

# A Long-Term Electricity Consumption Model adapted from the MMM-ARCH-M Framework for Strategic Greenhouse Gas Emission Reduction towards Smart City Goals in Thailand

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*Received: 27 January 2025 | Revised: 17 February 2025 and 7 March 2025 | Accepted: 13 March 2025*

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## **ABSTRACT**

This research aims to identify the factors for formulating management strategies that enhance energy consumption efficiency in the electricity sector to achieve the long-term goal of reducing greenhouse gas emissions and transitioning towards Smart City Thailand. The research employs a quantitative approach by developing an advanced model known as the Moderated Mediation Model based on Autoregressive Conditionally Heteroscedastic in Mean (MMM-ARCH-M). This model incorporates white noise and the best model methodology, serving as a decision-making tool for future national development. It fills gaps found in previous models, yielding more accurate and precise future forecasts. Additionally, the model demonstrates high validity, making it applicable to other sectors. The research findings reveal that the government needs to establish the most appropriate new scenario policies to develop long-term (2025-2044) national management strategies under sustainability policies aimed at achieving Smart City Thailand. The research identifies critical indicators that need to be immediately and urgently implemented nationwide through enforceable legislation. These indicators include clean technology, waste biomass, renewable energy, green material rate, and biomass energy. If the government adopts these indicators for national management, the total energy consumption growth rate (2044/2025) will increase by only 90.59%, which is lower than the defined carrying capacity of 150.45%. Furthermore, CO<sub>2</sub> gas emissions are found to

decrease by 35.09%, with CO<sub>2</sub> emissions reaching 42.50 Mt CO<sub>2</sub> Eq. by 2044, which is within Thailand's carrying capacity limit of 50.07 Mt CO<sub>2</sub> Eq. Thus, this model is highly beneficial as a decision-making tool for national management, supporting the realization of Smart City Thailand and ensuring long-term sustainability.

*Keywords-new scenario policy; Smart City Thailand; smart government; sustainability policy; smart environment; smart energy*

## I. INTRODUCTION

With the rapid advancement of technology and innovation, especially with the Internet of Things (IoT) serving as a fundamental element for connecting devices to internet-based communication networks, the concept of smart cities emerged in the late 2000s. Technology and innovation began to play a pivotal role in urban development and intelligent urban planning, aiming to support comfortable living and foster sustainable urban growth [1]. Smart City Thailand has become a primary national policy and a top strategic priority for Thailand, encompassing short-, medium-, and long-term strategies under the sustainability policy, with a strong focus on long-term national management [2, 3]. The concept was first introduced in Thailand in 2003 under the Ministry of Information and Communication Technology (now the Ministry of Digital Economy and Society). This initiative aimed at achieving Sustainable Development Goals (SDGs) included the idea of smart cities to maintain global economic competitiveness, attract talented and creative citizens, enhance transparent urban governance, stabilize the climate by reducing greenhouse gas emissions, and optimize the sustainable use of natural resources without exceeding the carrying capacity [4, 5].

In 2016, Smart City Thailand was integrated into the Thailand 4.0 policy, a strategic plan that aims to transition the country to a value-based economy [2, 4]. This policy seeks to break free from the middle-income trap, social inequality, and environmental imbalance by embedding technology and smart city concepts into its core framework. Thailand 4.0 is built around four main dimensions critical to national development [3, 4]:

- Economic wealth: Driving the economy through innovation, technology, and creativity.
- Social well-being: Reducing social inequality, promoting agricultural technologies to enhance farmer income, and upgrading Small and Medium-sized Enterprises (SMEs) and community enterprises through innovation.
- Human wisdom: Developing human capital, improving the standards of Thai children, and raising the quality of the workforce.
- Environmental wellness: Combining economic development with the creation of livable and sustainable societies.

In 2017, the Smart City Office was established, and smart city initiatives were incorporated into the 12th National Economic and Social Development Plan (2017–2021) under Strategy 9: Urban and Economic Area Development. This strategy emphasized the decentralization of prosperity and the

increase of citizens' income. The Smart City Office was established under the supervision of the Digital Economy Promotion Agency (DEPA) of the Ministry of Digital Economy and Society. Its mission is to formulate master plans, action plans, and promote smart city development in line with the Thailand 4.0 initiative and the 20-year national strategy [4, 5].

In 2018, a master plan for smart city development was adopted in line with the 20-year national strategy (2018–2037), focusing on five key pillars [4, 6, 7]:

1. Development of smart city models: Aiming to select potential cities as pilot projects to support smart city development.
2. Reform of related laws: Aiming to integrate and reform laws related to smart city development across all systems.
3. Establishment of management mechanisms: Ensuring responsible management of areas, organizations, systems, and information technology to enhance efficient and sustainable public services within the areas.
4. Promotion of research, development, and innovation: Supporting and extending smart city development innovations for application in future smart cities.
5. Data collection and accessibility: Promoting data dissemination, learning, and supporting planning and concrete smart city development.

In 2019, the DEPA under the Ministry of Digital Economy and Society established Smart City Thailand to drive the development of smart cities under the concept of creating livable, modern cities where citizens enjoy a high quality of life and sustainable happiness. Seven key aspects of smart city development were announced: smart environment, smart mobility, smart living, smart people, smart energy, smart economy, and smart governance [8, 9].

From 2023, smart city initiatives were incorporated in milestone 8 of the 13th National Economic and Social Development Plan (2023–2027). An evaluation of the 12th plan's strategy 9 revealed that, despite continuous urban development in Thailand, it remained concentrated in Bangkok and its metropolitan areas, with insufficient regional distribution. The COVID-19 pandemic further exacerbated economic and social challenges, leading to economic contraction, a slowdown in tourism and exports, widespread unemployment, and a significant migration of labor back to rural areas. Additionally, the environment continued to deteriorate, failing to meet the smart environment objectives, a crucial focus for achieving sustainable development [10, 12]. These challenges prompted the inclusion of smart city initiatives in milestone 8 of the 13th plan, emphasizing three

core areas: enhancing competitiveness, promoting opportunities and social equity, and fostering growth based on quality of life and environmental friendliness [13, 14].

The key objectives are to boost regional economic growth and investment in economic zones, reduce income disparities, and develop livable, sustainable cities capable of adapting to change. This is achieved through strategies, such as strengthening grassroots economies, fostering collaborative mechanisms for urban and regional development, improving infrastructure, logistics, and digital readiness, and enhancing area and urban management [15, 16].

