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Coursework Submission Sheet

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Executive summary

Business forecasting utilising accessible algorithms has become more complicated. Modern approaches: machine learning can learn from different data to produce adequate outcomes, depending on the data amount and method complexity. Many companies need help estimating business or sales direction using these methods. Researchers examined prediction model selection techniques to solve or clarify the previous problem. This research analyses regression, exponential smoothing, and Arima, three popular model-fitting algorithms. To provide relevant potential results followed by different kinds of business data. The initial part manually models a one-time series as industry data by assessing three algorithm ideas and generating forecasts and comments to help organisations choose these approaches. In the following section, we propose a framework that balances accuracy and computational cost and presents forecasting outcomes with three alternative methods, which are compared to select the best approach and evaluate the different aspects for applying with business to predict valuable results to reduce costs or resources by preparing materials following these forecasts. We offer reasonable comments and recommendations for three strategies to fit organisations interested in implementing our study. We will help firms and analysts develop this empirical experiment to improve their business strategy.

1) Introduction

Forecasts play an essential role for many firms as they assist in preparing for future situations and reducing costs, leading to improved customer service. These benefits are derived from knowledge and experience gathered through empirical experiments. This report analyses a time series dataset, specifically the monthly data from the M3 competition, to select appropriate methods while considering various factors such as time and type of series.

The first part involves exploring a specific time series dataset to identify characteristics and unusual patterns before estimating fitted models. Then, it brings them to select the proper model by using error measurements, producing the prediction data in the next 18 months, and considering the result properly.

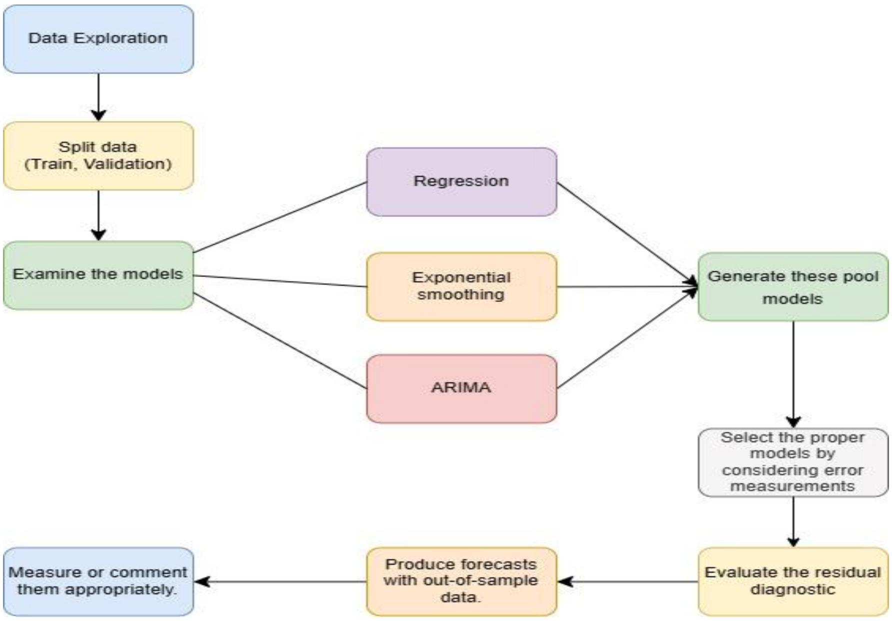
The second part concentrates on generating forecasts for multiple time series using automatic models (ETS, Arima) and proposes a suitable strategy for producing estimates for this group of time series.

Additionally, this section presents the evaluation process, demonstrating the reasons for recommending these approaches through an analysis involving three error measurements. It tests the accuracy and performance of each method with three benchmarks. It investigates the business aspects of each time series, including time horizon, characteristics of time series, and data categories. The paper concludes by providing some constraints and suggestions for future research.

2) Time series manual modelling

The first part explores the patterns and unusual of the target dataset. It shows the following steps to find the appropriate model using three models: regression, exponential smoothing, and Arima. These models are applied to forecast the next 18 months' data, followed by Figure 1.

Figure 1: the manual modelling process flowchart.



2.1) Data exploration

Table 1: showing the statistical descriptive summaries.

Minimum	Maximum	Average	Standard derivation
3721	6107	4826	513.5

We analysed the industry business monthly data (ID: 1910). Initially, evaluate it in trend terms. Figure 2 shows that this data has a downtrend in the beginning, roughly four years, and then moves sideways until 1991. The standard deviation, minimum, average, and maximum of the statistical data are 513.5, 3721, 4868, and 6107 (Table 1). However, the STL decomposition graph in the reminder section showed a substantial spike in 1985, indicating that the data had a higher error, which may have affected the estimated model's training model performance.

