EVALUATING THE RELATIVE PERFORMANCES AND COMPARING THE FORECASTING OF THAILAND'S TECHNICAL COEFFICIENTS COVERING 2016-2025 BY MTT AND RAS

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Abstract

Dealing with the timeliness of Thailand's technical coefficient tables, this research contributes the methodology by forecasting them by Matrix Transformation Technique (MTT) and RAS, determining the relative accuracy of these two methods. Regarding MTT, rather than predicting all elements of the transformed matrix as originally purposes, this research forecasts only some significant elements which have evidence of change generating a high correlation to the technical coefficients. For the evaluation, the analysis first compares the updating performance in relation to 2015, considering the cell-by-cell (or partitive) and whole matrix (or holistic) levels. The result shows that MTT is outstanding for both sector and whole matrix levels; however, when considered cell-by-cell, RAS is superior over MTT. Hereafter, the study uses MTT and RAS to forecast Thailand's technical coefficient tables covering the period 2016-2025. Most elements (71.50%) were predicted in the same direction. However, the remaining 28.50% showed a difference in the direction of the forecast. Hence, the cell-by-cell assessment for these 73 elements was also checked, finding that MTT offers better performance for 38 elements, while RAS exhibits better performance for 35 elements.

Keyword: MTT, RAS, Technical coefficient, Input-output table, Thailand

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1. INTRODUCTION

The Input-Output (IO) table illustrates interdependence in an economy, proposed by Leontief (1936). It describes the relationship of commodity flows between the sectors in the economy. The generally accepted method to construct an IO table is through a survey approach. However, this approach requires massive resources and a considerable time commitment, which causes a substantial time lag between the actual census period, construction, and publication of the survey IO tables. Additionally, IO tables cannot be conducted for each successive year, but are instead published every few years. Normally, the publication of an IO table occurs once in every five years (Rao & Tommasino, 2014), generating concern regarding the timeliness of IO publications among policymakers and analysts. To deal with the time lag of publication, users must either continue to use the most recently available survey IO tables or carry out updating techniques to estimate them (Dietzenbacher et al., 2013; Jalili, 2006). Some who insist on applying the old survey tables may base their beliefs on the original concept of Leontief (1936, 1951), assuming the stability of coefficients over time. However, many works of literature have found a change in the coefficients, such as Carter (2013) and Urata (1988). The difference of coefficients, specifically the technical coefficient, over time is also supported by Aroche Reyes (2020) who has reasoned that technological change, the mix of products in industry, and shifts in pricing lead to changes.

The technical coefficient or intermediate input table is calculated from the IO table, helping to illustrate the economic structures describing the input requirements from each sector per unit of output. The technical coefficient tables for Thailand are also related to IO tables. Thailand's IO tables are officially published by the Office of the National Economic and Social Development Council (NESDC) of Thailand. However, as mentioned above, they also have a five-year time lag; the IO for 2015 was the latest publication reported in 2020 (Office of the National Economic and Social Development Council of Thailand, 2020). The Asian Development Bank (ADB) provides an alternative source of Thailand's IO table, with the newest table being the IO for 2017 (Asian Development Bank (ADB), 2019). Nevertheless, the classification of IO sectors from the ADB is not consistent with NESDC.

Regarding the timeliness of Thailand's technical coefficient tables, this research aims to contribute to methodology, by comparing the relative accuracy of forecasting using the Matrix Transformation Technique (MTT) and the RAS method.

MTT was proposed by Wang et al. (2015); it combines the transformation matrix technique and time-series forecasting to predict the IO table. Instead of predicting all elements of a transformed-intersection matrix as originally proposed, only some significant elements are forecast following Pumjaroen and Sottiwan (2021); this helps to improve the method's performance. In order to evaluate the performance in terms of relative accuracy, RAS, a well-known and widely used technique for updating the IO table, was also used to update the technical coefficient tables of Thailand. RAS, proposed by Stone (1961) and Stone and Brown (1962), is an iterative bi-proportional adjustment.

Evaluating the update results of Thailand's technical coefficient tables by MTT and RAS, this research first compares the updating performance of 2015. The evaluation considers the cell-by-cell (or partitive) and whole matrix (or holistic) approaches, following the concept of Jensen (1980). Hereafter, the research uses MTT and RAS to forecast Thailand's technical coefficient tables covering the period from 2016 to 2025. The estimation of both MTT and RAS are carried out twice; once for evaluating and once for forecasting.

The remainder of the paper is arranged as follows. The following section provides an overview of the current literature, with an emphasis on the updating methods for IO tables. Section 2 and 3 describe the methodology and results. The conclusion and recommendations are presented in the last section.

2. LITERATURE REVIEW

This literature review emphasizes the known updating methods for IO tables. Since many IO updating methods have developed continuously, they can nevertheless be categorized into survey, semi-survey, and non-survey methods (Deng, Zhang, Wang, Li, & Zhang, 2014).

Although there are many methods for updating IO tables, it is widely accepted that survey-based methods are superior to either non-survey or semi-survey approaches. However, the strict survey process requires immense cost, time, and labor, making it not frequently achievable in practice. Hence, many non-survey methods have been proposed and widely applied (Zheng, Fang, Wang, Jiang, & Ren, 2018). Additionally, Stoeckl (2012) found that the results of updating between a survey and a non-survey approach provided similar results to the product of the IO table as a multiplier matrix.

The non-survey approach uses the historical survey-based IO data to update the target IO table. Most approaches apply a combination of statistical and optimization techniques. Naïve and RAS are the popular methods (Khan, 1993). The Naïve method is based on the initial framework of Leontief (1936, 1951), which assumes intertemporal stability of the coefficients. Hence the technique adopts the base year's coefficient for the target year. Naïve should be the first method considered when there is no clue of structural change in the economy, based on its simplicity (Jalili, 2000). Unfortunately, the intertemporal instability of IO coefficients is well-established in reality.