Smart City Thailand focuses on these three pillars to ensure balanced national growth, future sustainability, and holistic development across all smart city dimensions. However, based on studies conducted from 2003 to 2024, it was found that Thailand has not been able to adequately transition into a Smart City Thailand [4, 17, 18]. This is primarily due to the lack of two critical components: smart environment and smart energy. The country's total energy consumption has experienced continuous exponential growth, leading to a steady increase in greenhouse gas emissions, which have exceeded the carrying capacity [19]. The largest contributor to greenhouse gas emissions is the electricity sector, which has consistently experienced the highest annual growth in energy consumption. This sector is also the primary source of carbon dioxide emissions, making it a significant driver of greenhouse gas emissions [20-22]. Furthermore, Thailand has not prioritized or utilized the appropriate tools to advance Smart City Thailand in terms of smart environment and smart energy. The lack of essential analytical tools to determine which policies to implement and in what order has hindered progress.

A review of international studies on the use of tools to support government decision-making revealed several key findings. Shaikh in [23] reviewed traditional keyword extraction techniques for Topic Detection and Tracking (TDT), analyzing methods such as collocation techniques, word co-occurrence networks, and topic modeling. While these approaches provide useful insights, they remain limited in terms of automation, language independence, and handling of uncertain user-generated data. The study highlights the strengths and weaknesses of existing methods, but emphasizes the need for more adaptive and robust models for accurate unsupervised topic identification. Similarly, Shaikh et al. in [24] examined the use of recurrent neural networks to forecast the stock prices of solar energy companies, specifically Canadian Solar Inc. and First Solar Inc. The study underscores the growing role of machine learning in economic sectors, particularly in investment decision-making. While neural networks exhibit high confidence in predicting medium- and long-term trends, their accuracy remains insufficient for short-term trading. Additionally, Shaikh in [25] explored the role of green technologies in addressing environmental challenges, such as climate change, energy depletion, and ecological disruption. While these technologies contribute to economic sustainability, the study emphasizes the importance of a balanced approach that integrates environmental and social sustainability. These studies demonstrate the existence of decision-making tools that can be adapted to drive Thailand's

development. Currently, Thailand lacks high quality models that provide the government with clear guidance and effective regulatory capabilities. If this gap remains unaddressed, not only will the realization of Smart City Thailand become increasingly unattainable, but the escalating effects of climate change will exceed the country's carrying capacity, leading to irreversible consequences across all sectors. Therefore, this research has developed a new essential tool, distinct from previous models, to serve as a critical instrument for shaping national policies and plans. This tool aims to pave the way for the successful establishment of Smart City Thailand in the future. Previous models have failed to provide the government with clear guidance or the ability to effectively regulate these aspects. If this situation persists, not only will the realization of Smart City Thailand become increasingly unattainable, but it will also exacerbate the impacts of climate change, exceeding the carrying capacity and leading to irreversible consequences for all sectors. The proposed tool aims to pave the way for the successful establishment of Smart City Thailand in the future.

## II. MATERIAL AND METHOD

For this research, a new model was developed by applying existing concepts and theories to adapt to each sector, making it an important tool for the proper management of government operations, the Moderated Mediation Model based on Autoregressive Conditionally Heteroscedastic in Mean (MMM-ARCH-M). This model differs from previous models, because it assumes that the variance is constant (homoscedastic). The model's ability to calculate both mean and variance simultaneously leads to higher predictive accuracy compared to previous models or unconditional models. Therefore, the development of this model is based on the autoregressive moving average model, with details as follows [26, 27].

### A. Structure (Specification) of the MMM-ARCH-M Model

As depicted in Figure 1, the MMM-ARCH-M model has three main components:  $\xi$  is the exogenous latent variable, which consists of  $x$  as the observed variable,  $\eta$  is the endogenous latent variable, with  $y$  as the observed variable, and  $Mo$  is the moderator variable, with  $z$  as the observed variable. This model analyzes the influence of these three variables, determining which variable influences which type of variable and how it leads to changes. It demonstrates how the relationship emerges from  $\xi \rightarrow \eta$  and the extent of influence  $Mo \rightarrow \eta$  has, or whether the variable,  $Mo$ , can affect  $\xi \rightarrow \eta$  as a moderator. This allows for an accurate and reliable understanding of the direct effect, the indirect effect, and the total effect. Additionally, this model provides a clearer and more accurate representation of the direction and strength of relationships compared to previous models.

### B. Estimation of the Influence of Relationships Among Variables

In general, for models where the variance of the error term ( $\varepsilon_i$ ) is not constant, the estimation approach follows the model below [28, 29]:

