adjustment has great potential in energy conservation, and such an adjustment could save energy by 19% (1129.17 Mtce) at the average annual growth rate of GDP at 7%. Also, Ayvaz and Kusakci (2017) employed a Nonhomogeneous Discrete Grey Model (NDGM) to forecast electricity consumption from 2014 to 2030. Their findings proved that the grey model (GM) proposed a better forecasting performance.

According to previous research, sustainability policy and analysis results for the short term (1-5 years), medium term (1-10 years), and long term (1-20 years or more), particularly long-term research from the past, are exceedingly rare. Also, most previous model studies do not account for the best model, which can lead to inaccurate forecasting results. In addition, it was found that historical forecasting modeling lacks new scenario policy analysis, preventing the application of research results to the formulation of national policies and plans. In order to fill this gap, it is anticipated that the findings of this study will be utilized in the formulation of national policies and plans in the future. This study's indicators were secondary data gathered between 1990 and 2021. Figure 1 depicts the following research steps for this study.

1. Determine the properties of each indicator under the sustainability policy by using only stationary indicators. (Dickey and Fuller, 1981; Enders, 2010; Sutthichaimethee, 2018)
2. Apply the Johansen Juselius (1990) concept to error correction and co-integration. (MacKinnon, 1991; Johansen, 1995)
3. Develop a Path-GARCH model and compare its MAPE and RMSE values to those of the previous models, namely the Multiple Linear Regression model (MLR model), the Artificial Neural Network model (ANN model), the BP model, the Gray model, and the Autoregressive Integrated and Moving Average Model (ARIMA model) (Sutthichaimethee and Ariyasajjakorn, 2017; (Sutthichaimethee and Ariyasajjakorn, 2018)
4. Forecast long-term final energy consumption (2023-2042) by comparing the results of the forecast made when setting new scenarios policy with an undefined new scenarios policy.

Figure 1: The flowchart of the Path-GARCH model



The article is organized and divided into the following four sections. Section two describes the Path-GARCH forecasting model. Section three presents the empirical analysis illustrating the applicability and validity of the proposed model for forecasting and predicting final energy consumption from 2023 to 2042. And, Section four provides a summary of the discussion.

3. THE MATERIALS AND METHODS

3.1. Path Analysis-Generalized Autoregressive Conditional Heteroscedasticity Model (Path-GARCH Model)

According to the ARCH model, if m has a greater value, so will the parameter. To reduce the parameters, researchers have proposed a Path-GARCH model. The Path-GARCH model takes past short-term variance into account, and it can be represented as follows: Path-GARCH (*p, m*). (Harvey, 1989; Sutthichaimethee and Ariyasajjakorn, 2018).

$$\varepsilon_t = \sigma_t v_t \tag{1}$$

$$Var(\varepsilon_t \,|\, I_{t-1}) = \sigma_t^2 = \gamma_0 + \sum_{t=1}^{m} \gamma_1 \varepsilon_t^2 + \sum_{i=1}^{p} \theta_i \sigma_{t-1}^2 \tag{2}$$

Where v_t is white noise with a mean of zero, while the variance is equal to I_t, whereas $\gamma_1, \gamma_2, \ldots, \gamma_m$ indicates the parameters of ARCH, and $\theta_1, \theta_2, \ldots, \theta_p$ shows the parameters of Path-GARCH. If p = 0, Path-GARCH (*p*, *m*), = Path-GARCH (0, *m*) or ARCH (*m*). (Sutthichaimethee and Dockthaisong, 2018)

Since σ_t^2 and σ_{t-t}^2 are the parameters that do not keep information, Equation (2) is written with a certain condition, as shown below.

$$E(\varepsilon_t^2) = \sigma_t^2$$

$$\text{Therefore, } \varepsilon_t^2 = \sigma_t^2 + \eta_t$$

$$\text{Or rewritten as } \sigma_t^2 = \varepsilon_t^2 + \eta_t \quad (3)$$

$$\text{And } \sigma_{t-1}^2 = \varepsilon_{t-i}^2 - \eta_{t-i} \quad (4)$$

where η_t is a random variable with a mean of zero ($E(\eta_t) = 0$, $i = 1, 2,\ldots, T$)

When taking σ_t^2 and σ_{t-1}^2 from the above equation to substitute into Equation (2), a new equation can observed as follows. (Sutthichaimethee and Dockthaisong, 2018).