RAS is therefore the main and most widely applied method. It was developed by Stone (1961) and Stone and Brown (1962). Analytical clarity and operational simplicity are the most advantageous and attractive features of RAS, which updates the target table without having to estimate a completely new set of inter-industry data. The process uses the prior year’s tables with some information from the target table—the total intermediate industry inputs and outputs and the total industry outputs—to estimate the target IO coefficients. It attempts to minimize the dissimilarity between a prior table and a target table to balance the initial estimate rather than relying on pure updates. However, RAS can not work with negative tables. To cope with a table containing both positive and negative elements, Junius and Oosterhaven (2003) proposed the Generalized RAS (GRAS), as a modification of the method for RAS. Under the condition that each row and column of the balanced matrix has at least one positive element, GRAS separates the matrix into non-negative and absolute-value matrices. The row and column adjustments are later performed for the sum of two matrices. In the final step, the negative elements will be used to adjust the result. Temurshoev, Miller, and Bouwmeester (2013) further relaxed the condition of GRAS to update a matrix containing a column or row of only negative elements. Another modification of RAS is the Cell-Correction of RAS (CRAS), proposed by Mínguez, Oosterhaven, and Escobedo (2009). Unlike RAS, CRAS uses multiple previous matrices to update the target IO table, rather than proceeding with a single prior matrix. Firstly, the procedure estimates coefficient variation distributions between the projected and the true IO tables from the prior IO time series by the original RAS. Then, the matrix is modified by the distributions obtained from the first stage to obtain the projected values of the target matrix. Since both stages are based on RAS, CRAS can work only with non-negative matrices. Even though the literature is rich in modification methods of RAS, RAS is still the most accepted and applied method of bi-proportional technique (Szabó, 2015).

More recently, MTT was proposed by Wang et al. (2015). This method combines the transformation matrix technique with time series forecasting to update the IO table. This technique proposes to remove the IO constraints by matrix transformation before making the time series forecasting step. Hereafter, the approach conducts the matrix transformation again to restore the values and obtain the IO table. The procedure requires a historical time series of IO tables; the value-added in each sector and the total value-added (or the total final demand) of the target years.

Comparing MTT, RAS, and the modified RAS methods, Wang et al. (2015) concluded from simulation data and empirical evidence of the US IO tables that MTT outperformed GRAS. Additionally, Zheng et al. (2018) studied the Chinese IO table, confirming that MTT obtained a better forecasting result than RAS. However, no one has yet applied MTT to forecast the technical coefficient table, especially for Thailand.

3. METHODOLOGY

The purpose of this research was to apply MTT to forecast the technical coefficient tables of Thailand, and to compare the results of MTT and RAS forecasting to determine their relative accuracy. Therefore, this section describes the data and forecasting methods of MTT and RAS to fulfill the aims of the study.

3.1 Data and Notation

This section provides the data required for the research and their associated notation. Regarding the data set used for the study, the Thai IO tables containing 16 sectors of producer prices for 1975, 1980, 1985, 1990, 1995, 2000, 2002, 2010, and 2015 were collected from NESDC. In addition, the Gross Domestic Product (GDP) values of market price for 2015-2020 (the GDP of 2015 for evaluating the forecasting performance) were gathered from the Office of the National Economic and Social Development Council of Thailand (2021), while the forecasting GDP values covering the period 2021-2025 were collected from the International Money Fund (IMF) (January 2021).

Simplifying the notation, $x_{ij} \in X_{16\times16}$ represents the intermediate transaction of the IO; $v_j \in V_{1\times16}$ and $u_i \in U_{16\times1}$ serve as the sector's total intermediate input and output respectively, while $x_{17,j} \in VA_{1\times16}$ and $x_{i,17} \in FD_{16\times1}$ respectively represent the sector's added-value and the sector's final demand. $t_j \in T_{1\times16}$ and $t_i \in T_{16\times1}(t_i = t_j, \forall i = j)$ denote the sector's total input and output, respectively.

$$\left[\begin{array}{ccc:c|c|c}
x_{1,1} & \cdots & x_{1,16} & u_1 = \sum_{j=1}^{16} x_{1,j} & x_{1,17} & t_1 = \sum_{j=1}^{17} x_{1,j} \\
\vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\
x_{16,1} & \cdots & x_{16,16} & u_{16} = \sum_{j=1}^{16} x_{16,j} & x_{16,17} & t_{16} = \sum_{j=1}^{17} x_{16,j} \\
\hdashline
v_1 = \sum_{i=1}^{16} x_{i,1} & \cdots & v_{16} = \sum_{i=1}^{16} x_{i,16} & \sum_{i=1}^{16}\sum_{j=1}^{16} x_{i,j} & & \\
\hline
x_{17,1} & \cdots & x_{17,16} & & \mu = \sum_{j=1}^{16} x_{17,j} = \sum_{i=1}^{16} x_{i,17} & \\
\hline
t_1 = \sum_{i=1}^{17} x_{i,1} & \cdots & t_{16} = \sum_{i=1}^{17} x_{i,16} & & & \sum_{j}^{16}\sum_{i}^{17} x_{i,j} = \sum_{i}^{16}\sum_{j}^{17} x_{i,j}
\end{array}\right] \tag{1}$$

$$= \left[\begin{array}{c:c|c|c}
X_{16\times16} & U_{16\times1} & FD_{16\times1} & T_{16\times1} \\
\hdashline
V_{1\times16} & & & \\
\hline
VA_{1\times16} & & \mu & \\
\hline
T_{1\times16} & & &
\end{array}\right]$$

Letting $a_{ij} \in A_{16\times16}$ represent the technical coefficient ;

$$a_{ij} = \frac{x_{i,j}}{\sum_{i=1}^{17} x_{i,j}}, \quad A_{16\times16} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,16} \\ \vdots & \ddots & \vdots \\ a_{16,1} & \cdots & a_{16,16} \end{bmatrix} \quad (2)$$

3.2 Forecasting the Technical Coefficients by MTT

The application of MTT to forecast Thailand's technical coefficient table is described in this section. Since the combination of matrix transformation and time series forecasting is the vital technique of MTT, the procedure requires a historical time series of IO tables (IO). For the target years, it requires a value-added measure for each sector (VA) as well as the total value-added (or the total final demand) (μ).