Figure 2: the STL decomposing plot of M3 competition time series id = 1910

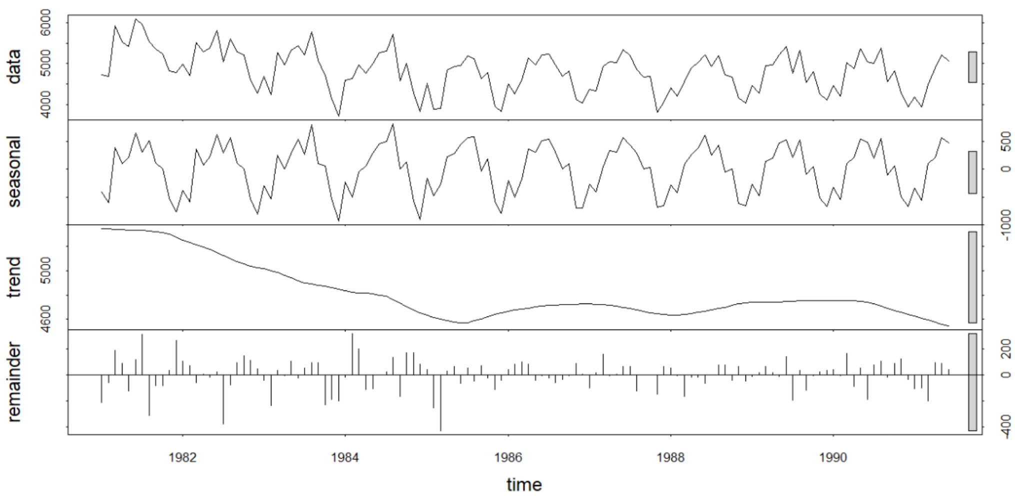
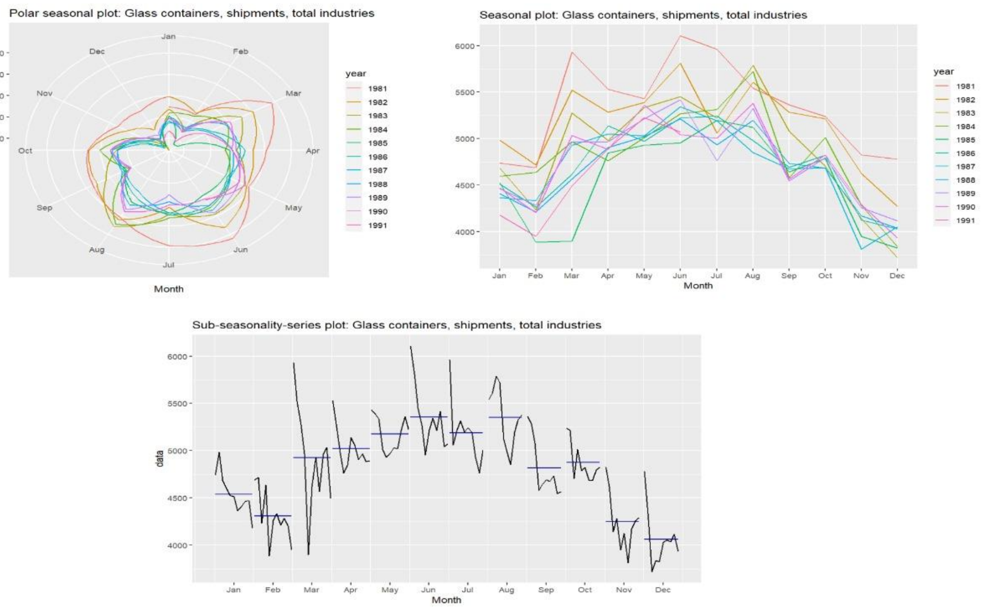
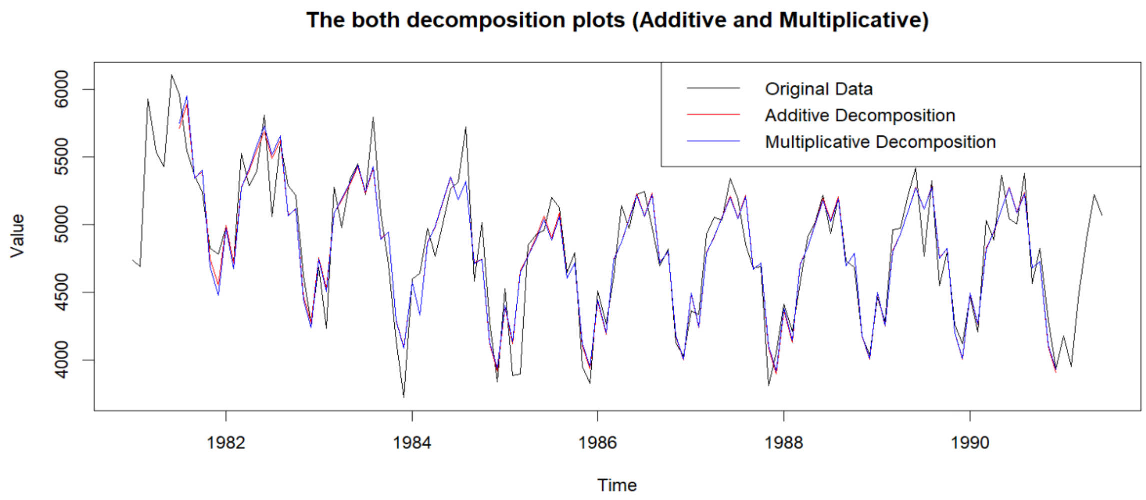


Figure 3: the seasonality plot of M3 competition time series id = 1910



[Figure 3](#) demonstrate typical and special seasonality, usually in August. Typically, June 1981 is the highest, indicating that this month sales more products. Winter is the low season for commerce, as shown on the charts. Sales peak in summer after rising in spring. Finally, it drops in October. In March and June 1985, unplanned some climbed, and others fell. In July 1981 and November 1987, there was a decline whereas many other periods increased and rose subsequently.

Figure 4: showing both of decomposition plots between additive and multiplicative.



The kind of seasonality cannot be concluded as additive or multiplicative because, from [Figure 4](#), there is doubt that the similar fluctuated trend is things that show two kinds of similar patterns. We will find a suitable model by examining these models later. This part displays some critical factors to consider in generating the pool models in the next section.

2.2) Training and selecting the best models

This subsection examines the pooled estimation of three methods: regression, exponential smoothing, and arima. It involves estimating the models, measuring the error benchmark, and observing the residual diagnostics to identify the suitable model. In the end, it forecasts the next 18 months' values and provides appropriate comments.