$$\varepsilon_t^2 - \eta_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \theta_i (\varepsilon_{t-1}^2 - \eta_{t-i}) \quad (5)$$

$$\varepsilon_t^2 = \gamma_0 + \sum_{i=1}^{m} \gamma_i \varepsilon_{t-i}^2 + \sum_{i-1}^{p} \theta_i \varepsilon_{t-i}^2 - \sum_{i=1}^{p} \theta_i \eta_{t-i} + \eta_t$$

$$\varepsilon_t^2 = \gamma_0 + \sum_{i=1}^{\max(m,p)} (\gamma_i + \theta_i) \varepsilon_{t-i}^2 - \sum_{i=1}^{p} \theta_i \eta_{t-i} + \eta_t \quad (6)$$

From Equation (6), it can be noticed that the ARMA (max (m, p) p) is the Path-GARCH, and that is a similar application of ARMA for time series ε_t^2. The following equation is formed to find out the long-term variance. (Sutthichaimethee and Dockthaisong, 2018; Sutthichaimethee and Ariyasajjakorn, 2018).

$$E(\varepsilon_t^2) = \gamma_0 + \sum_{i=1}^{\max(m,p)} (\gamma_i + \theta_i) E(\varepsilon_{t-i}^2) \quad (7)$$

Since ε_t is white noise, where the variance is constant, $E(\varepsilon_t^2) - E(\varepsilon_{t-1}^2)$, we will have:

$$Var(\varepsilon_t) - E(\varepsilon_t^2) = \frac{\gamma_0}{1 - \sum_{i=1}^{\max(m,p)} (\gamma_t + \theta_i)} \quad (8)$$

When considering Equation (2) and (8), we can conclude the following:

1. To ensure both short- and long-term variance to be positive, we must set a condition of $\gamma_0 > 0, \gamma_i \geq 0, \quad \theta_i \geq 0$ and $\sum_{i=1}^{\max(m,p)} (\gamma_i + \theta_i) < 1$
2. Equation (8) shows that the long-term variance of unexpected events (ε_t) is constant, and it does not relate to any previous unexpected events
3. According to Equation (2), the variance of unexpected events over the short term (ε_t) is not constant and is influenced by previous unexpected events. However, using the same method as ARCH, both the short-and long-term variances can be calculated, yielding a result of zero in both cases. Path-GARCH modeling is comparable to ARCH modeling, but it is utilized when the ARCH model's appropriate order is determined to be smaller. Path-GARCH is typically applied only when orders satisfying Path-GARCH (1,1) Path-GARCH (1,2) or Path-GARCH exist (2,1). In situations involving Path-GARCH-based forecasting of short-term variance, the calculation can be derived from an estimate of Equation (2). When variance forecasting is performed, the short-term variance tends to approach the long-term variance, as demonstrated by Equation (8). (Sutthichaimethee and Kubaha, 2018).

3.2. Measurement of the Forecasting Performance

To measure the forecasting performance, the study will examine and compare the accuracy of each model's forecasts by using mean absolute percentage error (MAPE) and root mean square error (RMSE) (RMSE). The following are the calculating formulas:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \quad (10)$$

4. EMPIRICAL ANALYSIS

4.1. Determine the Properties of Indicator to Develop Path-GARCH Model

The researcher defined three latent variables: economic, social, and environmental factors. In addition, the researcher identified the following observed variables, that is, urbanization rate (U_e), industrial structure (I_e), net exports (E_e), indirect foreign investment (F_e), employment (E_s), health and illness (H_s), social security (S_s), consumer protection (C_s), energy consumption (Een), renewable consumption rate (Ren), carbon dioxide emissions (CO_2), and green technology (Gen). Only the unit root test at level I(0) and the unit root test at level I (1) were conducted. Based on the theory of Augment Dickey Fuller at Level I(0) and Fist Difference I(1), as depicted in Table 1, if the indicator does not meet the specified criteria, it must be discarded.

4.2. The Results of Co-integration Test

Table 2 presents the findings of the co-integration analysis. It shows that all indicators pointed to co-integration at first difference, where the traces test were greater than the MacKinnon critical values at 1% and 5% significance levels. Comparatively, the maximum eigenvalue test results of 150.45 and 70.11 exceed the MacKinnon critical values at the 1% and 5% significance levels, respectively. This finding reveals that all short- and long-term indicators are interconnected. Consequently, it can be used to generate Path-GRACH models, as described below.

4.3. The Results of Path-GARCH Model

When all stationary variables at first difference are examined for co-integration test at the same level, the researcher then developed the best model, so-called "Path-GARCH model," as shown in Figure 2 and Table 3 below.