To update the IO table of the 16 sectors, a matrix of 17×17 is required for MTT. This includes the intermediate transaction ($X_{16\times16}$), the value-added measure ($VA_{1\times16}$), and the final demand ($FD_{16\times1}$) elements for each sector as shown in equation (3).

$$\mathrm{IO}_{17\times17} = \begin{bmatrix} X_{16\times16} & FD_{16\times1} \\ VA_{1\times16} & \mu \end{bmatrix} \quad (3)$$

To evaluate the forecasting performance, a time series of IO tables was applied, including eight matrices, $IO^{1975}, IO^{1980}, \ldots, IO^{2010}$ to forecast $\widehat{IO}^{2015}$. Regarding the forecasting purpose, MTT uses all nine available IO tables, including $IO^{1975}, IO^{1980}, \ldots, IO^{2015}$ to forecast $\widehat{IO}^{2016}, \widehat{IO}^{2017}, \ldots, \widehat{IO}^{2025}$. Afterward, those $\widehat{IO}^{t}$ are converted to $\hat{A}^{t}$.

3.2.1 Structural Change

Regarding Wang et al. (2015), MTT is suitable when there is evidence of economic structural change. Accordingly, the likelihood of changes in Thailand's economic structure was checked before proceeding with MTT. The conclusion of economic structural change is made in research when some elements of A show clues of a tendency.

A Least-Squares Linear Regression was applied to evaluate the linear trend (Hanke & Reitsch, 1998) for each time series for a_{ij}. The equation $a = \beta_0 + \beta_1 t + \varepsilon$ was applied for this task, where a denotes the tested element and t is the time variable. The parameters β_1 and β_0 represent the change rate of a for time and the intercept, respectively; ε is the error term.

The finding of trend analysis at the 0.05 significance level for the 16×16 elements indicated that 107 elements of A showed evidence of a significant trend during 1975-2010, followed by 128 elements for 1975-2015. Therefore, it was concluded that there was a change in Thailand's economic structure; the forecasting IO matrices can be proceeded by MTT.

3.2.2 Transformation

Due to the constraints of the IO table, MTT transforms the IO matrix before conducting the forecasting process. Firstly, breaking down the IO matrix's constraints of:

$$\sum_{j}^{16}\sum_{i}^{17} x_{i,j} = \sum_{i}^{16}\sum_{j}^{17} x_{i,j}$$

(total input = total output) and

$t_j = t_i, \forall i = j$

$(\sum_{i=1}^{17} x_{i,j} = \sum_{j=1}^{17} x_{i,j}; \forall i = j; i, j = 1, 2, ..., 16$

(total input of sector i = total output of sector j ; $\forall i = j$)

MTT transforms the elements of $IO_{17\times17}$ by $y_{ij} = \frac{x_{i,j}}{x_{i,17}}; i, j = 1, 2, ..., 17$.

The notation of the first transformation is:

$$\left[\begin{array}{ccc|c} y_{1,1} & \cdots & y_{1,16} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ y_{16,1} & \cdots & y_{16,16} & 1 \\ \hline y_{17,1} & \cdots & y_{17,16} & 1 \end{array}\right] = \left[\begin{array}{c|c} Y_{16\times16} & I_{16\times1} \\ \hline VAT_{1\times16} & 1 \end{array}\right] \quad (4)$$

However, the constraint, $\sum_{j=1}^{16} y_{17,j} = 1$, is in the matrix due to $\mu = \sum_{j=1}^{16} x_{17,j} = \sum_{i=1}^{16} x_{i,17}$ (The total value-added = Total final demand). Hence, MTT secondly transforms $z_j = \frac{y_{17,j}}{y_{17,16}}; j = 1, 2, ..., 16$. Hereafter, there are no constraints in the transformed matrix as in equation (5), $TIO_{17\times17}$, whereby the elements can be freely forecast.

$$TIO_{17\times17} = \left[\begin{array}{cccc|c} y_{1,1} & \cdots & y_{1,15} & y_{1,16} & 1 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ y_{16,1} & \cdots & y_{16,15} & y_{16,16} & 1 \\ \hline z_1 & \cdots & z_{15} & 1 & 1 \end{array}\right]$$

$$= \begin{bmatrix} Y_{16\times16} & I_{16\times1} \\ Z_{1\times16} & 1 \end{bmatrix} \quad (5)$$

3.2.3 Time Series Forecasting

Please note that Wang et al. (2015); Zheng et al. (2018) proceeded with MTT by forecasting all elements of the transformed matrix; however, this research predicts only some of them according to Pumjaroen and Sottiwan (2021), which is the previous work of this research. The result of evaluating performance when forecasting all elements showed 13-negative technical coefficients, indicating the model as meaningless. Hence, this research forecasts only some significant elements that show a trend in $y_{i,j}$ and a high Pearson's correlation between $a_{i,j}$ and $y_{i,j}$ (over 0.8). For these considerations, the significant trend of $y_{i,j}$ infers a change in that element. For a correlation between $a_{i,j}$ and $y_{i,j}$, MTT forecasts the transformed elements ($y_{i,j}$) in place of the original value of the IO matrices ($x_{i,j}$); nevertheless, the ultimate purpose is to forecast the technical coefficients ($a_{i,j}$).

The tendency of $y_{i,j}$ was

checked, in the same way as checking for the tendency of $a_{i,j}$ in section 3.2.1; the findings showed 59 and 68 elements having a significant trend during 1975-2010 and 1975-2015, respectively. The Pearson's correlation between $a_{i,j}$ and $y_{i,j}$ indicated 67 and 65 highly correlated elements for the periods of 1975-2010 and 1975-2010 respectively.

Considering both a significant trend of $y_{i,j}$ and a high Pearson's correlation between $a_{i,j}$ and $y_{i,j}$, the analysis showed 30 and 36 elements for 1975-2010 and 1975-2015. Those elements were forecast by the Box-Jenkins method known as the Autoregressive Integrated Moving Average (ARIMA) model. This model constructs the probabilistic or stochastic properties of the time series data, forecasting the data by their past or lagged value and their stochastic error term (Box, Jenkins, & Reinsel, 1976).