2.2.1) Regression

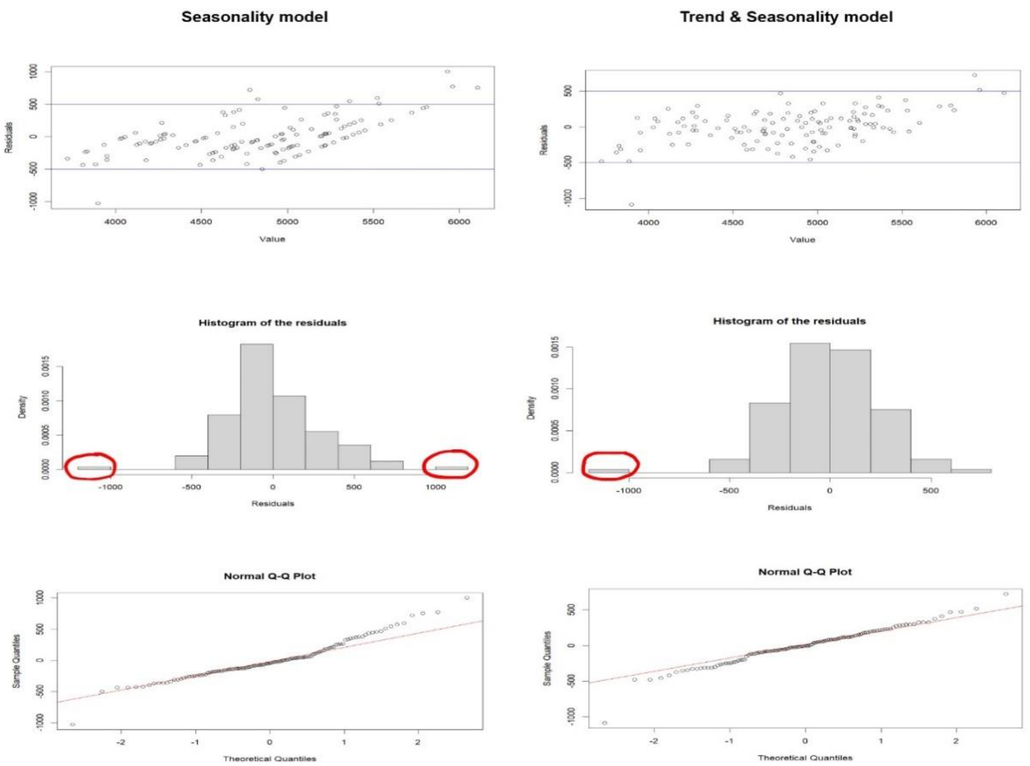
In the first stage, the experiment generates four fitted models: (non-trend, non-seasonality), (only-trend, non-seasonality), (non-trend and only-seasonality), and (trend, seasonality). The pooled models are evaluated to select the appropriate model by analysing the residual diagnostics and observing the residual distributions. After predicting the next 18-month data in the forecasting evaluation (2.3).

These methods are defined, utilizing two datasets: in-sample and out-sample. The first dataset trains the fitted models, while the second dataset validates the accuracies. They are considered to find the least error measurement to select the suitable approach. Before forecasting the next 18 months' data, we observe the error distributions to identify significant patterns for developing or reducing the failure of the models in future research.

Table 2: show the error measurements (MASE) of each regression models.

Regression models	MASE
No season, No trend	1.08
Trend, No season	1.25
Season, No trend	0.58
Trend,	0.63

Figure 5: comparing the residual diagnostic between seasonality and trend-seasonality fitted models.



Although the third model has the lowest error measurements, it is needs to be better in the distribution of residual terms like the last fitted model; this method has a better normal distribution of residuals and linearity terms than others. The fourth model seems to fit more with the target series than the third model, and this approach is related to the observation of the time series in the previous section, which has the trend and seasonality patterns. Thus, the trend-seasonality regression fitted model is the best choice from every option, concluding that it is selected as the suitable estimate schema to forecast in the next section.

2.2.2) Exponential smoothing

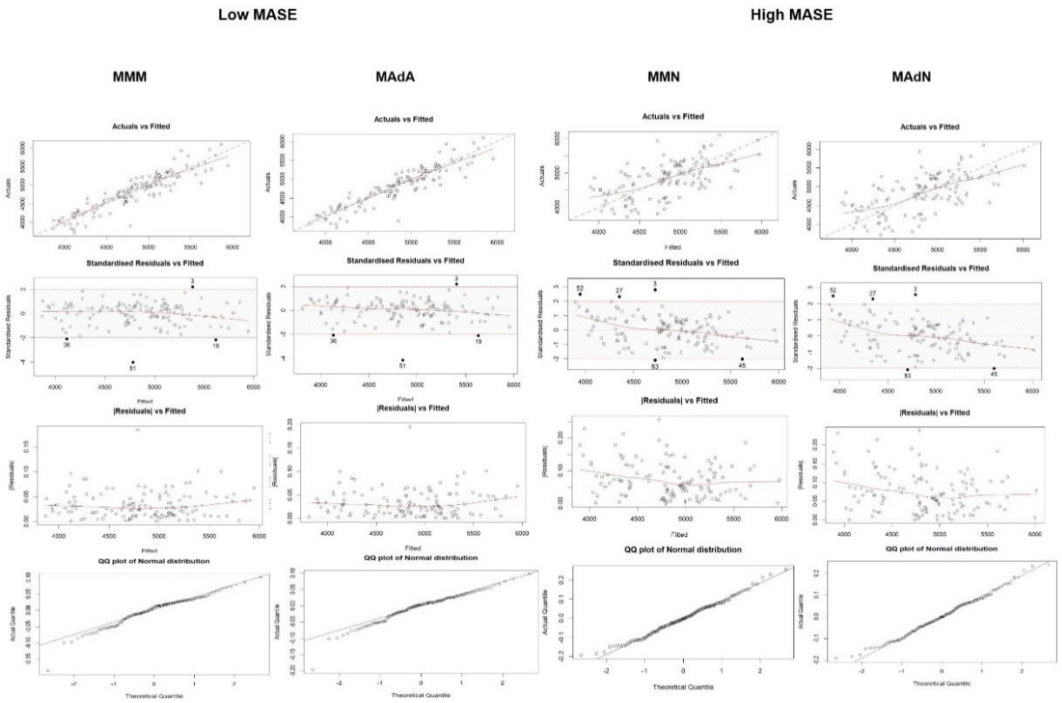
In this subpart, we will consider 19 exponential smoothing models from 30 models, as the remaining ones sometimes lead to approximation difficulties and unlimited predictions for long horizons (Hyndman et al., 2008, Chapter 15). For this reason, when implementing the estimation schemas using modern forecasting tools, such as the forecast package of the R statistical software, it avoids applying those models and after defining these fitted models, measuring the MASE, and exploring the residual diagnostic to find the suitable model with minimum errors and the most relevant residual plots. Lastly, the 18-month future data was forecasted in the examination section.