Table 1: Unit root test at level I (0) and first difference I (1)

Tau test				MacKinnon critical value		
Variables	**Level I (0) value**	**Variables**	**First difference I (1) value**	**1%**	**5%**	**10%**
ln*(Ue)*	−3.34	Δln *(Ue)*	−5.45***	−5.25	−3.20	−2.15
ln*(Ie)*	−3.05	Δln *(Ie)*	−5.55***	−5.25	−3.20	−2.15
ln*(Ee)*	−3.41	Δln *(Ee)*	−5.50***	−5.25	−3.20	−2.15
ln*(Fe)*	−3.20	Δln *(Fe)*	−6.05***	−5.25	−3.20	−2.15
ln*(Es)*	−3.52	Δln *(Es)*	−6.55***	−5.25	−3.20	−2.15
ln*(Hs)*	−2.55	Δln *(Hs)*	−5.35***	−5.25	−3.20	−2.15
ln*(Ss)*	−2.44	Δln *(Ss)*	−5.52***	−5.25	−3.20	−2.15
ln*(Cs)*	−3.01	Δln *(Cs)*	−5.59***	−5.25	−3.20	−2.15
ln*(Een)*	−3.65	Δln *(Een)*	−5.68***	−5.25	−3.20	−2.15
ln (CO_2)	−3.51	Δln (CO_2)	−6.63***	−5.25	−3.20	−2.15
ln *(Ren)*	−3.77	Δln *(Ren)*	−6.07***	−5.25	−3.20	−2.15
ln *(Gen)*	−4.90	Δln *(Gen)*	−6.49***	−5.25	−3.20	−2.15

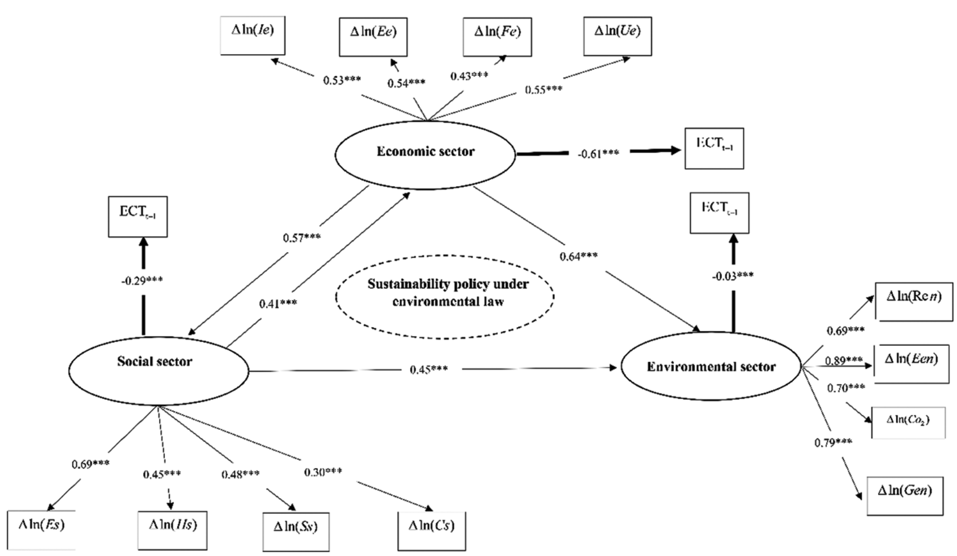
Note: ln *(Ue)* is the natural logarithm of urbanization rate; ln *(Ie)* is the natural logarithm of industrial structure; ln *(Ee)* is the natural logarithm of net exports; ln *(Fe)* is the natural logarithm of indirect foreign investment; ln *(Es)* is the natural logarithm of employment; ln *(Hs)* is the natural logarithm of health and illness; ln *(Ss)* is the natural logarithm of social security; ln *(Cs)* is the natural logarithm of consumer protection; ln *(Een)* is the natural logarithm of energy consumption, ln *(Ren)* is the natural logarithm of renewable consumption rate; ln (CO_2) is the natural logarithm of carbon dioxide emissions; ln *(Gen)* is the natural logarithm of green technology; ***Denotes significance α = 0.01