Regarding the target year's value-added measures for each sector, they were applied for analysis if available; however, they were not. Hence, it was necessary to forecast them, rather than directly predicting the value-added measurement for each sector; the research forecasts $z_1, z_2, \cdots z_{15}$ similar to the forecast for $y_{i,j}$.

3.2.4 Back-Transformation

Restoring the forecasting-transformed $(\widehat{TIO}_{17\times17})$ to the forecasting-IO $(\widehat{IO}_{17\times17})$ matrixes consists of four steps

1) $Z_{1\times16}$ to $VAT_{1\times16}$

$$y_{17,j} = \frac{z_j}{\sum_{j=1}^{16} z_j} = \frac{z_j}{\sum_{j=1}^{15} z_j + 1} \tag{6}$$

Yielding $\begin{bmatrix} Y_{16\times16} & I_{16\times1} \\ VAT_{1\times16} & 1 \end{bmatrix}$

2) $VAT_{1\times16}$ to $VA_{1\times16}$

Setting μ as an exogenous variable, the GDP of the target year was applied for this task.

$$x_{17,j} = \mu \bullet y_{17,j};\ j = 1,2,\ldots,16 \tag{7}$$

obtaining $\begin{bmatrix} Y_{16\times16} & I_{16\times1} \\ VA_{1\times16} & \mu \end{bmatrix}$

3) $I_{16\times1}$ to $FD_{16\times1}$

$$x_{i\ 17} = B^{-1} \bullet Tran(x_{17,\ j});\ i = 1,2,\ldots,16$$

$$\textit{where } B = Diag(1 + \sum_{j=1}^{16} y_{1j},\ 1 + \sum_{j=1}^{16} y_{2j}, \cdots,\ 1 + \sum_{j=1}^{16} y_{16j}) - Tran(Y_{16\times16}) \tag{8}$$

yielding $\begin{bmatrix} Y_{16\times16} & FD_{16\times1} \\ VA_{1\times16} & \mu \end{bmatrix}$

4) $Y_{16\times16}$ to $X_{16\times16}$

$$x_{ij} = y_{ij} \bullet x_{i\ 17};\ i,j = 1,2,\cdots,16 \tag{9}$$

Finally yielding $\begin{bmatrix} X_{16\times16} & FD_{16\times1} \\ VA_{1\times16} & \mu \end{bmatrix}$

Hereafter, obtaining the forecasting IO matrix ($\widehat{IO}_{17\times17}$) from MTT, the technical coefficient table ($\hat{A}_{16\times16}$) was calculated.

3.3 Forecasting the Technical Coefficients by RAS

The following describes the application of RAS to forecast the technical coefficient tables for Thailand. The procedure uses the latest IO table as the base IO information to predict the target IO table. As for the evaluation purpose, the IO table of 2010 was applied for updating to the IO table of 2015, while the IO of 2015 was applied to forecast the IO table of 2016-2025. The data required for the target year includes the sector's total intermediate, both inputs ($V^*_{1\times16}$) and outputs ($U^*_{16\times1}$), and the sector's total industry outputs ($T^*_{16\times1}$) (Jackson & Murray, 2004; Pavia, Cabrer, & Sala, 2009). The notation for the base IO and the target IO matrices for RAS are as follows:

Base IO table

$$\left[\begin{array}{c:c|c} A_{16\times16} & U_{16\times1} & T_{16\times1} \\ \hdashline V_{1\times16} & & \end{array}\right]$$

Target IO table

$$\left[\begin{array}{c:c|c} A^*_{16\times16} & U^*_{16\times1} & T^*_{16\times1} \\ \hdashline V^*_{1\times16} & & \end{array}\right]$$

For fulfilling the data requirement of the target year, the research sets $t^*_j \in T^*_{1\times16}$ equal to the value of MTT and computes $v^*_j \in V^*_{1\times16}$ and $u^*_i \in U^*_{16\times1}$ from the information in the base IO and GDP as follows.

$$x^*_{i,17} \in FD^*_{16\times1};$$
$$x^*_{i,17} = GDP \bullet \frac{x_{i,17}}{\sum_{i=1}^{16} x_{i,17}};\ i = 1,2,\ldots,16 \tag{10}$$

$$x^*_{17,j} \in VA^*_{1\times16};$$
$$x^*_{17,j} = GDP \bullet \frac{x_{17,j}}{\sum_{j=1}^{16} x_{17,j}};\ j = 1,2,\ldots,16 \tag{11}$$

$$u^*_i \in U^*_{16\times1};\ u^*_i = t^*_i - x^*_{i,17} \tag{12}$$

$$v^*_j \in V^*_{1\times16};\ v^*_j = t^*_j - x^*_{17,j};$$
$$\text{Noting that } t^*_j = t^*_i, \forall i = j \tag{13}$$

The procedure of RAS can be the function $A^* = f(A, U^*, V^*, T^*)$ where $a^*_{i,j} \in A^*_{1\times16}$, which aims to estimate the unknown non-negative of A^* from the independent row and column adding-up restrictions. The iterative process attempts to estimate the two diagonal matrices, which are R and S such that $A^* = RAS$ is a solution that satisfies aggregation constraints. The following steps describe the iterative procedure of RAS modifying the rows and columns repeatedly. Square brackets on variables denote the iterative step corresponding to the temporary values for those variables.

3.3.1 Row Modification

1) The vector of total intermediate output for the first

iteration is computed, $U^{[1]}$. In this procedure, there is no change in the intermediate structure (A), but the change occurring in the intervening period is responsible for differences between U and $U^{[1]}$

$$U^{[1]} = A \times T^{*} \tag{14}$$

2) R for the first-iteration is computed:

$$R^{[1]} = diag(U^{*}) \times (diag(U^{[1]}))^{-1} \tag{15}$$

3) The new structure, A^{*}, is estimated for the first iteration:

$$A^{*[1]} = R^{[1]} \times A \tag{16}$$

For now, the vector of total intermediate output or row summation of $A^{*[1]} \times diag(T^{*})$ is equal to the target, U^{*}; nevertheless, the vector of intermediate input or column summation of $A^{*[1]} \times diag(T^{*})$ may not equal the target, V^{*}.

