A Conceptual Model for Developing a Selection Error Measurement Method to Measure the Effectiveness of the Time Series Forecasting Method

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Abstract

The time series forecasting method is a forecast that relies on quantitative past data to create a forecasting process. In the forecasting process, forecasters must determine the accuracy of forecasting methods before applying them by measuring forecast errors. It is measured by the difference between the forecasted values and the actual values. The method of error measurement is also an appropriate consideration to be used to make decisions on choosing effective forecasting methods. Therefore, this research presented in the first part of the article also aims to present a literature review of the relevant topic of error measurement in the forecasting method. In the second part of the article, to identify research gaps in the relevant literature review, it was found that the error measurement of the forecasting method had more than one error measurement method. The results of each error are contradictory, or the results are not in the same direction. This made it difficult to decide on a forecasting method to use. This is a research gap and led to the introduction of a conceptual model for developing a selection error measurement method to measure the effectiveness of the time series forecasting method. This results in the accuracy of the chosen forecasting method. The researcher has set the structure of the research method to be used as a research process and will be presenting research results in the future.

Keywords
Error Measurement, Forecasting, Time Series, Conceptual Model, Research gap

1. Introduction
Forecasting is the expectation or estimation of future states, or the forecast of actual value in a particular situations and circumstances. It is also defined as the estimation of the unbeknownst. Speaking of which, forecasting is the future estimation of the variables. It is utilized as a tool for decision making procedures and future plans. If a business is able to forecast future circumstances, it will be able to adjust its current operations for better future.

Regarding common forecasting practices, the practices can be divided into two categories: qualitative forecasting and quantitative forecasting. Qualitative forecasting is a forecasting manner that does not require past information as a principle; judgement and experiences of the forecaster or person related to the matter will only be applied. This type of forecasting is aimed at determining basic changes; whereas quantitative forecasting requires past information as a fundamental to determine future situations. Statistical and mathematical models will be applied. A forecaster is to examine type of the data to be analyzed in the forecasting process, and select a forecasting method that best suits with the type of the data. Normally, accurate forecasting requires both qualitative and quantitative forecasting. Quantitative forecasting is an interesting model for the development of forecasting proficiency due to the factors that contribute to more accurate forecasting. With being said, time-series forecasting — a forecasting that relies on past quantitative data to establish forecasting process — is the simplest model to forecast quantitative demand as past data is the determination of what will happen in the future. The data will be arranged to make it appropriate with demand forecasting that differs over time. A practitioner can select a wide range of forecasting techniques that are suited best with the application. The selection of forecasting techniques must be determined based on the proficiency of the techniques prior to the application by calculate forecasting errors. The process is done so by comparing deviation between the forecasted value and the actual value, meaning that the forecasted value and the actual value slightly differ, that respective forecasting technique is remarkably accurate. On the other hand, if the forecasted value and the actual value show high different level, the forecasting technique applied is not accurate: such a technique usually shows high error rates. To wrap up, the technique to determine errors must also be carefully considered. The practitioner will adopt the technique in their decision-making process when selecting effective forecasting technique.

1.1 Objectives

To present a series of literature reviews associated with forecasting to fill the research gap, leading to the presentation of guidelines and concepts for the development of the appropriate application of errors in the performance metrics of time-series forecasting.

2. Literature review and associated studies

Time series is the sequence of data points collected over an interval of time e.g., daily gold price or global oil price, daily rainfall in a city. Time series requires only past variables to be applied as a basis of forecasting each dependent variable. Time series is also the process of adopting a forecasting model to forecast the future value of a dependent variable from an observed variable which had been recorded. To forecast time series, past variable will be prioritized. As there are many methods of forecasting that can be utilized to forecast existing data, a practitioner must seek the best or the most appropriate method. Therefore, there must be the evaluation of each forecasting method. On the other hand, if there is a single method that can be applied on the respective set of data, a practitioner might question about the effectiveness of such forecasting method. The techniques to evaluation the efficiency of the forecasting method then will be adopted by calculating errors. There are many calculation techniques which will be applied depending on types of data and forecast period. Practitioners might need various error calculations for the analysis in order to obtain the more accurate forecasting technique.

