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MUNICIPAL SOLID WASTE VOLUME FORECASTING IN KUCHING, SARAWAK MALAYSIA TO ADDRESS NON-FIXED SEASONAL VARIATIONS USING ADJUSTED TREND SEASONAL INDEX MODEL

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Abstract

Municipal Solid Waste (MSW) is a critical issue globally, particularly in developing countries experiencing rapid economic growth and urbanization. However, the resources, infrastructure and waste collection practices in these countries often struggle to keep up with the increasing waste generation, leading to public health and environmental sustainability concerns. Efficient MSW management necessitates strategies to meet growing waste collection demands within resource constraints, with waste collection planning playing a pivotal role. This research focuses on forecasting MSW volume to inform waste collection planning efforts. While various studies have explored predictive models using economic and population parameters, these approaches often face limitations, particularly concerning data availability and applicability for smaller timeframes and specific geographic areas. To address these challenges, this research proposes a novel time series forecasting method - the Adjusted Trend Seasonal Index Model with Non-Fixed Seasonal Component. Economic and social activities exert a substantial influence on MSW volume, with seasonal fluctuations playing a crucial role in accurate forecasting. Notably, in Malaysia, numerous non-fixed festive seasons, such as Chinese New Year and Hari Raya, significantly impact MSW generation. However, the dates of these festive seasons vary annually. By leveraging time series MSW volume data and non-fixed seasonal dates for specific areas, the proposed model calculates MSW trends and seasonal fluctuations, thereby enabling more precise forecasting of MSW volume. A real-world MSW volume dataset obtained from a local waste management company will be utilized as both training and testing data for model development. The performance of the forecasting models will be evaluated using MSE, RMSE and MAE. Additionally, the proposed model will be compared with the conventional Trend-Seasonal-Index model and SARIMA model. This comparative analysis aims to ascertain whether the proposed model can improve accuracy and successfully tackle non-fixed seasonal issues.

Keywords: Municipal solid waste, Seasonal index model, Time series forecasting, Waste generation forecasting.

1. Introduction

Municipal solid waste (MSW) management is a critical issue requiring attention due to its direct impact to our living environment, including environmental pollution, water and air pollution, public health concerns, safety crises, hazardous leachate, and more. In developing countries like those in Southeast Asia, rapid economic development urbanization contributes to an increase in municipal waste volume as well as the demand of waste collection.

However, the waste management infrastructure, resources, and practices in these countries struggle to keep pace with the speed of MSW generation. Malaysia as a developing country, grapples with MSW issues. Malaysia government has spent RM 1.9 billion per annum for solid waste collection and public cleansing [1]. Failure to address the MSW problem can severe consequences for the city and the country.

According to Ng et al. [2], Malaysia Government faces the waste management challenges due to rapid city development and improvements in living standard, resulting in an average daily waste generation of 38,207 tons, approximately 1.17 kg per person per day. The potential impact of 38,207 tons of uncollected and improperly disposed waste on cities and the country is considerable. According to Johari et al. [3], improperly managed MSW could lead to greenhouse gases issue, climate change, leachate water pollution etc. In addition, solid waste management in some areas of Malaysia remains self-sufficient, which can lead to open dumping and illegal disposal practices [4].

Therefore, an improvement of MSW management is important. While upgrading infrastructure and resources is a vital consideration for solving the MSW collection issue, achieving significant results may be time-consuming and costly. According to Zainu and Songip [5], high cost is one of the challenges in managing MSW. Most of the local authorities are not able to absorb the expenditure cost as managing MSW and public cleansing cost 40-80% of local authorities' expenditure.

A new landfill will cost around RM30 million in average, and the operation cost is around RM 40 per tonnage in average. In addition, Malaysia is lacking a decision support system in waste management industry, while it is compulsory as it can support good waste collection strategy. Therefore, this paper explores method to improve MSW collection planning and practices while considering limited resources, aiming to minimize the problems and the risks associated with MSW.

In Malaysia, most states employ a fixed cycle collection schedule for waste collection service. Waste management companies will design the collection area boundaries and determine collection team assignments and frequencies. In Kuching, Malaysia, the waste management company is using similar approach to do the waste collection task. First, the waste management company will divide the whole city into smaller unit, which are areas. Every collection area has its own boundary and collection frequencies (e.g., Mon-Thu, Tue-Fri, Wed-Sat). The management team must ensure the collection for every area fulfil it waste collection demands.