3.3.2 Column Modification

1) The procedure calculates a vector of total intermediate input for the first-iteration, $V^{[1]}$, where SUM is a column summation.

$$V^{[1]} = SUM(A^{*[1]} \times \ diag(T^{*}) \tag{17}$$

2) S for the first-iteration is computed:

$$S^{[1]} = diag(V^{*}) \times (diag(V^{[1]}))^{-1} \tag{18}$$

3) The new structure, A^{*}, is then estimated again:

$$A^{*[2]} = A^{*[1]} \times S^{[1]} \tag{19}$$

The vector of total intermediate input or column summation of $A^{*[2]} \times diag(T^{*})$ is now equal to the target, V^{*}; nonetheless, the vector of summation of the intermediate output or row summation of $A^{*[2]} \times diag(T^{*})$ is no longer necessarily equal to the target, U^{*}.

The above steps are iteratively processed until the estimated A^{*} converges to stability. The iteration in the research was stopped when the absolute difference of the estimating and the target values is less than the criterion or the estimated value between 2 iterations is less than the criterion. A stop criterion of 5×10^{-7} was set.

4. EMPIRICAL RESULTS

Evaluation of the forecasting performance and comparison of the technical coefficient forecasting results of MTT and RAS are shown in this section.

4.1 Evaluating the Forecasting Performance

To assess the forecasting accuracy performance between MTT and RAS, the research compared the closeness between the technical coefficient forecast and survey-based values for 2015. Besides this, the analysis also checks the negative forecasting values of the technical coefficients. A higher number of negative technical coefficients are considered as representative of the model's weakness (Jalili, 2000). When forecasting all elements of $Y_{16\times16}$, the result shows 13-negative technical coefficients. However, when predict-ting only some significant elements, the results of the MTT do not present any negative technical coefficients (For more information, please see Pumjaroen and Sottiwan (2021).

In terms of matrix comparison, the concept of accuracy can be separated into cell-by-cell (partitive) and whole matrix (holistic) (Jensen, 1980). The quantitative differences between the two methods were assessed by considering three terms; cell-by-cell, sector, and whole matrix.

Regarding the cell-by-cell comparison, considering the quanti-tative differences between the forecast and the actual survey, ($|\widehat{a_{i,j}} - a_{i,j}|$) was assessed, where $\hat{a}_{i,j}$ is the forecast and $a_{i,j}$ is the actual value.

According to the sectors and the whole matrix evaluation, three common indices were employed: Standardized Total Percentage Error (STPE) (Miller & Blair, 1985), Theil's U (U) (Theil, 1971), and the Standardized Weighted Absolute Difference (SWAD) (Lahr, 1998) (Table 1).

Regarding the results of the forecasting performance of 2015, RAS obtained a smaller error for 132 elements in the cell-by-cell accuracy, while MTT showed 124 elements of smaller error. Regarding sector accuracy considered through three indices, as shown in Table 2, conduction of MTT provided better results for nine sectors, while for the remaining eight sectors, RAS showed the higher performance. Evaluation of the whole matrix of the technical coefficient table, revealed that all three indices showed consensus that MTT offers better performance (Table 3).

This conclusion is also the same as Zheng et al. (2018), who studied the Chinese IO table, confirming that MTT obtains a better result than RAS.

Table 1: STPE, U, and SWAD for Assessing the Forecast Performance for Each Sector and the Whole Matrix.

Sector	Whole Matrix
$STPE = \frac{100\sum_{i=k}\sum_{j=1}^{n}\left\|\hat{a}_{i,j} - a_{i,j}\right\|}{\sum_{i=k}\sum_{j=1}^{n}a_{i,j}} + \frac{100\sum_{i=1}^{n}\sum_{j=k}\left\|\hat{a}_{i,j} - a_{i,j}\right\|}{\sum_{i=1}^{n}\sum_{j=k}a_{i,j}} - \frac{100\left\|\hat{a}_{k,k} - a_{k,k}\right\|}{a_{k,k}}$	$STPE = \frac{100\sum_{i=1}^{n}\sum_{j=1}^{n}\left\|\hat{a}_{i,j} - a_{i,j}\right\|}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{i,j}}$
$U = \sqrt{\frac{\sum_{i=k}\sum_{j=1}^{n}\left(\hat{a}_{i,j} - a_{i,j}\right)^2}{\sum_{i=k}\sum_{j=1}^{n}a_{i,j}^2}} + \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=k}\left(\hat{a}_{i,j} - a_{i,j}\right)^2}{\sum_{i=1}^{n}\sum_{j=k}a_{i,j}^2}} - \sqrt{\frac{\left(\hat{a}_{k,k} - a_{k,k}\right)^2}{a_{k,k}^2}}$	$U = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\hat{a}_{i,j} - a_{i,j}\right)^2}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{i,j}^2}}$
$SWAD = \frac{100\sum_{i=k}\sum_{j=1}^{n}a_{i,j}\left\|\hat{a}_{i,j} - a_{i,j}\right\|}{\sum_{i=k}\sum_{j=1}^{n}a_{i,j}^2} + \frac{100\sum_{i=1}^{n}\sum_{j=k}a_{i,j}\left\|\hat{a}_{i,j} - a_{i,j}\right\|}{\sum_{i=1}^{n}\sum_{j=k}a_{i,j}^2} - \frac{100(a_{k,k}\left\|\hat{a}_{k,k} - a_{k,k}\right\|)}{a_{k,k}^2}$	$SWAD = \frac{100\sum_{i=1}^{n}\sum_{j=1}^{n}a_{i,j}\left\|\hat{a}_{i,j} - a_{i,j}\right\|}{\sum_{i=1}^{n}\sum_{j=1}^{n}a_{i,j}^2}$

4.2 Comparing Forecasting Results

Comparing the forecasting direction by MTT and RAS of the technical coefficients covering 2016-2025, a Pearson's correlation coefficient was applied between the results of MTT and RAS ($r_{RAS_{i,j},MTT_{i,j}}$). The results demonstrate that for most elements (71.50% or 183 elements), the two methods predict in the same direction (having $r_{RAS_{i,j},MTT_{i,j}} \geq 0$). However, 28.5% or 73 elements, were forecasted differently. Regarding these 73 elements, the cell-by-cell assessment results from section 4.1 were considered, indicating that MTT showed better performance for 38 elements, while RAS exhibiting better performance on 35 elements, as shown in Figures 1 and 2. Regarding those 73 elements, 12 elements had $r_{RAS_{i,j},MTT_{i,j}} \langle -0.95$ as shown in Figure 3.