According to the review of studies associated with error calculation, there are the presentations of types of error calculation. Error calculation is divided into three types: 1) scale-based measures (SBM) — the regularly used measures include mean absolute error (MAE), mean of squared error (MSE), root mean squared error (RMSE), etc., 2) percentage-based measures (PBM) — the regularly used measures include mean absolute error (MAPE) and symmetric mean average percentage error (SMAPE), and 3) relative-based measures (RBM) — the regularly used measures include mean relative absolute error (MRAE) and geometric mean relative absolute error (GMRAE). Furthermore, there are a variety of error calculation that features distinct manners from the first three measures. One of them is Theil's U Statistic, which is an error calculation is focused on large errors, utilizing the same manners as the MSE. It is also an error measure that compares forecast results calculated from the utilized method with Naïve Method. Similarly, the calculation in a form of McLaughlin's Batting Average — an error calculation with a mean ranging 300–400 — can tell differences in each time interval: the mean of 300 refers to the errors having indifferent accuracy, while the mean of below 300 means that the errors have lower accuracy.

According to the review of literatures and studies associated with error calculation, in order to assess the proficiency of forecasting techniques, more than one error calculations will be applied. The result of each calculation will be analyzed to weigh up the efficiency of the methods or techniques before its practical application. This is relevant to a study conducted by Demir and Akkas (2018) which indicated that the Support Vector Regression (SVR) forecasting technique was way more efficient that other forecasting techniques with the application of MAE, MAPE and MSE. Meanwhile, Artificial Neural Network (ANN) forecasting technique offered better forecasting results than other techniques with the application of MAE and MSE on some groups of data being forecast. This reflected that in some specific groups of data were more suitable with each of their respective forecasting techniques. This study, however, had not yet been clearly discussed; there had not yet been any conclusions from the conflict underlying the results of such error calculations. Correspondingly, a study conducted by Zhang and Na (2018) showed that Mind Evolutionary Algorithm (MEA) and SVR offered more accurate forecasting results than Grid Search Method (GSM) in 1) food price indices, 2) meat price indices, 3) sugar price indices, 4) dairy price indices and 5) grain price indices. On the other hand, the study showed that GSM offered better forecasting results than MEA-SVM in oil price indices with the assistance of MSE and R2 error calculations. This reflected the that oil price indices were must more suitable with GSM. Nevertheless, the study on the suitability of data analyzed by both forecasting techniques was not accurately discussed, as cited in a study conducted by Natchapol, Ampai and Saowapa (2018) which showed that Ensemble Empirical Mode Decomposition (EEMD) and Autoregressive Integrated Moving Average Model (ARIMA) forecasting methods offered better forecasting results than Empirical Mode Decomposition (EMD)- ARIMA in a form of polynomial time series with the application of MSE. Meanwhile, the EEMD-ARIMA models offered better forecasting results than the EMD-ARIMA models in time series with negative exponent from the MAPE error calculation. Oh the other hand, EMD-ARIMA forecasting technique offered better forecasting results than EEMD-ARIMA in positive exponent from the MAPE error calculation.

The analysis of this study indicated that time-series factors affect affecting accuracy differently in each error calculation method, all of which made it impossible to find the conclusions or explanations to the conflicts towards accuracy, thus the application of forecasting techniques on time-series data will be affected by lack of determination on suitability of teach type of data. This is in accordance with a study conducted by Andrea and Melville (2010) which showed that the Seasonal Autoregressive Integrated Moving Average Model (SARIMA) offered better forecasting results than other forecasting techniques with the exception of the Naïve technique, which provided better forecasting results in the 3-month dataset of time series with the assistance of MAPE. The study also showed that the SARIMA technique offered better results than other forecasting techniques, with the exception of the Holt-Winters Exponential Smoothing (Holt-Winters), which provided better forecasting results in the 6-month dataset of time series with the assistance of Theil's U statistics error calculation. Nevertheless, the study illustrated conflicts of errors emerged from different calculation techniques clearly. The collection of time-series forecasting dataset from different time interval did also affect the accuracy of each forecasting techniques. In addition, there were no discussions or conclusions associated with the differences of dataset applied on forecasting, and there were no discussions of the conflicts of the errors; this might affect the efficiency of forecasting techniques based on time interval and the errors of accuracy.