Table 3: show the error measurements (MASE) of each exponential smoothing models.

Exponential Smoothing			
Additive	**MASE**	**Multiplica**	**MASE**
ANN	1.227	MNN	1.22
ANA	0.471	MNA	0.462
AAN	1.154	MNM	0.482
AAA	0.506	MAN	1.412
AAdN	1.226	MAA	0.503
AAdA	0.449	MAM	0.542
First digit:		**MAdN**	**1.59**
(Additive/Multiplcative) Error		**MAdA**	**0.44**
Second digit: Trend		MAdM	0.448
		MMN	**1.588**
Third digit: Damped		**MMM**	**0.407**
(acronym has 3 digits it		MMdN	1.577
Last digit: Seasonality		MMdM	0.443

Table 3 shows that MMM and MAdA models perform best, with the lowest error rate of 0.407. In contrast, MMN and MAdN models perform worst; compared with the highest error rate, there is a considerable difference, roughly four times. Before selecting the suitable model, we will explore the distribution of residuals to observe the relationship between actual and fitted values.

Figure 6: comparing the residual diagnostic between two lowest MASE and two highest MASE models.

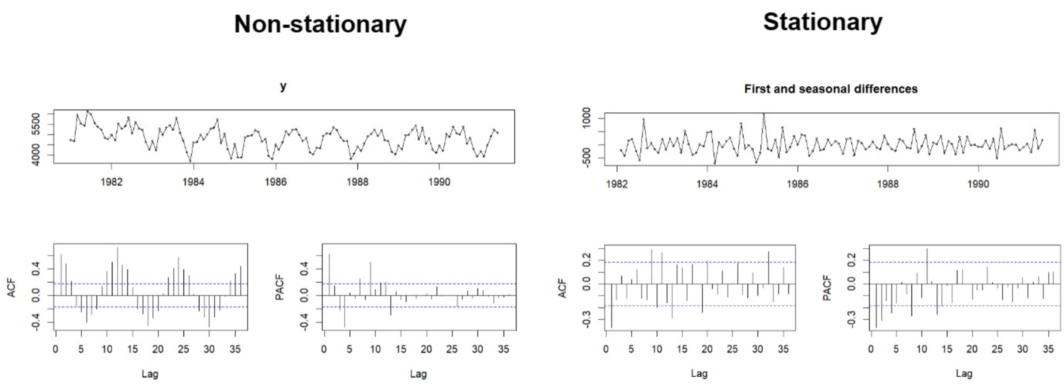


To analyse these distributions, admirable models present reasonably grouped distributions, whereas higher error rate models provide unsatisfactory distributions because they are more widely distributed than other groups. It shows that their models need to relate to the time series more. Consequently, we chose the MMM model because distributing the good model group is quite similar in evaluating residual diagnostic terms. We considered the suitable model by the lowest error rate (MASE).

2.2.3) ARIMA

In the initial step, it observed the unusual patterns. It tried to modify non-stationary to stationary by taking differences in both non-seasonality and seasonality terms, taking the differences once per Arima schema. We can see the difference between these types from Figure 7, in which stationary does not have trend and seasonality patterns.

Figure 7: comparing between non-stationary and stationary patterns though plotting time series.



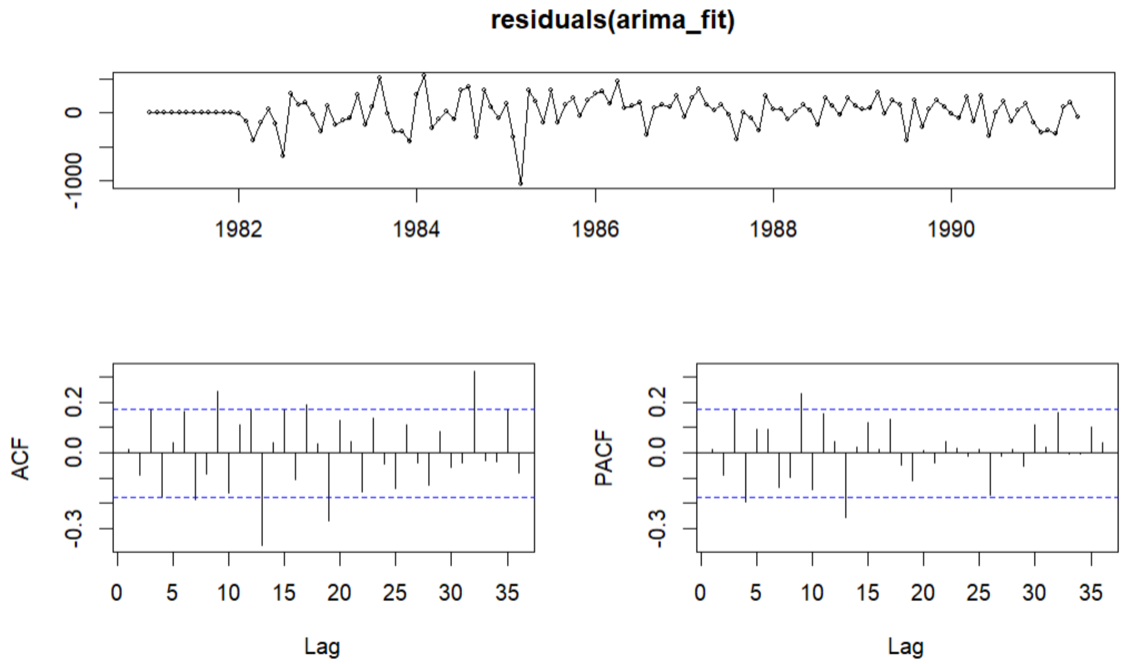
We will bring this data to reduce the estimated models after fitting models from the previous information. In this case, we will use d, D = 1 (non-seasonality, seasonality) because taking the difference two times from the experiment above, one time in season and non-season. Four models of this pool of Arima model are defined, and the benchmark measurements (AICc) are displayed in Table 4.