Table 2: Results of the Sector Forecasting Performance for 2015.

Sec-tor	STPE		U		SWAD		The number of indices showing the smallest error		The method showing the better performance
	MTT	RAS	MTT	RAS	MTT	RAS	MTT	RAS	
01	**13.51**	13.70	**0.14**	0.14	**10.67**	11.02	3	0	MTT
02	**7.75**	7.77	0.08	**0.08**	6.68	**6.49**	1	2	RAS
03	13.01	**12.74**	**0.12**	0.12	8.26	**8.22**	1	2	RAS
04	**8.17**	9.43	**0.06**	0.08	**3.32**	5.82	3	0	MTT
05	**21.21**	21.22	0.23	**0.22**	21.13	**20.44**	1	2	RAS
06	**11.73**	12.14	**0.07**	0.08	**5.83**	5.86	3	0	MTT
07	13.07	**12.69**	0.18	**0.17**	12.42	**11.91**	0	3	RAS
08	**9.64**	9.92	**0.09**	0.09	**6.67**	7.14	3	0	MTT
09	**6.76**	6.80	0.05	**0.05**	**4.12**	4.14	2	1	MTT
10	**6.69**	7.09	**0.05**	0.05	**3.99**	4.48	3	0	MTT
11	11.94	**11.89**	**0.15**	0.15	6.26	**5.88**	1	2	RAS
12	**10.15**	10.85	**0.08**	0.09	**5.83**	6.08	3	0	MTT
13	11.60	**11.22**	0.13	**0.13**	10.04	**9.91**	0	3	RAS
14	24.81	**24.55**	0.34	**0.33**	25.61	**25.20**	0	3	RAS
15	**11.50**	12.41	**0.15**	0.15	**10.21**	11.94	3	0	MTT
16	**28.17**	28.29	**0.30**	0.30	**20.69**	20.87	3	0	MTT

Table 3: Results of the Whole Matri Forecasting Performance for 2015

STPE		U		SWAD		The number of indices showing the smallest error		The method showing better performance
MTT	RAS	MTT	RAS	MTT	RAS	MTT	RAS	
11.5 195	11.6 554	**0.1 197**	0.1 199	**7.3 850**	7.6 127	3	0	MTT

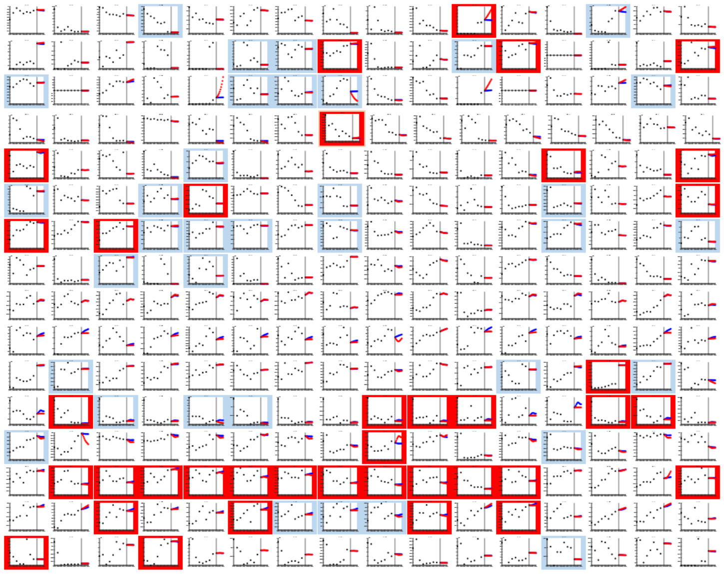


Figure 1 The Actual-technical Coefficients Covering 1975-2015 and the Forecasting Results Between MTT and RAS Covering 2016-2025