This study showed relevance toward a study conducted by Zhang and Wang (2018) which showed that the Swarm Optimization Wavelet Neural Network (CPOWNN) offered better forecasting results that PSOWNN in datasets of 500 and 1,000 with the assistance of the Average Absolute Percentage Error (AAPE). Meanwhile, PSOWNN offered better forecasting results than CPSOWNN in datasets of 500 and 1,000 with the assistance of MSE. All of these indicated that different error analysis techniques affect the accuracy of different forecasting techniques. The results of these studies also showed that conflicting error analysis techniques affect the ineffective implementation of forecasting techniques. Likewise, Warankhana (2016) showed that combined forecasting method offered better forecasting results than the Box-Jenkins method and Winters' Multiplicative Exponential Smoothing Method with the assistance of MAPE. On the other hand, the Winters' Multiplicative Exponential Smoothing Method offered better forecasting results than the Box-Jenkins and combined forecasting method with the assistance of RMSE. This study also concluded that both forecasting techniques were accurate thanks to indifferent accuracy rates. However, this study did not conduct a test to distinguish the accuracy rates, thus making the forecasting results untrustworthy and the forecasting techniques seemed incomplete for the implementation. The review of literatures and associated studies related to the use of error analysis methods to analyze the efficiency of forecasting techniques could be summarized per the Table 1:

Table 1. The summaries of literature review and associated studies

Item	Researchers (Year)	Research Title	Forecasting Method(s)	Error analysis method(s)
1	Demir and Akkas (2018)	A comparison of sales forecasting methods for a feed company	Moving Averages, Exponential Smoothing, Holt's Linear Method, Winter's Method, Artificial Neural Network, Support Vector Regression (MA, ES, HLM, WM, ANN, SVR)	MAE, MSE, MAPE
2	Zhang and Na (2018)	A Novel Agricultural Commodity Price Forecasting Model Based on Fuzzy Information Granulation and MEA-SVM Mode	Mind Evolutionary Algorithm, Support Vector Machine (MEA, SVM)	MSE, R^2
3	Natchapol, Ampai and Saowapa (2018)	Comparison of Forecasting Methods for Non-Linear and Non-Stationary Time Series	Comparison of Forecasting Methods for Non-Linear and Non-Stationary Time Series	MSE, MAPE

Item	Researchers (Year)	Research Title	Forecasting Method(s)	Error analysis method(s)
4	Andrea and Melville (2010)	Forecasting Tourist Arrivals in South Africa	Naïve, ARIMA, Holt-Winters Exponential Smoothing, Seasonal-Non-Season ARIMA (Naïve, Holt Winters, ARIMA, SARIMA)	MAPE, RMSE, Theil's U

Table 1. The summaries of literature review and associated studies (continued)

Item	Researchers (Year)	Research Title	Forecasting Method(s)	Error analysis method(s)
5	Zhang and Wang (2018)	Traffic flow forecasting method based on improved particle swarm optimization algorithm	Wavelet Neural Network Model, Particle Swarm Optimization Wavelet Neural Network, Cloud Particle Swarm Optimization Wavelet Neural Network (WNN, PSOWNN, CPSOWNN)	MSE, AAPE
6	Warangkhana (2016)	Forecasting Model for the Export Values of Rubber Wood and Furniture of Thailand	Box-Jenkins Method, Winter's Multiplicative Exponential Smoothing Method, Combined Forecasting Method (Box-Jenkins, Winter's ES, Combined)	RMSE, MAPE

In summary, error analysis methods are significant to the accuracy of the selection of forecasting method to offer the most effective results. The implementation of more than one error analysis methods to compare the accuracy of forecasting methods should be based on the appropriate error analysis methods along with factors associated with forecasting techniques. This resulted in the channels for this study, leading to the conceptual model of the selection of the appropriate error analysis for the measurement of efficiency of time-series forecasting and reducing the conflicts from the implementation of more than one methods. This thus reflects the efficiency of forecasting methods and techniques, resulting in more accurate results.