$$y_i = \beta_0 + \beta_i y_{i-1} + \varepsilon_i \quad (1)$$

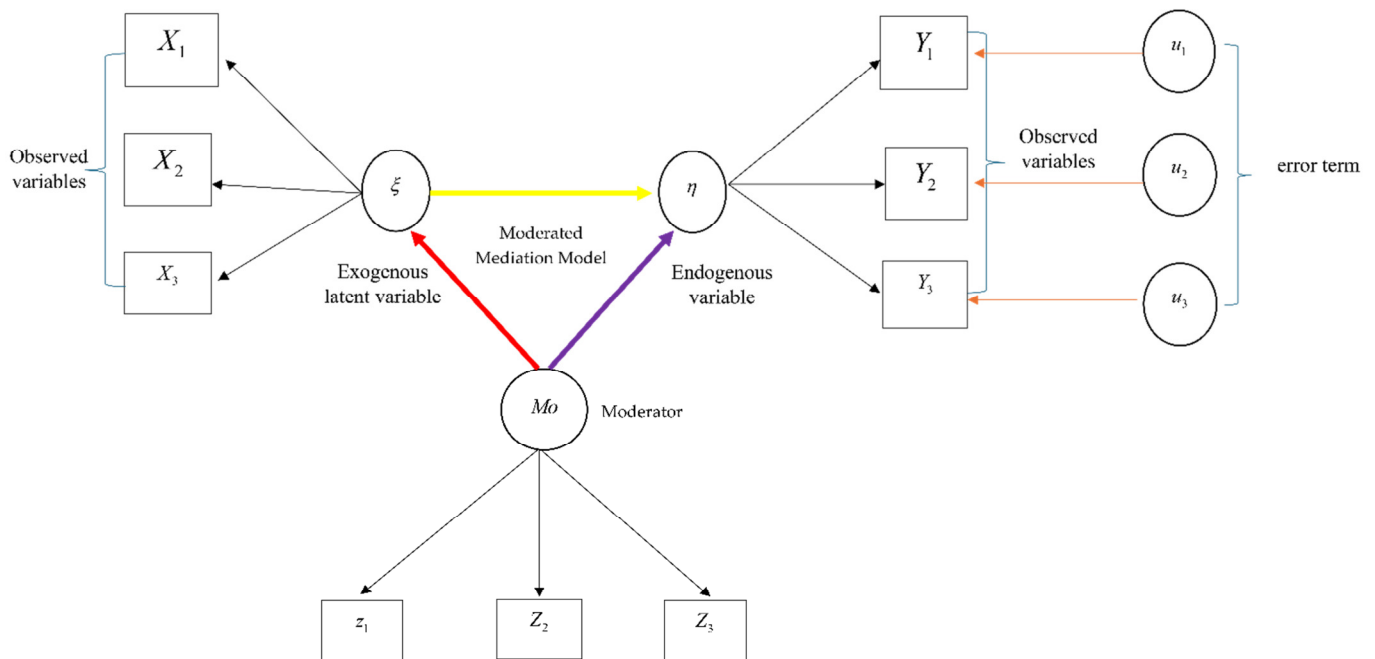


Fig. 1. The relationship structure of the MMM-ARCH-M model.

From (1), let  $y_t$  be the variable studied in the current period, while  $y_{t-i}$  is a variable with a lag period extending back to time  $t-i$ . If the conditional variance is not constant, we apply a model where the variance follows an AR(q) process, as shown below [30]:

$$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{\varepsilon}_{t-1}^2 + \gamma_2 \hat{\varepsilon}_{t-2}^2 + \dots + \gamma_q \hat{\varepsilon}_{t-q}^2 + v_t \quad (2)$$

From (2), let  $\hat{\varepsilon}_t$  represent the estimated residuals, and  $v_t$  be a white noise process. Therefore, if  $\gamma_1 = \gamma_2 = \dots = \gamma_q = 0$ , the estimated variance will be constant, and the conditional variance will be as per (2). The forecasted values can be expressed as follows:

$$E\hat{\varepsilon}_{t-1}^2 = \gamma_0 + \gamma_1 \hat{\varepsilon}_t^2 + \gamma_2 \hat{\varepsilon}_{t-1}^2 + \dots + \gamma_q \hat{\varepsilon}_{t+1-q}^2 \quad (3)$$

From (1) to (3), it is clear that the best estimates must be determined simultaneously using likelihood techniques. We define  $v_t$  as a multiplicative disturbance, which can be simplified as shown below [31]:

$$\varepsilon_t = v_t \sqrt{\gamma_0 + \gamma_1 \varepsilon_{t-1}^2} \quad (4)$$

From (4), let  $v_t$  represent a white noise process where  $\sigma_v^2 = 1$ ,  $v_t$  and  $\varepsilon_{t-1}$  are independent, and  $v_0, v_1$  are constants, where  $v_0 > 0$ ,  $0 < v_t < 1$ . Hence, from (4), we find [30, 31]:

$$E\varepsilon_t = E[v_t(\gamma_0 + \gamma_1 \varepsilon_{t-1}^2)]^{1/2} = 0 \quad (5)$$

From (5), we can calculate the conditional mean of  $\varepsilon_t$  as follows:

$$E(\varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) = E v_t E(\gamma_0 + \gamma_1 \varepsilon_{t-1}^2)^{1/2} = 0 \quad (6)$$

From (6),  $v_t$  and  $\varepsilon_{t-1}$  are independent, and  $E v_t = 0$ . Therefore, the impact of (4) is on the conditional variance for the variance of  $\varepsilon_t$  under the condition of  $\varepsilon_{t-1}, \varepsilon_{t-2}, \dots$ , which can be expressed as follows [30]:

$$E(\varepsilon_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 \quad (7)$$

From (7), we see that the conditional variance follows a first-order autoregressive process, represented as ARCH(1), which is in contrast to the normal autoregression model. The values of  $\gamma_0, \gamma_1$  are positive only to ensure stability of the autoregressive process. To maintain this stability, constraints must be placed on  $\gamma_1$ , where  $0 < \gamma_1 < 1$ , as follows [31].

The conditional heteroscedasticity in  $\{\varepsilon_t\}$  leads to  $\{y_t\}$  being an ARCH process. This model can capture the volatility period in  $\{y_t\}$ . The conditional mean of  $y_t$  under the condition of  $y_{t-1}, y_{t-2}, \dots$  is expressed as follows:

$$\text{var}(y_t | y_{t-1}, y_{t-2}, \dots) = E_{t-1}(y_t - \beta_0 + \beta_1 y_{t-1}^2)^2 = \gamma_0 + \gamma_1 (\varepsilon_{t-1})^2 \quad (8)$$

From (8), the minimum value of the conditional variance is equal to  $\gamma_0$ , since  $\beta_0, (\varepsilon_{t-1})^2$  cannot be negative.

Hence, the MMM-ARCH-M model delves into the aspect of risk aversion by compensating for risks arising from the environment. This can be measured by the variance of returns. Risk compensation is a function of the conditional variance of returns, which accounts for the remaining portion of returns due to environmental risks as follows [27]:

$$y_t = \mu_t + \varepsilon_t \tag{9}$$

From (9),  $y_t$  represents the excess return from the use of natural resources and the environment compared to the benchmark return over a given time period,  $\mu_t$  is the necessary risk compensation to encourage risk-averse individuals in the long term, and  $\varepsilon_t$  is the unforecastable shock. Equation (9) shows that the expected value of the residual portion of the returns from the use of natural resources and the environment in the long term is equal to the risk compensation.

$$E_{t-1}y_t = \mu_t \tag{10}$$

From (10), if we define the risk compensation as a function that increases the conditional variance of  $\varepsilon_t$ , a larger value of this function indicates that  $h_t$  is a conditional variance,  $\varepsilon_t$ . The risk compensation capability can be expressed as follows [30]:

$$\mu_t = \beta + \delta h_t, \delta > 0 \tag{11}$$

From (11), when  $h_t$  is specified as an ARCH(q) process, it is represented as follows:

$$h_t = \alpha_0 + \sum_{i=0}^q \alpha_i \varepsilon_{t-i}^2 \tag{12}$$

From (12), the conditional mean of  $y_t$  depends on the conditional variance from the ARCH(q) process. If this variance is constant, it indicates that the risk compensation remains constant. This risk compensation depends significantly on the influence of  $h_t$ .