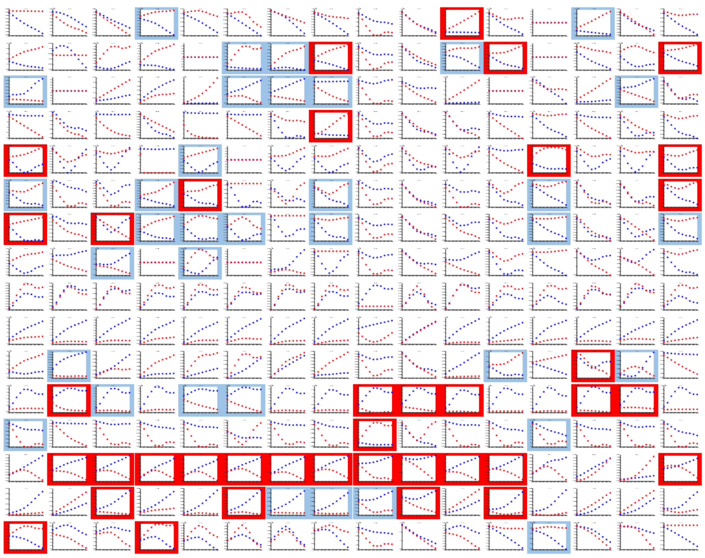
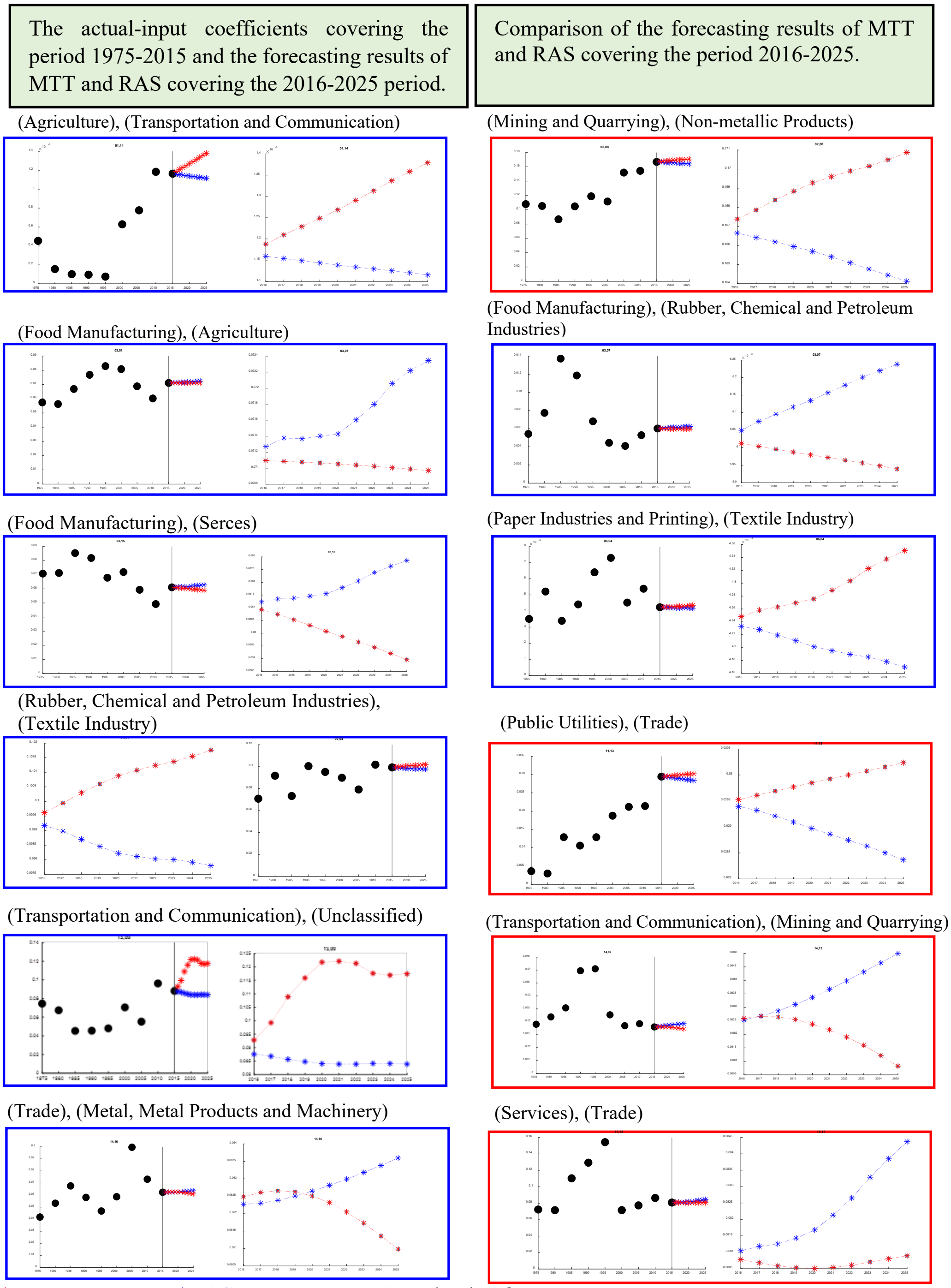


Figure 2 Comparison of the Forecasting Results Between MTT and RAS Covering 2016-2025



*MTT *RAS ● Actual value from survey

☐ MTT obtaining a better forecasting performance ☐ RAS obtaining a better forecasting performance

Figure 3 Comparison MTT and RAS, regarding the 12 elements in the technical coefficient table in the period 2016-2025

5. CONCLUSION AND RECOMMENDATION

Dealing with the timeliness of Thailand's IO tables, this research contributes to the methodology for forecasting technical coefficient tables, using MTT and RAS, by determining their relative accuracy. The study firstly evaluated the methods' performance for updating the technical coefficients for 2015; hereafter comparing the forecasting results for the period 2016-2025.

Regarding MTT, instead of forecasting all elements of the transformed matrix as originally proposed by Wang et al. (2015), the analysis predicted only the elements with evidence of change, providing a high correlation with the technical coefficient following Pumjaroen and Sottiwan (2021).

Regarding the evaluation of method performance, the results of the cell-by-cell, sector, and whole matrix are not unanimous. Considering the cell-by-cell assessment by the absolute value of difference between the forecast and actual survey of 2015's technical coefficients, RAS was superior over MTT. However, according to the three indices of STPE, U, and SWAD, MTT gives a better result than RAS when considering the sector and whole matrix. According to Jalili (2000, 2006); Jensen (1980); and Round (1983), when there is no consensus result in the assessment, more attention should be given to the whole matrix assessment (a holistic accuracy) than the cell-by-cell accuracy (a partitive accuracy), as not assessing the whole matrix, especially when considering cell-by-cell, each cell does not have equal weight, which might lead to misinterpretation. The proposed method gives more cell numbers with a better assessment of which cells are less important or less conclusive measures. Therefore, users are frequently more concerned with the accuracy of the complete matrix than a table's cell-by-cell accuracy. Following this support, it is concluded that MTT performs better than RAS.

Comparing the forecast results of the technical coefficients covering 2016-2025 from MTT and RAS, most elements (71.50% or 183) were forecast in the same direction. However, the remaining 28.50% showed a difference in the direction of the forecast. Hence, the cell-by-cell assessment of these 73 elements was checked, determining that conduction of MTT provided better performance for 38 elements, while RAS exhibited better performance for the other 35 elements.

Regarding recommendations, it is suggested that forecasts of Thailand's technical coefficients utilize MTT whenever there is evidence of economic structural change. Additionally, much literature has focused only on whole matrix assessment. It is hereby recommended to additionally consider sector and cell-by-cell assessment, as the sector and cell-by-cell evaluation can help to identify the root of forecasting problems inside the matrix.