Table 4: show the AICc of each ARIMA model.

ARIMA		AICc
(p,d,q)	(P,D,Q)	
0,1,1	0,1,1	1572.74
1,1,0	1,1,0	1609.66
0,1,2	0,1,1	1574.77
2,1,0	1,1,0	1592.14

It is evident that the arima model (0,1,1) (0,1,1) is the best model for this time series dataset because it has the lowest AICc at 1572.74, indicating the slightest error among the pool of models.

Figure 8: residual diagnostic of ARIMA (0,1,1) (0,1,1) model, showing the stationary and white noise.

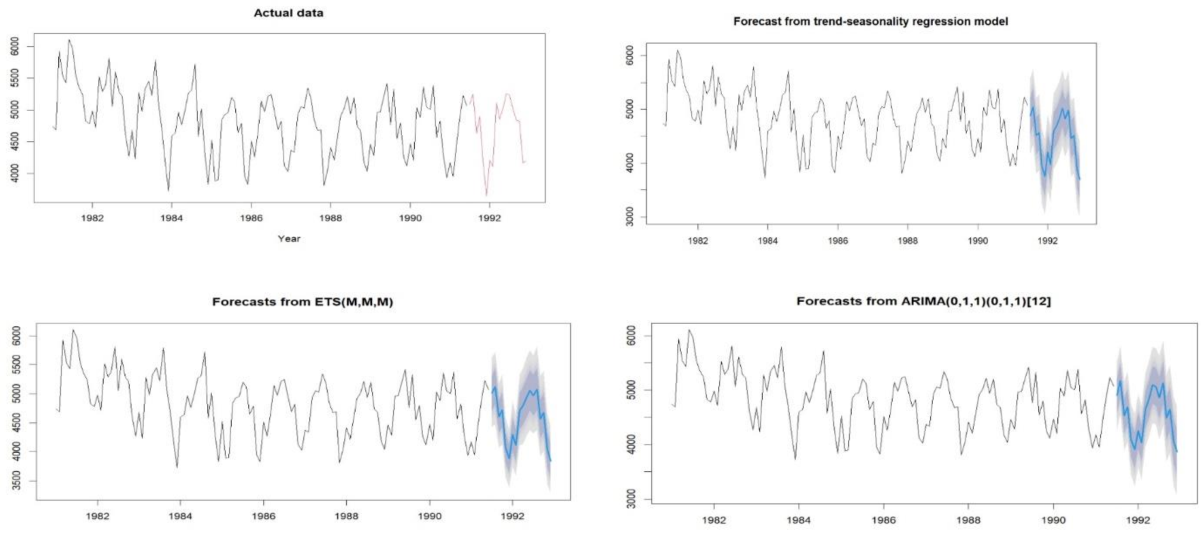


From the evaluation of Figure 8, this arima fitted model displays the stationary in residual term. Moreover, ACF and PACF present the white noise patterns, it means that this model is suitable for the time series by the best AICc and residual diagnostic terms. Thus, we decided to select Arima model, which are d, D, q, Q = 1, in the next section, we will bring best three models to produce the forecasts of horizontal 18 months of the industry data and provide some proper comments.

2.3) Examination and interpretation of forecasted outcomes

We will produce the forecasts by three models and provide the error measurements (MASE) to consider the best performance of this time series.

Figure 9: comparing forecasts of the M3(1910) in 18 months from three suitable models with actual data.



From these forecasts, it is evident that before 1992, there was a significant decrease, and the forecast models consistently provided overestimated values compared to reality. Furthermore, at the top, around 1992, in the second quarter, the predictions appear to rise, contrasting with the actual data, which has a drop in a short period before moving up. This has contributed to the drop in the accuracy performance of these models. Consequently, the prediction interval of each model has been closed in the range of 3500 to 5500. For this reason, considering the seasonality components makes the predicted results quite similar.

Table 5: show the MASE of each pool models.

Model	MASE
Regression	0.682
ETS	0.444
ARIMA	0.51

In terms of error measurement, exponential smoothing can provide the best performance to give the forecasts when compared to others for the time series. This model has more adaptable capacity with unknown data than the remaining models, which are pretty overfitted because it can produce good results only training dataset. It concludes that the part presents how to explore the data to find the significant information before fitting the model, how to find the justified model by self-adjusted model and produce the forecasts. It gives some remarkable comments for each schema. In the next part, we will explore the data 100 series and define the strategy model to produce the appropriate forecasts on empirical results in the chapter.