C. Validity Testing of the MMM-ARCH-M Model

In this research, the validity of the MMM-ARCH-M model was tested as follows [30, 31]:

- Discriminant validity: This refers to  $HTMT_{ij} < 1$ , which is calculated using the average heterotrait-hetero method correlation divided by the geometric mean of the average monotrait-hetero method correlation for construct  $\xi_i$ , and the average monotrait-heteromethod correlation for construct  $\xi_j$ .
- Convergent validity: For this model, convergent validity is assessed based on the following criteria:

$$AVE_q = \frac{1}{p_q} \lambda_{\xi_q \rightarrow x_{pq}}^2 \geq 0.5 \quad , \quad \text{Cronbach's alpha}$$

$$\alpha_q = \frac{\sum_{p \neq p}^{pq} corr(x_{pq}, x_{p/q})}{p_q + \sum_{p \neq p}^{pq} corr(x_{pq}, x_{p/q})} \cdot \frac{p_q}{p_{q-1}} \geq 0.7 \quad , \quad \text{Composite}$$

$$\text{Reliability (CR)} \quad pq = \frac{\left(\sum_{p=1}^{pq} \lambda_{pq}\right)^2}{\left(\sum_{p=1}^{pq} \lambda_{pq}\right)^2 + \sum_{p=1}^{pq} (1 - \lambda_{pq})} \geq 0.06 \quad ,$$

and the absence of multicollinearity issues among

indicators, which can be measured using the Variance Inflation Factor (VIF),  $VIF = \frac{1}{1 - R^2} \leq 5$ .

D. Measurement of Model Fit

For the MMM-ARCH-M model, it is necessary to conduct a detailed measurement of the model fit, and the values obtained from the test must meet the following criteria [29, 30]:

- The chi-square statistic should meet the criterion:  $2 < \chi^2 / df \leq 3$ .
- The Root Mean Squared Residual (RMSR) should meet the criterion:  $0.05 < RMR \leq 0.08$ .
- The Root Mean Square Error of Approximation (RMSEA) should meet the criterion:  $0.05 < RMSEA \leq 0.08$ .
- The Standardized Root Mean Square Residual (SRMR) should meet the criterion:  $0 < SRMR \leq 0.05$ .
- The Normal Fit Index (NFI) should meet the criterion:  $0.90 < NFI \leq 0.95$ .
- The Non-Normed Fit Index (NNFI) should meet the criterion:  $0.95 < NNFI \leq 0.97$ .
- The Comparative Fit Index (CFI) should meet the criterion:  $0.95 < CFI \leq 0.97$ .
- The Goodness of Fit Index (GFI) should meet the criterion:  $0.90 < GFI \leq 0.95$ .
- The Adjusted Goodness of Fit Index (AGFI) should meet the criterion:  $0.85 < AGFI \leq 0.90$ .

E. Performance Evaluation of the MMM-ARCH-M Model

In this research, the performance of the MMM-ARCH-M model was compared with previous models to assess its suitability for future forecasting applications. The comparison was made with various previous models, including: Ordinary Linear Regression (OLS), Artificial Neural Network (ANN), Anisotropy Factor (ANIF), Grey Model GM(1,1), Bayesian Network BG(1,1), Neural Network (NN), Autoregressive Integrated Moving Average (ARIMA), Convolutional Neural Network (CNN), and Autoregressive Integrated Moving Average Explanatory with Variable (ARIMAX).

The MMM-ARCH-M model utilizes advanced statistical methods to provide the most reliable and accurate analysis results based on real-world situations. Additionally, this model measures control variables to determine whether civil policies can be effectively applied and identifies which factors must be immediately utilized to achieve effective management in the future. This approach differs significantly from previous models, which failed to provide a clear direction for the country's governance, making it impossible to achieve Smart City Thailand. Without the best model, the country's ecosystem will be irreversibly damaged in the future, negatively impacting all sectors.

The study demonstrates the process of conducting research using the MMM-ARCH-M model, with the following steps:

- Select indicators from the national governance framework towards Smart City Thailand.
- Analyze the suitability and characteristics of each indicator for inclusion in the MMM-ARCH-M model.
- Analyze the influence path of relationships and the adaptability of each sector.
- Analyze the prioritization of the new scenario policy using the MMM-ARCH-M model, considering the moderator analysis and confirming the new scenario policy through sensitivity analysis.
- Forecast energy consumption and carbon dioxide emissions in the electricity sector in the electricity sector for the long term (2025-2044).
- Discuss the research findings to provide a decision-making tool for the management of Thailand.

III. EMPIRICAL ANALYSIS

A. Selection of Indicators from the National Management Framework toward Smart City Thailand

The proposed MMM-ARCH-M model includes four factors: smart economic, smart government, smart social, and smart environmental. These four factors are defined as latent variables. The study selected all indicators currently used in the management of Thailand to analyze their suitability for inclusion in the development of the MMM-ARCH-M model. The analysis revealed that only 23 indicators were deemed suitable and were used as observed variables, including indicators such as urbanization rate (*Uree*), industrial structure (*Urtt*), export-import (*Exmm*), foreign investment (*Pimm*), government expenditure (*Pgee*), foreign tourism rate (*Ftrr*), employment rate (*Erri*), health and illness rate (*Herr*), education rate (*Edru*), income distribution rate (*Dimm*), protection rate (*Teda*), clean technology (*Gtrr*), biomass energy rate (*Biee*), renewable energy rate (*Eirr*), green material rate (*Cmrr*), waste biomass (*Wbtt*), taxonomy rate (*Txrr*), biofertilizers rate (*Biff*), total energy consumption (*Tere*), energy intensity rate (*Tirr*), carbon dioxide emissions ( $CO_2$ ), methane ( $CH_4$ ), and nitrous oxide ( $N_2O$ ). During the selection of indicators, it was found that some indicators did not meet the required characteristics and were therefore excluded from the research. The indicators selected for the MMM-ARCH-M model all exhibited stationarity at the first difference level. The final set of 23 suitable indicators is presented in Table I, where it can be observed that the results of the characteristic tests for all indicators show that each indicator is stationary at the first difference level. All indicators are at the same level, and they are statistically significant at the 99% confidence interval. Therefore, these indicators can be used in building the MMM-ARCH-M model.