Recommendations regarding future research include using this research as a platform for adding up the sectors of forecasting the Thailand IO table to fulfill policy analysis needs. While still involving MTT in the forecasting method, future study could apply another forecasting technique to compare with the Box-Jenkins approach. In addition, since MTT is under the assumption of economic structural change, the research encourages consideration of the rate of economic change, and whether it affects the method performance.

Moreover, regarding improvements in the forecasting of the technical coefficient table for Thailand, even where RAS is the most accepted and applied bi-proportional technique (Szabó, 2015), Mínguez et al. (2009) found that CRAS outperforms RAS when evidencing economic structural change. Therefore, comparing MTT and CRAS for updating IO products should be considered.

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REFERENCES

Aroche Reyes, F. (2020). On growth regimes, structural change and input coefficients. *Economic Systems Research*, 1-18.

Asian Development Bank (ADB). (2019). *Thailand: Input-Output Economic Indicators*. Retrieved from: https://data.adb.org/dataset/thailand-input-output-economic-indicators

Box, G. E., Jenkins, G. M., & Reinsel, G. C. (1976). *Time Series Analysis: Forecasting and Control*. The United States of America: John Wiley & Sons.

Carter, A. P. (2013). *Structural change in the American economy*: Harvard University Press.

Deng, X., Zhang, F., Wang, Z., Li, X., & Zhang, T. (2014). An extended input output table compiled for analyzing water demand and consumption at county level in China. *Sustainability, 6*(6), 3301-3320.

Dietzenbacher, E., Lenzen, M., Los, B., Guan, D., Lahr, M. L., Sancho, F., Suh, S., & Yang, C. (2013). Input–output analysis: the next 25 years. *Economic Systems Research, 25*(4), 369-389.

Hanke, J. E., & Reitsch, A. G. (1998). *Business Forecasting* (6th ed.): Upper Saddle River, NJ: Prentice-Hall.

International Money Fund (IMF). (January 2021). *World Economic Outlook Update*. Retrieved from: https://www.imf.org/en/Publications/WEO/weo-database/2020/October

Jackson, R., & Murray, A. (2004). Alternative input-output matrix updating formulations. *Economic Systems Research, 16*(2), 135-148.

Jalili, A. R. (2000). Evaluating relative performances of four non-survey techniques of updating input-output coefficients. *Economics of Planning, 33*(3), 221-237.

Jalili, A. R. (2006). Impacts of Aggregation on Relative Performances of Nonsurvey Updating Techniques And Intertemporal Stability of Input–Output Coefficients. *Economic Change and Restructuring, 38*(2), 147-165.

Jensen, R. C. (1980). The concept of accuracy in regional input-output models. *International Regional Science Review, 5*(2), 139-154.

Junius, T., & Oosterhaven, J. (2003). The solution of updating or regionalizing a matrix with both positive and negative entries. *Economic Systems Research, 15*(1), 87-96.

Khan, A. Q. (1993). Comparisons of Naive and RAS Methods of Updating Input–Output Tables: The Case of Pakistan. *Economic Systems Research, 5*(1), 55-61.

Lahr, M. L. (1998). A strategy for producing hybrid regional input-output tables.

Leontief, W. W. (1936). Quantitative input and output relations in the economic systems of the United States. *The review of economic statistics*, 105-125.

Leontief, W. W. (1951). *The structure of American economy, 1919-1939: an empirical application of equilibrium analysis*. Retrieved from

Miller, R. E., & Blair, P. D. (1985). Input-Output Analysis: Foundations and extensions Prentice-Hall. *Englewood Cliffs, New Jersey*.

Mínguez, R., Oosterhaven, J., & Escobedo, F. (2009). Cell-Corrected Ras Method (Cras) For Updating Or Regionalizing An Input–Output Matrix. *Journal of Regional Science, 49*(2), 329-348.

Office of the National Economic and Social Development Council of Thailand. (2020). *Input-Output Tables*. Retrieved from: https://www.nesdc.go.th/nesdb_en/more_news.php?cid=158&filename=index

Office of the National Economic and Social Development Council of Thailand. (2021). *Gross Domestic Product* Retrieved from: https://www.nesdc.go.th/main.php?filename=QGDP_report

Pavia, J. M., Cabrer, B., & Sala, R. (2009). Updating input–output matrices: assessing alternatives through simulation. *Journal of Statistical Computation and Simulation, 79*(12), 1467-1482.

Pumjaroen, J., & Sottiwan, T. (2021). How to obtain a better result of updating the IO table from the MTT method. *Economics Bulletin, 41*(3), 1697-1710.

Rao, M., & Tommasino, M. (2014). Updating technical coefficients of an input-output matrix with RAS–the TRIOBal software. *Roma: ENEA*.

Round, J. I. (1983). Nonsurvey techniques: a critical review of the theory and the evidence. *International Regional Science Review, 8*(3), 189-212.

Stoeckl, N. (2012). Comparing multipliers from survey and non-survey based IO models: An empirical investigation from Northern Australia. *International Regional Science Review, 35*(4), 367-388.

Stone, R. (1961). *Input-output and national accounts*: Organisation for European Economic Co-operation.

Stone, R., & Brown, A. (1962). A Programme for Growth, vol. 1: A Computable Model of Economic Growth. In: London: Chapman and Hall.

Szabó, N. (2015). Methods for regionalizing input-output tables. *Regional Statistics*(01), 44-65.

Temurshoev, U., Miller, R. E., & Bouwmeester, M. C. (2013). A note on the GRAS method. *Economic Systems Research, 25*(3), 361-367.

Theil, H. (1971). Applied economic forecasting.

Urata, S. (1988). Economic growth and structural change in the Soviet economy, 1959-72. *M. Ciaschini (comp.), Input-Output Analysis. Current Developments, Londres y Nueva York, Chapmand and Hall*.

Wang, H., Wang, C., Zheng, H., Feng, H., Guan, R., & Long, W. (2015). Updating input–output tables with benchmark table series. *Economic Systems Research, 27*(3), 287-305.

Zheng, H., Fang, Q., Wang, C., Jiang, Y., & Ren, R. (2018). Updating China's input-output tables series using MTT method and its comparison. *Economic Modelling, 74*, 186-193.