3) Defining the model selection strategy

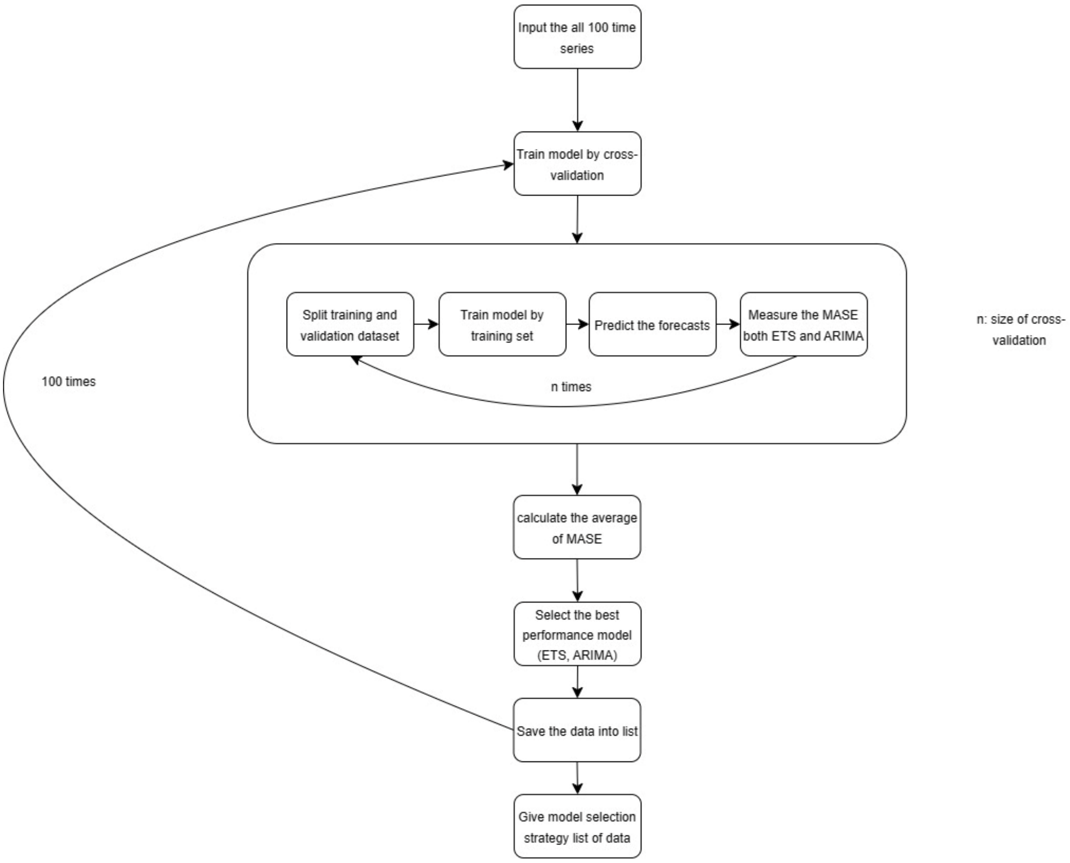
In this section, we present the strategy to select the suitable model in each time series by defining the method to justify the proper model from two options (automatic exponential smoothing and arima models) and then implementing this strategy to classify the best choice for each time series.

3.1) Definition and justification

We present the concept to justify the model of these groups of time series; researcher studied the experimental model selection design of Robert and Fotios (2015), adapting and reducing some steps to reduce the complexity of implementation of this approach.

It applies cross-validation to reduce overfitted events in manual modelling by letting models learn with different data and adapt to unknown data while predicting future data. They get better outcomes by using reality more than previously.
We will justify the evaluation of the model using the mean absolute square error (MASE), assessing the lowest desired model value.
Run all one hundred time series with half of each in-sample time series data size times for cross-validation. Combining time-series data and cross-validation times costs 100 * n (assuming the average size of running cross-validation every series = n) and calculating two automatic selection procedures.
Dynamic computing complexity depends on the cross-validation training dataset. Around 200 * n is this case's combination.

Figure 10: the diagram shows how to construct the model selection strategy.



From the diagram above, we will do the cross-validation firstly, splitting the training and validation datasets and then calculating the average of MASE to compare between ets and arima model finding the least error, doing the previous process every time series. Finally, it displays the selection model information. We can use this to justify proper model for each time series in the next section.

3.2) Implementation
This subsection discusses the method of constructing the model selection strategy; it explains more detail in Figure 10 in implemental terms and explains when we use this strategy to provide forecasts.

Initially, determining how to take the suitable model between ETS and ARIMA by using automatic model selection, we choose the model by averages of MASE, which this value can get from the cross-validation process that is more clarified in the next paragraph. If what model can provide the least error measurement, we decide to select it.

In the cross-validation step, this method can develop the adaptable skill of the predicted model because it will help the model learn with various data, and it can help them provide the results flexibly when using different kinds of data, such as predicting with reality information. These had mentioned in the previous part. First, we run a training model with data around half of the training data size and collect the MASE by calculating the average of this error measurement by considering the forecasts of the fitted model and validation dataset and following to select the best performance between automatic ETS and ARIMA models.

Table 6: showing the summary number of individual model selection between arima and exponential smoothing.

Choose	Amount
arima	45
ets	55

Table 6 displays that the exponential smoothing family is chosen over the arima family, revealing that the ets selection approach suits the datasets. A list of data stores each time series' suitable model selection.

The model selection list of data is used to justify model selection while performing batch forecasting, using Choose attributes to determine which model should predict results.

In conclusion, cross-validation can reduce overfitted models, but it may take a long time (25 minutes for training) and produce unsatisfactory results, depending on computer performance and target data size. We recommend parallel computing, which uses several computer cores to compute predictions. This strategy can reduce the substantial time needed to calculate empirical results.