In addition, tests were conducted on the ability of all selected indicators to reach long-term equilibrium. All the indicators were tested simultaneously. If the results indicated

that equilibrium could not be reached, or if any indicator failed to meet the necessary criteria, that indicator would be removed from the model, even if it had passed the stationarity test. From Table I, it was found that all indicators at the first difference level were able to adjust to the long-term equilibrium, with the values of the trace statistic test and the max-eigen statistic test being higher than the MacKinnon critical value at a significance level of  $\alpha = 0.01$ . Therefore, if a shock occurs in any of the systems, the system will be able to adjust to equilibrium. This research led to the discovery that, in the short term, the smart environmental sector has the greatest ability to adjust to equilibrium. If a loss occurs, it can return to its normal state at a rate of 0.001%. On an annual basis, it would take approximately 1,000-1,500 years to reach equilibrium. However, at a significance level of  $\alpha = 0.01$ , this duration could lead to a situation where equilibrium cannot be reached at all. This shows that if environmental destruction continues without correction, or if it is improperly corrected, or if essential tools are lacking, it will result in long-term detrimental effects on the ecosystem, ultimately making it impossible to reverse the damage, and all sectors will be severely affected.

TABLE I. RESULTS OF THE AUGMENTED DICKEY-FULLER TEST FOR INDICATORS AT THE FIRST DIFFERENCE LEVEL

Variables	Tau test	
	First difference I(1) value	Augment dicky fuller (sig. $\alpha = 0.01$ )
$\Delta \ln(Uree)$	-4.25***	$p < 0.01$
$\Delta \ln(Urtt)$	-4.01***	$p < 0.01$
$\Delta \ln(Exmm)$	-4.11***	$p < 0.01$
$\Delta \ln(Pimm)$	-4.20***	$p < 0.01$
$\Delta \ln(Pgee)$	-4.44***	$p < 0.01$
$\Delta \ln(Ftrr)$	-4.05***	$p < 0.01$
$\Delta \ln(Erri)$	-4.01***	$p < 0.01$
$\Delta \ln(Herr)$	-4.19***	$p < 0.01$
$\Delta \ln(Edru)$	-5.10***	$p < 0.01$
$\Delta \ln(Dimm)$	-4.52***	$p < 0.01$
$\Delta \ln(Teda)$	-4.48***	$p < 0.01$
$\Delta \ln(Gtrr)$	-5.29***	$p < 0.01$
$\Delta \ln(Biee)$	-5.64***	$p < 0.01$
$\Delta \ln(Eirr)$	-5.39***	$p < 0.01$
$\Delta \ln(Cmrr)$	-5.15***	$p < 0.01$
$\Delta \ln(Wbtt)$	-5.77***	$p < 0.01$
$\Delta \ln(Txrr)$	-4.01***	$p < 0.01$
$\Delta \ln(Biff)$	-5.25***	$p < 0.01$
$\Delta \ln(Tere)$	-4.01***	$p < 0.01$
$\Delta \ln(Tirr)$	-4.77***	$p < 0.01$
$\Delta \ln(CO_2)$	-5.75***	$p < 0.01$
$\Delta \ln(CH_4)$	-4.45***	$p < 0.01$
$\Delta \ln(N_2O)$	-4.70***	$p < 0.01$

a. \*\*\* denotes a significance,  $\alpha = 0.01$ .  
 b. Source: author's estimate (2025).

Furthermore, it was found that the smart government sector has the quickest ability to adjust and meets the required threshold. This indicates that if the government needs to take action, it can immediately implement the necessary policies under a prioritization framework. This means that if the government understands which policy is most crucial, it can enforce that policy quickly and make it law in the most efficient manner.

#### B. Analysis of the Influence Magnitude of Relationships in MMM-ARCH-M Model

In the analysis of the magnitude of causal relationships, this research initially defined four latent variables: smart economic, smart social, smart environmental, and smart government. The research findings will reveal which sector influences changes in which other sectors, showing both direct effects and indirect effects, as illustrated in Figure 2. From Figure 2, the validity of the MMM-ARCH-M model and its overall fitness were evaluated and summarized in Table II. It is evident from Table II that these findings demonstrate that the MMM-ARCH-M model is a valid and reliable model, exhibiting a good fit with no spurious issues, thus confirming its robustness as the optimal model for the intended application. Based on the evaluation, it was found that the model passed all the assessment criteria, indicating that it is suitable and effective to clearly analyze the influence size. Therefore, it is appropriate to use the MMM-ARCH-M model for future forecasting, especially for long-term forecasting. In this research, the influence size of each latent variable is detailed as follows.

TABLE II. RESULTS OF THE MODEL FIT ASSESSMENT MEASUREMENT FOR THE MMM-ARCH-M MODEL

Measurement of model fit	Validity	Spurious problems check	Test results
$\chi^2 / df = 2.52$	$HTMT_{ij} = 0.75$	heteroscedasticity ( $LM - test > LM - value$ )	Passed the criteria
$RMR = 0.06$	$AVE_q = 0.90$	multicollinearity ( $VIF = 2.5$ )	Passed the criteria
$RMSEA = 0.06$	$\alpha_q = 0.91$	autocorrelation (Durbin Watson: $D.W. = 2.00$ )	Passed the criteria
$SRMR = 0.02$	$pq = 0.09$		Passed the criteria
$NFI = 0.91$			Passed the criteria
$NNFI = 0.95$			Passed the criteria
$CFI = 0.97$			Passed the criteria
$GFI = 0.94$			Passed the criteria
$AGFI = 0.89$			Passed the criteria

From Figure 2, it was found that out of the 4 latent variables, the smart government sector had the largest direct

effect on the smart economic sector, with an influence size of 0.85%. The next highest effect was found for the smart government sector on the smart social sector with an influence size of 0.81%, followed by the smart government sector having a direct effect on the smart environmental sector with an influence size of 0.80%. Additionally, the smart economic sector was found to have a direct effect on the smart environmental sector with an influence size of 0.71%, the smart economic sector was found to have a direct effect on the smart social sector with an influence size of 0.33%, and the smart social sector was found to have a direct effect on the smart environmental sector with an influence size of 0.25%, at a statistically significant level.