3. Methods

The presentation of conceptual models of the selection of the appropriate error analysis for the measurement of efficiency of time-series forecasting was conducted using the review of literatures and associated studies, with the specification of four aspects of presentation: 1) the study of factors affecting the conflicting results of errors, 2) the study of error analyses, 3) the presentation of conceptual models of the selection of the appropriate error analysis for the measurement of efficiency of time-series forecasting and 4) the presentation of research structure for the selection of appropriate error analysis for the measurement of efficiency of time-series forecasting.

3.1 The study of factors affecting the conflicting results of errors

According to the study of factors affecting the conflicting results of errors from the implementation of more than one error analysis methods, there were three factors associated with the analysis of accuracy of forecasting techniques from the literature review and associated studies: 1) data pattern, 2) horizon time and 3) quality of historical data. These factors led to the presentation of presentation of conceptual models of the selection of the appropriate error analysis for the measurement of efficiency of time-series forecasting.

3.2 The study of error analyses

According to the study of error analyses focusing on the implementation of more than one error analysis methods with conflicting errors in the selection of forecasting techniques from the literature review and associated studies, it was found that more than one error analysis methods were often implemented with the measurement of efficacy of the forecasting techniques. This allowed a particular forecasting technique to be more trustworthy, so did reflect the conflicting results of the comparison of more than one error analyses due to different analysis methods. The review of associated studies is shown on Table 2:

Table 2. Review of studies associated with the implementation of more than one error analysis methods with conflicting error rates in the selection of forecasting techniques

Items	Researcher (Year)	Research Title	The implemented error analysis methods	Conflicting error rates in the selection of forecasting techniques
1	Demir and Akkas (2018)	A comparison of sales forecasting methods for a feed company	MAPE, MAE and MSE	SVR offered the most accurate results if being determined from MAPE, conflicting with ANN forecasting technique, but most accurate if being determined from MAE and MSE.
2	Zhang and Na (2018)	A Novel Agricultural Commodity Price Forecasting Model Based on Fuzzy Information Granulation and MEA-SVM Model	MSE and R^2	MEA-SVM offered the most accurate results if being determined from MSE an R2, conflicting with GSM but offered the most accurate results if being determined from MSE and R2 once implemented on some particular datasets.
3	Natchapol, Ampai and Saowapa, (2018)	Comparison of Forecasting Methods for Non-Linear and Non-Stationary Time Series	MSE and MAPE	EEMD-ARIMA offered the most accurate results in polynomial time series if being determined from MSE, conflicting with EEMD-ARMIA offering the most accurate results in negative exponential time-series dataset when being determined from MAPE.
4	Andrea และ Melville (2010)	Forecasting tourist arrivals in South Africa	MAPE, RMSE และ Theil' U	SARIMA offered the most accurate results inf 3-month time-series dataset if being determined from MAPE, conflicting with 6-month time-series dataset when being determined from RMSE; while in 3-month and 6-mont time-series datasets, SARIMA offered the most accurate results if being determined from Theil' U.
5	Zhang and Wang (2018)	Traffic flow forecasting method based on improved particle swarm optimization algorithm	AAPE and MSE	CPSOWNN offered the most accurate results if being determined from AAPE, conflicting with PSOWNN being the most accurate if determined from MSE.
6	Warangkhan a (2016)	Forecasting Model for the Export Values of Rubber Wood and Furniture of Thailand	RMSE and MAPE	Combined forecasting method offered the most accurate results if being determined from MAPE, conflicting with Winters' Multiplicative Exponential Smoothing Method being the most accurate if being determined from RMSE.
7	Kantasa-ard, Bekrar, cadi and Sallez (2019)	Artificial intelligence for forecasting in supply chain management: a case study of White Sugar consumption rate in Thailand	RMSE, and Theil' U	LSTM RNN offered the most accurate results if being determined from RMSE, conflicting with MLP FNN being the most accurate if being determined from Theil' U.