However, this collection planning method is assuming steady MSW volume and the team's capacity to meet collection demands, but, in actual fact there will always have fluctuation for MSW volume. Hence, the waste management company requires MSW volume forecasts to adjust on collection resources based on MSW demand fluctuations. This paper aims to develop a forecasting model that can forecast MSW volume to provide insights for optimizing waste collection planning.

2. Literature Review

In recent years, predictions and forecasting using computers have gained popularity, facilitated by the creation of numerous mathematical models and advancements in computing capabilities. This trend extends beyond the waste management industry; it is also a focal point for researchers across various fields. The following section will outline the existing forecasting methods in the waste management sector and other related industries.

Machine learning has become a common tool for prediction. According to Nguyen et al. [6], they applied machine learning techniques to predict solid waste generation in Vietnam, and they emphasized that feature selection is a critical factor influencing prediction outcomes. Within the domains of population, economy, and consumption, they identified urban population, average monthly consumption expenditure, and total retail sales as the most influential features affecting prediction models.

Additionally, Du et al. [7] also mentioned MSW generation is largely dependent on economic and social activities. It is because MSW is the byproduct of daily consumables, it will increase when people have better purchasing power. Moreover, population size is a significant factor affecting MSW generation; more people result in more waste, and vice versa. In Nguyen et al. [6] research, various machine learning methods were compared to identify reliable prediction models. Following the comparison of Random Forest [8], K-Nearest Neighbour [9], Linear Model [10], Support Vector Machine [8], and Artificial Neural Network [11], it was found that Random Forest and K-Nearest neighbour exhibited superior predictive capabilities in the waste management field.

While demographic and economic factors have been proven to be crucial in forecasting MSW volume, the availability and usability of data are equally important when selecting features. Notably, not all inputs are suitable and available for constructing prediction models in certain study cases. Before developing a prediction model, consideration should be given to the accessibility of economic and demographic data for waste management companies, and whether such data inputs are suitable for their waste collection strategy. In Malaysia, where most waste management companies oversee waste collection for specific cities, planning often occurs on a smaller time frame, such as weekly and for specific areas. Consequently, economic and demographic data might not be readily available in these cases, given that such data typically pertains to entire countries or states, rather than specific city areas.

Time series forecasting stands out as a prominent method for predicting municipal solid waste (MSW) volume. In a study in XIAMEN, China, by Xu et al. [12], the authors forecasted MSW generation at multiple time scales using a hybrid model - Seasonal Autoregressive Integrated Moving Average (SARIMA) model and the Grey System. This model effectively forecasted MSW generation across different time scales without considering economic and societal factors, focusing solely on MSW weight and time series data. The hybrid model accurately predicted maximum and minimum MSW generation throughout the year, revealing a continuous increase in MSW generation over five years due to rapid economic growth in the developing city.

In addition to waste management, forecasting methods from related fields can also be considered, especially when the results are influenced by economic factors. Ismail and Ramli [13] studied seasonal indices for crime forecasting in Malaysia to prevent crimes before they occurred. They studied the relationship between crime occurrence and seasonality, determining which months crimes typically happen and whether special events during the season have any impact, and use Trend-Seasonal Index Model to forecast crime occurrences.

Additionally, in the study by Sharin et al. [14], network analysis and support vector regression were used to predict future COVID-19 cases in Malaysia. Their paper claims that the festive season in Malaysia is one of the potential factors affecting COVID-19 cases. Moreover, Foo et al. [15] conducted research on spatio-temporal clustering analysis for COVID-19 cases in Johor, Malaysia. Their study also found that festive seasons could influence the number of COVID-19 cases. These studies demonstrate that festive seasons impact the living habits of people in Malaysia, indicating that such factors could be crucial for accurately forecasting MSW volume as well.

Several considerations arise when employing the time series forecasting method. Firstly, one must consider data accessibility and appropriateness. As previously mentioned, for the purpose of generating weekly municipal solid waste (MSW) volume forecasts for specific areas, a historical weekly waste volume dataset is essential. Secondly, it is crucial to address seasonal fluctuations in time series data.