However, based on the findings of this analysis, it was discovered that the MMM-ARCH-M model indicates that the smart government sector, with an influence size of more than 0.8%, has the power to drive changes and impacts on the influence size, or can induce a shock to the latent variables. Therefore, the MMM-ARCH-M model suggests that the smart government sector is suitable to be used as a moderator in future models. The results of the MMM-ARCH-M model analysis show that the inclusion of a moderator variable causes a reduction in the influence of the relationship between the exogenous latent variable and the endogenous latent variable. It was found that the smart government sector had the largest direct effect on the smart economic sector, but the size of the relationship influence increased to 0.92% at a statistically significant level of 0.01 ( $\alpha = 0.01$ ). The next highest impact was found for the smart government sector having a direct effect on the smart social sector, with the influence size increasing to 0.84% at a statistically significant level of 0.01 ( $\alpha = 0.01$ ). Furthermore, the smart government sector had a direct effect on the smart environmental sector, with the influence size increasing to 0.82% at a statistically significant level of 0.01 ( $\alpha = 0.01$ ). Additionally, it was found that the smart economic sector had a direct effect on the environmental sector, with a reduction in influence size to 0.30% at a statistically significant level of 0.01 ( $\alpha = 0.01$ ), and the smart economic sector had a direct effect on the smart social sector, with an influence size of 0.19% at a statistically significant level of 0.01 ( $\alpha = 0.01$ ).

These findings show that the smart government sector plays a key role in controlling the smart economic, smart social, and smart environmental sectors. The control exerted by the smart government sector results in changes across all sectors according to the size of the relationship influence. Therefore, in this research, the analysis also tested whether the indicators could be used to define a new scenario policy. To ensure appropriateness, all indicators were tested to determine if they could be categorized as a new scenario policy. The results of the MMM-ARCH-M model analysis revealed the prioritization of each indicator, which is consistent with the previous analysis. The most appropriate indicators to be used in defining the new scenario policy include clean technology, waste biomass, renewable energy, green material rate, and biomass energy. To further validate the results, a sensitivity analysis was conducted.

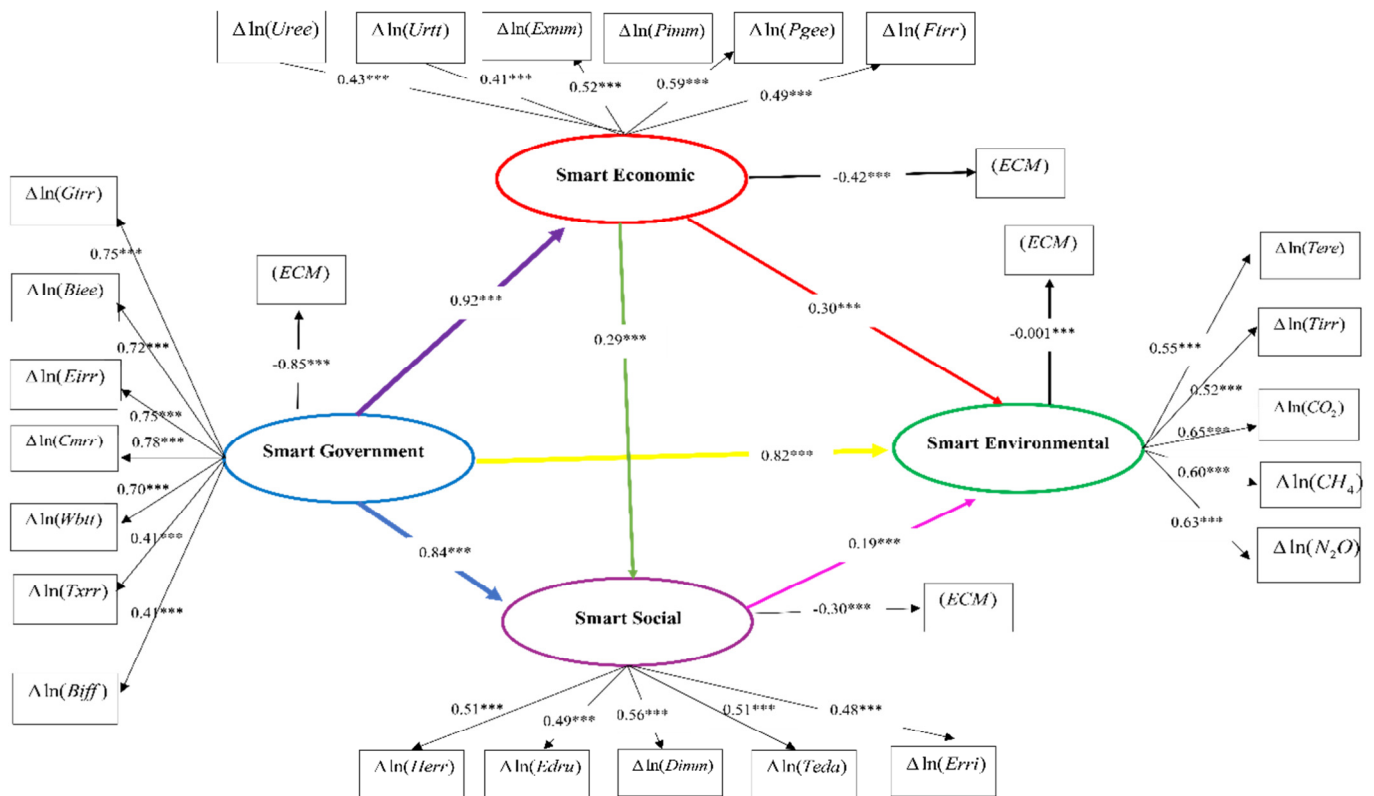


Fig. 2. Results of the impact analysis of influence size changes using a moderator in the MMM-ARCH-M model.

The research results from the sensitivity analysis on the suitability of indicators for the new scenario policy revealed that the most high-potential and appropriate indicator for defining long-term policies is clean technology, which showed the highest sensitivity at 95%. This is followed by renewable energy with a sensitivity of 92%, waste biomass with a sensitivity of 91%, green material rate with a sensitivity of 91%, and biomass energy with a sensitivity of 89%. Other indicators were found to be less suitable for long-term policy formulation due to their lower potential scores. Therefore, the indicators that passed the evaluation criteria are deemed appropriate for use in creating a new scenario policy. These findings were applied to predict electricity consumption and the growth rate of CO<sub>2</sub> emissions.

However, the research also identified that within the smart government sector, two indicators, the taxonomy rate and the biofertilizers rate, are not suitable for use in creating a new scenario policy. These two indicators have been continuously supported and promoted by the Thai government. A significant amount of the national budget has been allocated to implement the taxonomy rate and biofertilizers rate, with these indicators being prioritized in the national policy agenda since 2003. They have been included in the national strategy aimed at achieving the goal of Smart City Thailand from 2003 to 2024.