Table 2. Review of studies associated with the implementation of more than one error analysis methods with conflicting error rates in the selection of forecasting techniques (continued)

Items	Researcher (Year)	Research Title	The implemented error analysis methods	Conflicting error rates in the selection of forecasting techniques
8	Andrea Kolkova (2018)	Indicators of Technical Analysis on the Basic of Moving Averages as Prognostic Methods in the Food Industry	RMSE and MAPE	Simple Exponential Smoothing offered the most accurate results if being determined from RMSE, conflicting with Damped Exponential forecasting method and Holt's being the most accurate if being determined from MAPE, but applicable only on some particular datasets.
9	Phichet and Pajaree (2015)	The Study of Forecasting Models and Appropriate Inventory Management Case Study: Carton Packaging	MSE, MAD, MAPE	SMA offered the most accurate results if being determined from MAD and MAPE, conflicting with Decomposition Additive being the most accurate if being determined from MSE.
10	Aykan,Izzettin and Erol (2011)	An Application of Exchange Rate Forecasting in Turkey	MAE, RMSE, MAPE	AMIRA (1,1,0) offered the most accurate results when being determined from MAE, conflicting with ARIMA (2,1,2) being the most accurate if being determined from MAPE and RMSE AMIRA (1,1,0).

3.3 The presentation of conceptual models of the selection of the appropriate error analysis

According to the review of literatures and associated studies which resulted in a research gap, the researcher here by presented the conceptual model for the development of the selection of the appropriate error analysis for the measurement of efficiency of time-series forecasting. The reason was to offer accuracy in the implementing forecasting technique, as shown in Figure 1:

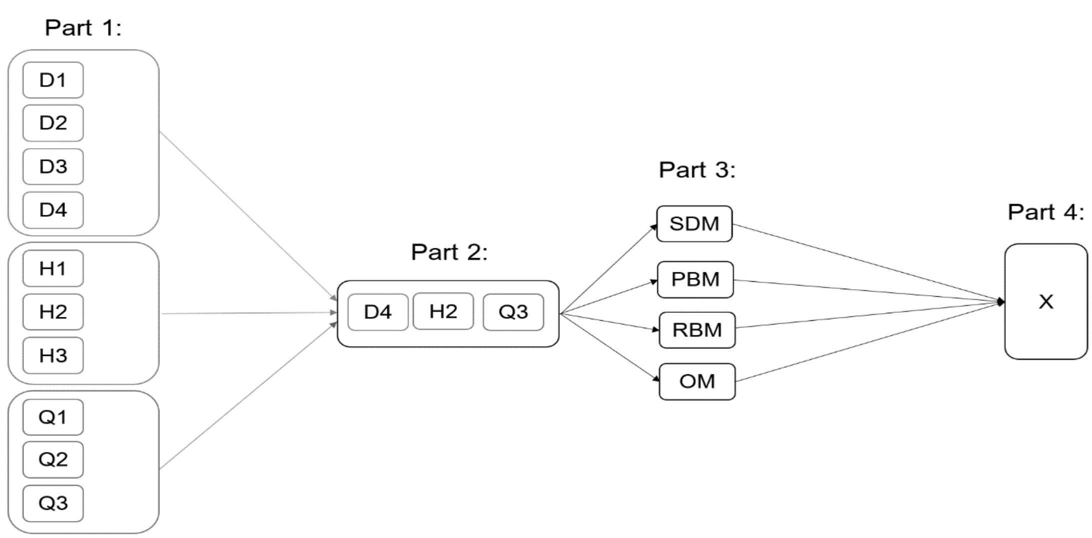

Figure 1. The presentation of the conceptual model

Figure 1 explains the presentation of the conceptual model as follows:

Part 1: Input is the factor affecting conflicting errors. According to the review of associated studies, it is divided into three categories:

1. Data pattern
To select the forecasting method, changes of historical data is to be determined. Each time-series dataset displays increases and decreases in data. Changes in data are influenced by four components, namely;

Trend: D1 is specified as data increasing or decreasing in a long term. It does not have to be linear. Sometimes it will be referred to a trend as "changing direction", when it might go from an increasing trend to a decreasing trend.

Seasonal: D2 is specified as data increasing or decreasing in a seasonal basis. It occurs when time series is affected by seasonal factors, such as a time in a year or the day of the week, as well as a cycle lasting for 6-10 years; this trend might not be specific, but will be shown as seasons in a year, which is more specific.

Cyclic: D3 is specified as data exhibiting rises and falls that are not of a fixed frequency. The fluctuation is usually occurred from economic situations, and is mostly related to "business cycles." The duration of fluctuation is usually at least 2 years.

1.4 Irregular components: D4 is specified as data with variations of uncertainty resulted from a condition, making it impossible for a forecast. It is, however, incidentally occurs in a number of factors difficult to be identified in a specific period of time.

The conclusion is that data patterns influence conflicting results of error analyses. This leads to the selection of forecasting methods that might possess errors, in line with a study conducted by Demir and Akkas (2018), which stated that different data patterns and datasets are suitable with different forecasting methods. Zhang and Na (2018) also stated significance of data appropriate to the implementation of forecasting methods.

2. Horizon Time
Forecasting methods can be divided into three ranges as follows:
2.1 Shot-Range Forecasting: H is specified as a range of time below 1 year.
2.2 Medium-Range Forecasting H2 is specified as a range of time between 1-3 years.
2.3 Long-Range Forecasting H3 is specified as a range of time beyond 3 years.

The conclusion is that horizon time ranges for each forecasting influence conflicting errors. This must be determined when forecast annual forecast, quarterly forecast, monthly forecast or even daily forecast. All of these are influenced by the selection of forecasting techniques.

3. Quantity of Historical Data
Quantity of historical data specifies the direction to collecting historical data for the input into forecasting procedures. Quantity of data and historical data are to be determined, and the practitioner must analyze the directions of data and specify units of data to segregate the overall components before forecasting or selecting effective forecasting methods. The quantity of historical data can be classified periodically as follows:

3.1 Data for 1-3 months is specified as Q1
3.2 Data for 3 months – 2 years is specified as Q2
3.3 Q3 Data for more than 2 years is specified as Q3

The conclusion is that quantity of historical data affects conflicting results of errors, as cited in Andrea and Melville (2010), which showed that the collection of time-series data based on ranges of time and different quantity of data influence the accuracy of each forecasting method. Zhang and Wang (2018) also showed that different quantity of dataset implemented in forecasting methods offered vary rates of accuracy of each forecasting method.

Part 2: Selecting factors for examination. According to factors influencing conflicting errors from Part 1, the analysis will be implemented to categorize features of data, horizon time and quantity of data to be forecast as shown in Table 3:

Table 3. The categorization based on factors influencing conflicting errors from the implementation of more than one error analysis methods