Table 2: Co-integration test by Johansen Juselius

Variables	Hypothesized no of CE (S)	Trace statistic test	Max-Eigen statistic test	MacKinnon critical value		Status
				1%	**5%**	
Δln *(Ue)*,	None***	225.05	150.45	19.25	15.05	I (1)
Δln *(Ie)*,	At most 1***	85.05	70.11	7.25	5.25	I (1)
Δln *(Ee)*,						
Δln *(Fe)*,						
Δln *(Es)*						
Δln *(Hs)*,						
Δln *(Ss)*,						
Δln *(Cs)*,						
Δln *(Een)*,						
Δln (Co_2),						
Δln *(Ren)*,						
Δln *(Gen)*,						

***Denotes significance α=0.01

Figure 2: The results of correlation influences analysis of the Path-GARCH model



According to Figure 2 and Table 3, the Path-GARCH model is the best valid model with no spurious issues such as heteroskedasticity, multicollinearity, or autocorrelation. In addition, when examining the goodness of fit, it was determined that all criteria were satisfied because RMSEA and RMR were close to 0, and AGFI was close to 1 for GFI. The results indicated that, at a significance level of

Figure 3: Predictions of Thailand's final energy consumption from 2023 to 2042

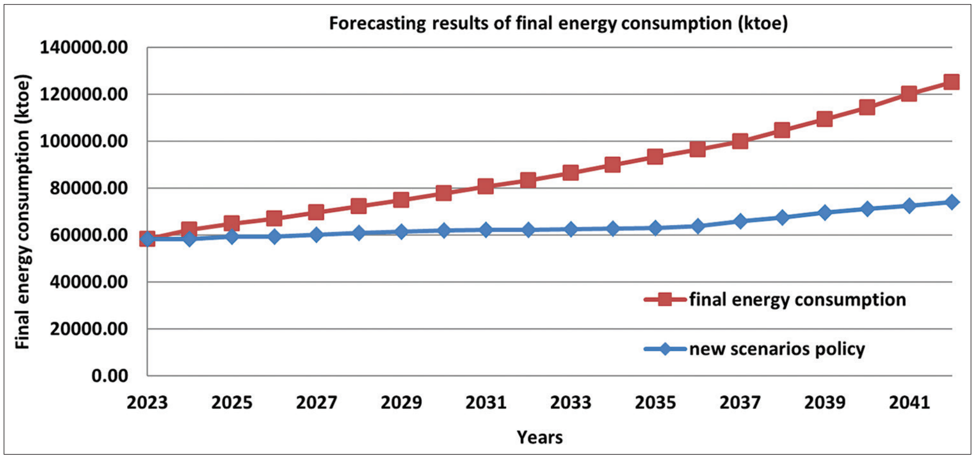


Table 3: The results of causation influences analysis of the path-GARCH model

Dependent variables	Type of effect	Independent variables			
		Economic	Social	Environmental	Error correction mechanism (ECT_{t-1})
Economic	DE	-	0.41***	-	−0.61***
	IE	-	-	-	-
Social	DE	0.57***	-	-	−0.29***
	IE	-	-	-	-
Environmental	DE	0.64***	0.45***	-	−0.03***
	IE	0.25***	0.26***	-	-

In the above, *** denotes significance α=0.01, x^2/df is 1.10, is 0.01, is 0.001, is 0.95, is 0.95, R-squared is 0.96, the F-statistic is 225.05 (probability is 0.00), the ARCH test is 20.10 (probability is 0.1), the LM test is 1.20 (probability is 0.10), DE is direct effect and IE is indirect effect

Table 4: Results of performance between Path-GARCH model and other models

Forecasting model	MAPE (%)	RMSE (%)
MRL model	16.59	18.19
ANN model	8.55	9.98
BP model	6.59	7.79
Gray model	4.22	5.96
ARIMA model	3.25	4.92
Path-GARCH model	1.11	1.55

Source: Author's estimate (2022)

1%, economic had a direct effect on social to the extent of 57%, that economic had a direct effect on the environment to the extent of 64%, that social had a direct effect on the economy to the extent of 41%, and that social had a direct effect on the environment to the extent of 49%.

In addition, the Path-GARCH model analysis revealed that the economic error correction mechanism (ECT_{t-1}) was −0.61 at significant level of 1%, which was capable of adjusting to equilibrium the quickest, with a magnitude of 61%, followed by the social and environmental error correction mechanisms with sizes equal to −0.29 and −0.03, respectively, at a significance level of 1%. Based on the results, the researcher looked at the performance using MAPE and RMSE values as well as models like MLR, ANN, BP, Gray, and ARIMA.