4) Batch forecast experiments
In this section, it presents the determine three error measurements and three benchmarks, which are used in this test, and the result of batch experiments and provides the evaluation detail in three main parts, such as performance by calculating the three error measurements, comparing the accuracy between the benchmark methods and the selection methods, and analysing the significant components likes horizontal, characteristic, and type of time series.

4.1) Justify the error measurements and benchmark methods
The batch forecast process uses three error measurements and three benchmark methods to analyse and compare the performance of each approach. This part will define and explain why we choose to use these values to consider the performance and accuracy of these techniques.

To determine the error measurements in this case, working with different time series data (one hundred time-series datasets) is essential. We have chosen to utilize sMAPE and sMdAPE to explore forecast errors because these formulas are designed to compare prediction efficiency across different datasets and prevent division by a number close to zero case (Hyndman et al., 2006, p. 683). Additionally, we have selected MASE, as it addresses statistical distributions with an undefined mean and infinite variance (Hyndman et al., 2006, p. 685), making the performance accurately. Therefore, these measurements are appropriate for analysing our dataset.

The benchmarks are selected, considering three features: seasonality, trend, and damped. We chose Naive2, Holt's (linear trend), and damped (Makridakis et al., 2000). Naive2 is the method consider the last seasonal observations, it is good at fast level change, but have problems with data with outliers. Holt's approach considers the trend and additive error, it fits with trend information. Damped is one kind of the exponential smoothing model that consider about trend and damped, it is extension of Holt's to develop working data which may be damped patterns. These criteria are compared with three approaches in Section (4.3).

In conclusion, this section provides the determination of error measurements and benchmark methods to analyse in the batch experiments including performance and cost, accuracy of these practices and significant time-series components (horizon period, characteristic, type). These values are analysed and give some proper comments in the next section.

4.2) Forecasting performance and cost.

This part shows three approaches' forecast error (the next 18 months). It explains the experiment's insight to clarify why the method best fits the target group of time-series and gives some opinions to expand the worth of the aspect of strategy selection methods.

Table 7: showing the error measurements of three approaches across the forecast of the next 18 months.

Approach	MASE	sMAPE	sMdAPE	Cost (sec)
ETS	0.88	15.03	13.34	14.56
ARIMA	0.89	15.64	14.01	55.32
Model selection strategy	0.86	14.69	12.99	29.12

Table 7 displays the performance of the three model selection processes, evaluated using MASE, sMAPE, and sMdAPE measurements. The model selection strategy is the most effective method for overall performance in producing forecasts with the most minor error compared to other options. This strategy selects the best-performing model between ETS and ARIMA selection, calculating the average error measurements, and reducing the error rate from selecting the best model for each time series.

Although automatic ETS selection can save more time, cost, and energy in running models than other approaches, it poses a higher risk of failure than our determination strategy. Regarding the ARIMA selection process, it fails to provide satisfactory performance and cost-effectiveness. It is the most time-consuming at 55.32 seconds to produce forecasts for the next 18 months, roughly double and triple the time taken by the model selection strategy and ETS selection, respectively.

Despite the exponential smoothing family providing good forecast results, it may not always work with another time-series dataset. In this case, the time series may fit more with ets than arima selection strategy, but if it works with dataset with varied characteristics or patterns. arima may be better to give the least forecast error because it is more flexible, it has the infinite possibility to fit models (Box et al., 2008). Even though this may provide good performance, it appears to spend more time to compute. In this case, determining strategy is the most suitable approach.

4.3) Benchmark method accuracy comparison

This subsection shows the comparing accuracy between three approaches and three benchmarks Additionally, providing some comments of each benchmark and concluding overall of every benchmark.

Table 8: Comparison relative percentage of various methods with Naïve 2 as the benchmarks.

Approach	MASE	sMAPE	sMdAPE
ETS	19%	19%	20%
ARIMA	14%	16%	14%
Model selection strategy	20%	21%	21%

From the table above, it is evident that the determination model selection strategy can provide outstanding performance, more efficient by over 20% compared to the Seasonality Naïve method. Generally, all three approaches are more effective than the Naïve 2 method, roughly 14 to 21 percent. It reflects that the Naïve 2 benchmark may not be well-suited for the group of time series datasets, as considering only the seasonality feature is insufficient to analyse the forecasts accurately. It could be why this benchmark still provides relatively high error rates. However, Naïve 2 is the fastest and least costly method compared to other processes. Thus, our model selection is the best schema when compared with others.

Table 9: Comparison relative percentage of various methods with Holt's as the benchmarks.

Approach	MASE	sMAPE	sMdAPE
ETS	2.2%	7.0%	6.8%
ARIMA	1.8%	2.9%	0.2%
Model selection strategy	6.4%	7.2%	7.5%

Table 9 shows that the three model selection approaches are more effective than Holt's benchmarks in the 0.2% to 7.5% range. The self-determined model selection is a remarkably better strategy, providing more accuracy than other methods.

Regarding MASE, the combination of ets and arima selection is more accurate, around three times better than ets and arima selection strategies alone. Interestingly, the three model selection processes are less efficient when compared with Holt's; they show more significant differences in performance when compared to Naïve 2. The considered features of Holt's method, namely level and trend patterns, slightly affect prediction accuracy.

Although this benchmark produces good forecasts, these three model selection strategies can provide more satisfactory results.

Table 10: Comparison relative percentage of various methods with Damped as the benchmarks.