Researcher (Year)	**Research Title**	**Error Measurement Method**	**Data pattern (D)**				**Horizon Time (H)**			**Quantity of Historical Data (Q)**		
			D1	D2	D3	D4	H1	H2	H3	Q1	Q2	Q3
Demir and Akkas (2018)	A comparison of sales forecasting methods for a feed company	MAE, MSE, MAPE				✓		✓			✓	
Zhang and Na (2018)	A Novel Agricultural Commodity Price Forecasting Model Based on Fuzzy Information Granulation and MEA-SVM Model	MSE, R^2				✓		✓				✓
Zhang and Wang (2018)	Traffic flow forecasting method based on improved particle swarm optimization algorithm	MSE, AAPE				✓	✓		✓		✓	
Natchapol, Ampai and Saowapa (2018)	Comparison of Forecasting Methods for Non-Linear and Non-Stationary Time Series	MSE, MAPE				✓		✓				✓
Warangkhana (2016)	Forecasting Model for the Export Values of Rubber Wood and Furniture of Thailand	RMSE, MAPE	✓	✓				✓				✓
Andrea and Melville (2010)	Forecasting Tourist Arrivals in South Africa	MAPE, RMSE, Theil's U	✓					✓				✓
phichet and Pajaree (2015)	The Study of Forecasting Models and Appropriate Inventory	MSE, MAD, MAPE				✓		✓			✓	

	Management Case Study: Carton Packaging											
Aykan,İzzettin and Erol (2011)	An Application of Exchange Rate Forecasting In Turkey	MAE, RMSE, MAPE				✓			✓			✓

Table 3. The categorization based on factors influencing conflicting errors from the implementation of more than one error analysis methods (continued)

Researcher (Year)	**Research Title**	**Error Measurement Method**	**Data pattern (D)**				**Horizon Time (H)**			**Quantity of Historical Data (Q)**		
			D1	D2	D3	D4	H1	H2	H3	Q1	Q2	Q3
Kantasa-ard, Bekrar, cadi and Sallez (2019)	Artificial intelligence for forecasting in supply chain management: a case study of White Sugar consumption rate in Thailand	RMSE, Theil's U				✓			✓			✓
Andrea Kolkova (2018)	Indicators of Technical Analysis on the Basic of Moving Averages as Prognostic Methods in the Food Industry	RMSE, MAPE				✓		✓			✓	
Frequency			**2**	**1**	**0**	**8**	**1**	**7**	**3**	**0**	**4**	**6**

From Table 3 is the categorization based on factors influencing conflicting errors from the implementation of more than one error analysis methods. From frequency, it was found that most of them were irregular components (D4), a range of time between 1-3 years or medium-range forecasting (H2) and data for more than 2 years (Q3). The data then was presented in a form of irregular components with a range of forecasting time between 1-3 years with the assistance of data for more than 2 years: all of which were used to examine the suitability of the selection of error analyses.

Part 3: Examining factors. The researcher examined 4 types of error analyses: SDM, PBM, RBM and OM based on the studied error analysis methods in order to select the suitable error analysis method for factors implemented in forecasting.

Part 4: Creating patterns of the implementation of error analysis. After examining factors from the created dataset, the researcher conducted the examination by adopting the results of analyzed forecasting techniques to test the efficiency with various error analyses. This was to analyze the results of errors in the directions of conflict and finalize the patterns of selecting suitable error analyses to test the efficacy of time-series forecasting (X).

4. The Structure of the Research Method Proposed to Conceptual Model

This study is aimed at presenting the review of literatures to fill the research gap and pave ways to the presentation of conceptual models for the improvement of the implementation of error analyses that are suitable with the efficiency of time-series forecasting. According to the literature review, forecasting techniques usually implement more than one error analyses to compare the accuracy rates of each technique. After that, more than one error analyses implemented often offered conflicting results, influencing the researcher's decision to select the most effective forecasting technique, thus creating a study gap. The determination to select the most suitable error analysis for underlying factors in forecasting techniques then manifest the conceptual model for the improvement of the implementation of error analyses that are suitable with the efficiency of time-series forecasting in order to reduce conflicts from the implementation of more than one analyses. All of these reflect the effectiveness of forecasting techniques and the increased accuracy rates of the methods. From Figure 2, there are 7 associated steps:

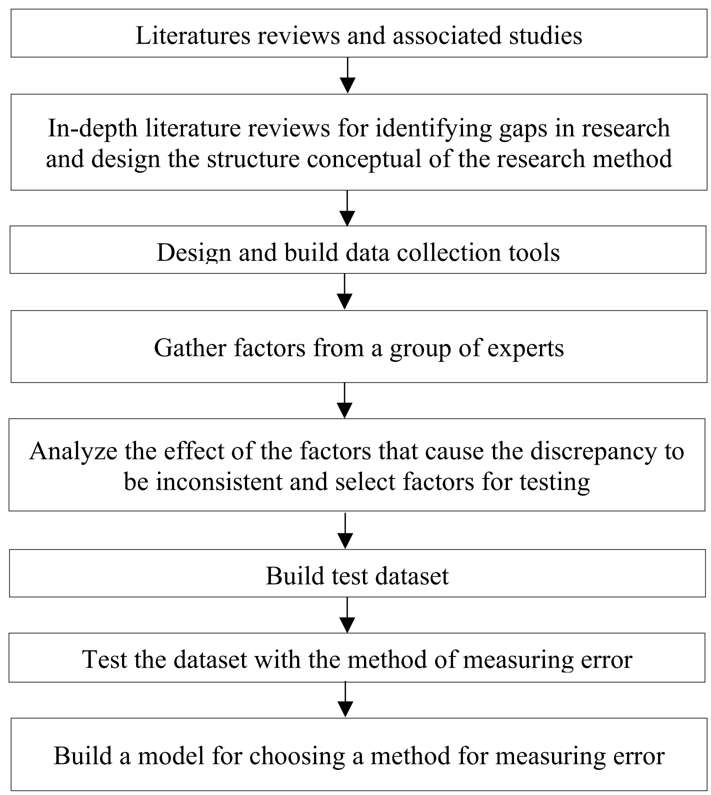

Figure 2. Conceptual models for the improvement of the implementation of error analyses that are suitable with the efficiency of time-series forecasting.

The structure of the research method proposed for the conceptual model is more detailed as follows

4.1 Review of associated literatures: 1) Studies of time-series forecasting and quantitative forecasting, and 2) studies of error analyses from research articles.

4.2 In-depth review of associated literatures: This is aimed at studying the implementation of more than one error analyses in the determination of forecasting techniques with underlying conflicts, filling the research gap and designing research structure in the form of conceptual models.

4.3 Designing and creating instruments for data collection related to factors influencing conflicting errors. The researcher collected the data from the review of associated literatures and thus created the tools for data collection, namely in-depth interview and the validation of questions based on the Index of item objective congruence (IOC).

4.4 Gathering factors influencing conflicting errors with the assistance of in-depth interview in 5-10 specialists

4.5 Analysis of factors influencing conflicting errors: Mean and standard deviation of all factors were calculated, thus factors with the highest mean were selected.

4.6 Creating dataset for examination using the selected factors. The said factors were used to determined quantitative datasets from the Industrial Statistics, the National Statistical Office, in the next step.

4.7 Examining datasets with the implementation of error analyses: The test was conducted by putting the dataset into forecasting procedures and the errors would be calculated based on each of their respective group (Figure 1). The results were used to determined errors, leading to the selection of appropriate error analysis for such a dataset.

4.8 Creating patterns for the selection of error analyses: The test results were used to design and create patterns for the selection of error analyses to be implemented on the time-series forecasting, leading to effective selection of forecasting methods.

5. Conclusion

From the review of literatures and associated studies of the error analyses to determine the effectiveness of forecasting techniques, mostly, the implementation of more than one error analyses and the results are usually conflicting, rarely moving onto the same directions. This makes difficult for the selection of forecasting techniques, leading to a research gap. This study is the first part of content that presents the review of literatures and associated studies to fill the research gap and lead to the concepts towards the improvement of the selection of suitable error analyses for time-series forecasting. This paves ways to the accuracy rates of the selected forecasting techniques. The researcher, therefore, specifies this research structure for use as research procedures for the next presentation of the and research results shall be presented in the next issue.

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