The Path-GARCH model has the best performance, as its MAPE and RMSE values are the lowest (1.11 and 1.55%, respectively) as shown in Table 4. Comparatively, the ARIMA model has MAPE and RMSE values of 3.25 and 4.92%; the Gray model has MAPE and RMSE values of 4.22 and 5.96%; the BP model has MAPE and RMSE values of 6.59 and 7.79%; the ANN model has MAPE and RMSE values of 8.55 and 9.98%; and the MRL model has MAPE and RMSE values of 16.59 and 18.19%. Long-term forecasting, in particular, requires an accurate model in order to continue optimizing forecasts.

4.4. The Results of Final Energy Consumption Forecast by Path-GARCH Model

The Path-GARCH model, according to the analysis, is suitable for forecasting, particularly long-term forecasting (2023-2042). To create the most effective sustainability policy, governments must define a new scenario policy. The researchers concluded that a new scenario policy in the environment sector should be defined based on the study's findings because green technology has the lowest adaptability to equilibrium, with a minimum usage of 20%. Furthermore, the capacity of the specified country should be compared so that it can avoid past environmental damage. The details of the long-term forecast are as follows:

Figure 3 shows that final energy consumption increased steadily from 2023 to 2042, reaching 125,055 ktoe (2042) and a high growth rate (2042/2023). However, final energy consumption jumped to 74,091 ktoe after a new scenario strategy requiring at least 20% green technology use was defined (C.O.). It may be noted that the rise is a declining one and does not exceed Thailand's carrying capacity. Therefore, the formulation of a new scenario policy is a crucial guideline for sustained growth. As a result of the analysis, this model is a significant instrument for developing long-term national strategies and plans.

5. DISCUSSION AND CONCUSSION

In this research, an economic variable, a social variable, and an environmental variable have each been singled out as latent variables. Economic indicators include urbanization rate (*Ue*), industrial structure (*Ie*), net exports (*Ee*), indirect foreign investment (*Fe*). Social indicators include employment (*Es*), health and illness (*Hs*), social security (*Ss*), consumer protection (*Cs*), and the environmental indicators are energy consumption (*Een*), renewable consumption rate (*Ren*), carbon dioxide emissions (CO_2), and green technology (*Gen*).

The results demonstrated that all indicators were stationary at the first difference when all indicators were utilized in the model. Analysis of long-term equilibrium (co-integration) and short-term equilibrium (error-correction mechanism) led the researcher to conclude that the environmental sector has the least ability to adjust to equilibrium compared to the economic and social sectors, respectively.

Due to its validity and white-noise characteristics, the Path-GARCH model was deemed suitable for long-term forecasting (2023-2042). The estimation results were accurate (no problems with heteroskedasticity, multicollinearity, or autocorrelation). Accordingly, the Path-GARCH model had the best performance when compared to the ARIMA model, the Gray model, the BP model, the ANN model, and the MRL model, and could be used for both short-term and long-term forecasting.

In addition, the analysis of the Path-GRACH model to predict the final energy consumption in the long term reveals that Thailand's sustainability policy is ineffective and unsuitable in the long term, given that the economic sector is growing rapidly and in tandem with the social sector, while the environmental sector's growth has continued to decline due to higher energy consumption. Green technology has been the most influential indicator of environmental sector change since the 1990s, followed by CO_2 emissions and renewable energy, in that order.

Consequently, the researcher has formulated a new scenario policy stating that the consumption of green technology must be at least 20% per year, resulting in a reduced rate of growth for Thailand's future energy consumption (2023-2042). In addition to not exceeding the carrying capacity specified by Thailand, this approach is crucial. Therefore, Thailand should immediately establish a national strategy for managing sustainability.

According to the researcher, conventional policies and national administration are ineffective. To achieve sustainable development of the nation, new scenario-based policies must be implemented as outlined in this model. The destruction of Thailand's ecosystems, the increase in carbon dioxide emissions, and the expansion of human influence in the environmental sector have rendered the future unrecoverable. Therefore, Thailand must implement this model immediately and strictly.

Regarding the limitations of this model, it was discovered that Thailand had delayed i-o tables and had not updated the data, preventing its use for research. As a result, the new scenario policy may not be fully defined, but updating the country's i-o table will allow researchers to integrate such data more appropriately into life cycle energy research.

As stated, this is the first study that attempts to bridge the gap between previous models and research. Based on relevant research studies and prior application, the results cannot be compared to the path-GARCH model. The Path-GARCH model will facilitate the application of the model in additional sectors or different contexts. In addition, this model is suitable for short-and medium-term forecasting.

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