### C. Forecast Model for Electricity Consumption and CO<sub>2</sub> Gas Emissions

In this research, the performance of the MMM-ARCH-M model was examined before applying it for forecasting

purposes. The comparison was made with previous models, including OLS, ANN, ANIF, GM(1,1), BG(1,1), NN, ARIMA, CNN, and ARIMAX. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) statistics were used to evaluate the models. The analysis results indicate that the performance of the MMM-ARCH-M model surpassed that of the other models tested and demonstrated the highest performance. The MMM-ARCH-M model achieved the lowest MAPE and RMSE values of 1.19% and 1.35%, respectively. For comparison, the next best performing models are as follows: ARIMAX with MAPE of 3.05% and RMSE of 3.44%, CNN with MAPE of 3.09% and RMSE of 3.49%, NN with MAPE of 3.29% and RMSE of 3.92%, BG(1,1) with MAPE of 3.99% and RMSE of 4.02%, GM(1,1) with MAPE of 5.15% and RMSE of 5.23%, ANIF with MAPE of 5.52% and RMSE of 7.12%, ANN with MAPE of 5.55% and RMSE of 7.89%, and OLS with MAPE of 18.41% and RMSE of 17.05%. Therefore, the MMM-ARCH-M model has the best performance and is most suitable for forecasting the total energy consumption and CO<sub>2</sub> gas emissions in the long term, from 2025 to 2044.

Based on the forecast analysis of electricity consumption using the MMM-ARCH-M model, the results are compared in the case of a new scenario policy, as shown in Figure 3. It can be observed that the total energy consumption from 2025 to 2044 shows a rapid increase, with a growth rate of 401.41% (from 2025 to 2044). This is a significant increase that exceeds the carrying capacity by a considerable margin. However, when the new scenario policy was applied, based on the

indicators from this study, including clean technology, waste biomass, renewable energy, green material rate, and biomass energy, the growth rate decreased to 90.59% (from 2025 to 2044). This growth rate is significantly lower and within the carrying capacity threshold of 150.45%.

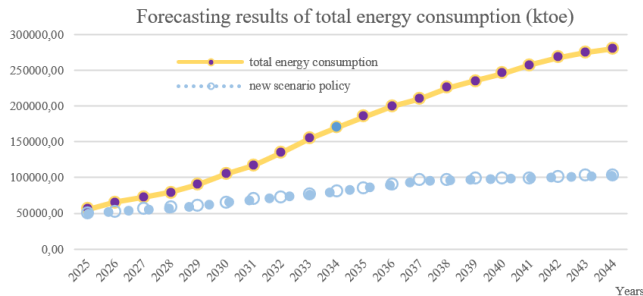


Fig. 3. The forecasting results of total energy consumption from 2025 to 2044 in Thailand.

The forecasted CO<sub>2</sub> gas emissions for the future (2025-2044) using the MMM-ARCH-M model are shown in Figure 4. It can be observed that the long-term (20-year) forecast (2025–2044) of the growth rate of CO<sub>2</sub> gas emissions shows a sharp, exponential increase of 179.05%, with CO<sub>2</sub> emissions reaching 205.59 Mt CO<sub>2</sub> Eq. by 2044, far exceeding the carrying capacity limit of 50.07 Mt CO<sub>2</sub> Eq. However, when the indicators from this research, clean technology, waste biomass, renewable energy, green material rate, and biomass energy, are integrated into the new scenario policy, the growth rate slows down to 35.09% (2044/2025), with CO<sub>2</sub> emissions increasing to only 42.50 Mt CO<sub>2</sub> Eq. by 2044, remaining within the carrying capacity limit. Based on these results, the implementation of the MMM-ARCH-M model as a decision-making tool is crucial to guide Thailand towards a smart city transformation.

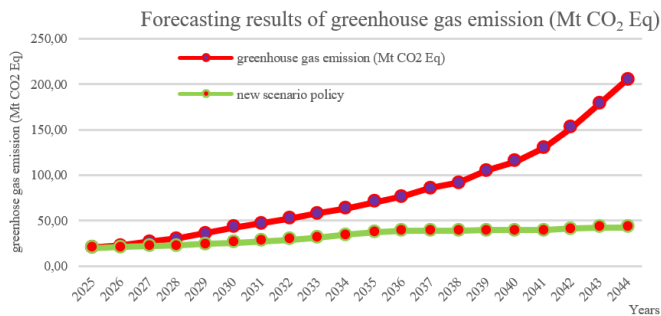


Fig. 4. The forecasting results of CO<sub>2</sub> gas emission from 2025 to 2044 in Thailand.

IV. DISCUSSION

This research developed the MMM-ARCH-M model, which has validity, no spuriousness, and complete white noise. It is considered to be the best model that addresses the weaknesses and performs better than previous models, resulting in minimal forecast errors. Therefore, this model is suitable for use in decision-making and long-term strategic

planning. The selected indicators fully meet the necessary criteria for building the model. The findings provide new knowledge, including insights into the ability of each factor to reach equilibrium. The smart economic sector is the most responsive to returning to equilibrium, indicating that it can quickly return to normal in the event of a shock. However, the smart environmental sector has a very slow rate of adjustment, taking 1,000 to 1,500 years to return to normal, and after such a long time, it may never return to its original state. Additionally, this research identifies indicators for formulating new scenario policies, such as clean technology, waste biomass, renewable energy, green material rate, and biomass energy. These indicators can serve as strategies to help Thailand transform into a smart city in the long run. The research also reveals that in the past, Thailand's national management did not follow the right direction, with excessive focus on policies related to taxonomy rates and biofertilizer rates as key indicators. Specifically, the government heavily promoted the taxonomy rate within the system, but this priority should have been placed lower. Instead, the indicators identified in this research should have been prioritized first to ensure the creation of a truly sustainable smart city in Thailand. If inappropriate indicators with minimal impact on change are selected, long-term policies and strategies could fail and the environmental condition could deteriorate beyond repair. Historically, Thailand has never successfully reduced greenhouse gas emissions due to flawed management strategies that lacked effective tools for analysis and decision-making. Additionally, to achieve the goal of a smart city in Thailand, it is essential to analyze the approach across all sectors. However, in the past, Thailand has only conducted sector-specific analyses, failing to integrate a comprehensive, cross-sector strategy. This approach has hindered the ability to see the overall direction and create accurate long-term policies. Moreover, policy formulation must include international collaboration, which is a key factor in driving the smart city agenda forward. However, in the past, Thailand has lacked important cooperation, which has prevented the success of such policies. Moreover, it has been observed that Thailand, both in the past and present, lacks consideration of international policies and their adaptation to reduce greenhouse gas emissions within the country. As a result, the direction of the national administration remains unclear regarding the necessary actions to achieve sustainability in the future. A successful example of effective greenhouse gas emission reduction is the United States. The United States has focused on domestic development, positioning itself as a leader in addressing environmental issues while cooperating with allied countries and members of groups, such as the G20 or G7. Key initiatives include halting financial support for high-carbon projects, eliminating financial aid for coal-related businesses, preventing China from subsidizing coal exports and outsourcing jobs to other countries under the Belt and Road Initiative (which would lead to severe pollution), and signing agreements with China to reduce carbon emissions. Furthermore, the United States has integrated trade policy with climate action and is likely to take the following actions: 1) domestic actions, including the enforcement of policies that require domestic polluters to bear the costs associated with carbon emissions, the enactment of a carbon tax, an increase in taxes on coal, oil, and gas, an increase in fossil fuel prices, and