Approach	MASE	sMAPE	sMdAPE
ETS	2.65%	2.04%	-1.08%
ARIMA	-4.72%	-4.91%	-10.47%
Model selection strategy	-0.05%	0.01%	-2.80%

For the last benchmark, it is well-fitted with the datasets. arima and our determination selection approaches produce unsatisfactory forecasts, with negative differences in every error measurement. In contrast, the exponential smoothing family can give outstanding performance, producing more accuracy than damped benchmarks by around 2%. However, it provides a negative sMdAPE, reflecting that damped can work with median data better than the ets selection strategy.

In conclusion, despite the model selection strategy producing the best performance compared to Naïve 2 and Holt's methods, the ets selection approach can provide remarkable forecasts compared to the damped benchmark. As displayed in the previous experiments, it is obvious that trend, level, and damped are significantly affected by prediction results.

4.4) Component analysis

We analysed the performance of three model selection strategies in Table 7, but it is analysed in overall term. To categorise sub significance components in this subsection has three categories: different across horizonal time, different across time series characteristics, and different across time series type. Giving some reasonable comments and concluding in the end of this part.

Table 11: Comparison the performance across different time horizons.

	Short-term (quarter)			Medium-term (3 quarters)			Long-term (6 quarters)		
Methods	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE
ETS	0.58	12.5	11.39	0.73	13.66	12.21	0.88	15.03	13.34
ARIMA	0.62	13.02	12.03	0.75	13.71	12.57	0.89	15.64	14.01
Model selection strategy	0.57	12.33	11.12	0.71	13.23	11.83	0.86	14.69	12.99

With the exploration of different horizons shows that these approaches can produce better short and medium terms forecasts than long-term forecasts, as the period has a significant impact on prediction. Long-term forecasts deliver unsatisfactory results. Overall, short-term forecast error rates are 1.5 times lower than long-term predictions. These selection algorithms exhibit similar forecast errors, implying that time has seriously influenced every schema.
As observed, the relative effectiveness of different methodologies shows that the duration considerably affects forecast accuracy. We propose applying a quarter-horizon (three months) to forecast future information using these selection methods because it is more accurate. Estimating four quarters of data for the following year may be more likely to be wrong than predicting one quarter. Thus, firms' future usage of these forecasts depends on their expectations.

Table 12: Comparison the performance across different time series characteristics.

Methods	Trend			Seasonality			Trend/Seasonality			Not Trend/seasonality		
	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE
ETS	1.04	13.84	13.21	0.77	17.27	14.08	0.83	7.28	6.54	0.79	24.08	20.96
ARIMA	0.89	15.24	13.73	0.68	7.09	5.4	0.89	5.05	4.5	1.03	31.93	28.81
Model selection strategy	1	13.11	12.42	0.63	16.81	13.72	0.84	6.51	5.68	0.76	26.34	22.41

In terms of time series characteristics, arima family can produce excellent trend, seasonality, and trend and seasonality results but disappointing results in other features. Our determination selection offers satisfactory outcomes, although some error measures have larger error rates than exponential smoothing. The experiment showed that every technique struggles to identify untrendy and non-seasonality, making them unsuitable for this kind of data.

Table 12 demonstrates that the arima and model selection groups have lower MASE values for seasonality than other variables. This feature greatly affects forecast accuracy. Three approaches can provide surprising trends and seasonality results that are lower than other aspects. The model selection strategy works best in the time horizon component (Table 11), but when considering time series characteristics, arima selection approach can provide outstanding findings in various characteristics if its value is not the lowest error rate across all approaches.

Table 13: Comparison the performance across different type of time series.

Methods	INDUSTRY			MACRO			MICRO		
	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE	MASE	sMAPE	sMdAPE
ETS	0.91	11.52	9.97	1.02	8.28	8.52	0.75	23.56	20.22
ARIMA	0.93	11.25	10.16	0.88	6.82	6.55	0.86	26.58	23.39
Model selection strategy	0.86	10.48	9.15	1	8.2	8.43	0.75	23.56	20.22

Labelling time series by industry, macro, and micro companies. The 18-month forecast error is shown in Table 13. These time series reveal that the three techniques work better with micro than other types, with MASE errors of 0.75, 0.86, and 0.75. However, these selection methods provide insufficient consequences for the industry at 0.16, 0.07, and 0.11 with optimal MASE compared to micro field.

The three methods give good MASE values but unsatisfactory sMAPE and sMdAPE. The three model selection methods may not work for this data if we evaluate the accuracy of model selections using these two-error metrics. In contrast, their techniques perform well in every error measurement with macro type.

Obviously, we can use this empirical result to predict the future trend of macro-organizations. Our three model selection procedures perform well with short-term projections, trend and seasonality data, and macro business information.

5) Conclusion

The empirical results of both parts indicate that the exponential smoothing selection approach produces outstanding results; it affects the individual model selection strategy can provide satisfactory outcomes because it selects the slightest errors between ets and arima automatic selection. Overall, this strategy can produce the best performance with the group of datasets.

The constraints have occurred: the size of target data and complex automatic selection as a lack of computation cost. Firstly, having an enormous amount of data will affect the calculating time to provide the forecasting consequences. Another factor is the complexity of fitting any selection approaches, which influences the time of calculations and consequences.

Regarding lack of accuracy, exponential smoothing is suitable for working with patterns data: level, trend, and seasonality. It may not offer the appropriate forecasts when it works with fluctuating data. Arima family will be suitable for this case because it has infinite fitting schemas.

We recommend uses the model selection strategy to predict in short and medium because it can provide more reasonable results when compared in long term. In addition, this approach has been efficacy with trend and seasonality characteristic of data appropriately as well as overall forecasting consequences of various kinds of business, it performs pretty good results, especially in micro firms. Moreover, before using the individual selection approach, companies and analysts should prepare the appropriate data or insights with some significant patterns like trend or seasonality to improve forecasting performance; it can estimate the proper business plan to receive the most benefit.

6) References

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