a reduction in consumer incentives to consume fossil fuels; and 2) international actions, including affirmative measures such as green debt relief for developing countries committed to addressing climate change, working with international financial institutions to provide debt relief to countries seeking financing for climate-friendly development. Additionally, Singapore has actively addressed air pollution by implementing measures to control carbon dioxide emissions in line with the Paris agreement. Singapore aims to reduce greenhouse gas emissions by 36% by 2030, with one of its key strategies being the introduction of a carbon tax. This has led to the drafting of the carbon pricing bill to regulate carbon pricing mechanisms. These examples of successful international efforts to reduce greenhouse gas emissions should serve as key guidelines for adapting such strategies into this research model. Doing so would improve the efficiency of national governance in the long run and help Thailand achieve its net-zero greenhouse gas emissions target by 2065.

The research findings are consistent with the hypotheses and contribute to the development of appropriate strategies to guide the country towards a future smart city. Furthermore, the research is consistent with previous research by Dorji et al. [32], Junsiri et al. [19], Wattana et al. [17], Frikha [33], Wattana and Wattana [18], and Ramadan and Boubaker [34]. If Thailand can reduce total energy consumption and greenhouse gas emissions in the long run, it will be able to achieve the goal of a sustainable smart city.

As for the recommendation, this research developed the MMM-ARCH-M model as a key tool for formulating new scenario policies. In the past, the lack of appropriate models led to unsuccessful policy formulations. Therefore, the application of this model requires careful and appropriate implementation at each step. The selection of appropriate indicators is crucial to ensure the effectiveness of the model. Furthermore, combining the model with primary data, such as interviews or surveys, would further enhance its usefulness in guiding the development of concrete and clear policies. If the government applies the research methods and scientific data from this study to national policy planning, long-term plans will be more accurate and aligned with the right direction.

In terms of a policy recommendation for the electricity sector, it is worth noting that the electricity sector is the largest energy consuming sector and has the highest greenhouse gas emissions. Therefore, national executives need to take urgent action on the following issues:

- Energy sector proposals: Electricity reform towards clean energy, liberalization, net metering.
- Transport sector proposals: End fossil fuel subsidies in transportation, implement carbon tax, enhance rail efficiency, improve public transit.
- Manufacturing sector proposals: Encourage innovation in low-carbon manufacturing, improve access to green finance, develop a green economy.
- Labor sector proposals: Promote green jobs, upskill workforce for green businesses.

- Business sector proposals: Establish low-carbon business data management systems, improve access to financial support.

In terms of future research directions, for those interested in applying this research to national policy planning, future studies should focus on adapting the model to fit the specific context of each area. This can be done by modifying key indicators based on suitability and predefined criteria. Additionally, integrating qualitative research methods, such as surveys, interviews, and focus group discussions, can help develop more comprehensive national strategies. This approach will minimize research gaps and ensure that findings can be effectively implemented in real-world policymaking.

## V. CONCLUSION

For this research, the Moderated Mediation Model based on Autoregressive Conditionally Heteroscedastic in Mean (MMM-ARCH-M) was developed with four latent variables: smart economic, smart government, smart social, and smart environmental. A total of 23 indicators, which are stationary at first difference  $I(1)$ , were included, such as urbanization rate, industrial structure, export-import, foreign investment, government expenditure, foreign tourism rate, employment rate, health and disease rate, education rate, income distribution rate, protection rate, clean technology, biomass energy, renewable energy rate, green material rate, waste biomass, taxonomy rate, biofertilizers rate, total energy consumption, energy intensity rate, carbon dioxide emissions, methane, and nitrous oxide. Moreover, these indicators were found to be co-integrated, which meets the required criteria and makes them suitable for constructing the MMM-ARCH-M model to analyze the causal relationships among the factors. The MMM-ARCH-M model demonstrates validity, goodness of fit, complete white noise properties, and the highest performance compared to previous models. Therefore, the MMM-ARCH-M model is highly suitable for use in this research analysis. The results indicate that the smart government sector has the strongest direct effect on the smart economic sector, followed by its direct effects on the smart social sector and the smart environmental sector. These findings suggest that the smart government sector plays a crucial role in regulating the smart economic, smart social, and smart environmental sectors. Any control exerted by the smart government sector will influence all other sectors in proportion to the strength of their relationships.

Nevertheless, this research adopts a new scenario policy that includes clean technology, waste biomass, renewable energy, green material rate, and biomass energy. The findings indicate that the growth rate (2044/2025) increases at a declining rate, with a growth of only 90.59% (2044/2025), which remains below the carrying capacity threshold of 150.45%. However, when the growth rate of CO<sub>2</sub> gas emissions is projected from 2025 to 2044, the results show that CO<sub>2</sub> emissions increase significantly, reaching 205.59 Mt CO<sub>2</sub> Eq., which exceeds the carrying capacity limit of 50.07 Mt CO<sub>2</sub> Eq. To address this issue, the study incorporates clean technology, waste biomass, renewable energy, green material rate, and biomass energy into the new scenario policy, resulting in a growth rate increase at a declining rate of 35.09%

(2044/2025), which remains within the carrying capacity limit. Thus, the MMM-ARCH-M model is considered highly suitable as a decision-making tool for long-term governance and sustainable management in Thailand.

#### ACKNOWLEDGMENT

This research was financially supported by Mahasarakham University. The authors would like to thank the Faculty of Engineering, Mahasarakham University, and the Electrical and Computer Engineering Research Unit, Mahasarakham University.

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