According to Tang et al. [16], time series data comprises trend, seasonal, and irregular components. In the MSW time series forecasting model, seasonal fluctuations play a vital role, given that the economy is also influenced by the seasonal component. In countries with frequent festive seasons, such as Malaysia with its diverse cultural celebrations, these events can significantly impact MSW volume. Different ethnic groups celebrating their respective festive seasons could bring about notable fluctuations in MSW generation.

Therefore, this study focuses on analysing seasonal fluctuations to enhance the accuracy of the forecasting model. Last but not least, a primary objective of this research is to address the issue of non-fixed festive seasons. Non-fixed festive seasons occur at varying times within each cycle. While they do impact MSW volume, their non-constant nature poses a challenge for traditional time series forecasting models in capturing data patterns. This challenge can result in decreased forecasting performance and accuracy.

3. Methods

This research introduces an adjusted trend-seasonal model to forecast MSW volume, incorporating considerations for non-fixed festive seasons. The adjusted trend-seasonal index model is based on the conventional trend-seasonal index model and is designed to address the challenges associated with forecasting local waste management. With the conventional trend-seasonal index model, it assumes the time series data contain three main components, which are trend, seasonal, and irregular component. The trend component reflects the long-term movement of the data over time, showing an upward, downward or a stable trend.

Seasonal components represent the predictable fluctuations occurring at fixed intervals, such as weekly, monthly, quarterly, or annually. The irregular component captures random fluctuation in the data, stemming from unexpected events or measurement errors. According to Ismail and Ramli [13], the time series data can be decomposed and get the respective component value by using multiplicative or additive decomposition analysis, and the final prediction result can be obtained by multiply or add the components' value.

The workflow of the conventional trend-seasonal index model is illustrated in Fig. 1. First, the most suitable trend equation, such as linear, exponential, or logarithmic trend equation, needs to be determined. Secondly, the chosen trend equation can be applied to calculate the trend value of the time series data. This future trend value will be used in the final step to forecast the weight of waste. Thirdly, the historical trend value will be utilized to eliminate the trend value from the time series data and obtain the detrended data, in order to calculate the seasonal value. Fourthly, seasonal indices can be extracted from the detrended data by calculating the weight ratio of the season's value. Lastly, both the trend value and seasonal indices can be multiplied or added to obtain the forecast result.

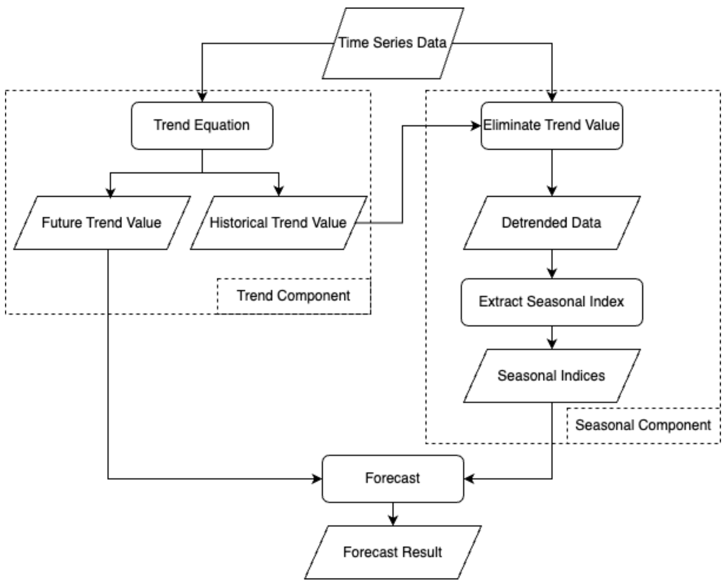

Fig. 1. Conventional trend seasonal index model workflow.

However, during the research we found that the historical MSW volume data might not have a significant trend, as in the real-life situation, the population in the particular area have an upper limit, it is because the population will not keep increasing year over year in a limited of living area, which means the MSW volume data will have its own upper limit as well. If we use the traditional trend component, which it calculates the trend for the overall time frame of the data, the trend will either go upward or downward year over year, however there will be a limit in the actual situation. In this research, the trend component has been adjusted, which the data will split into year, one year will represent one cycle, instead of calculating an overall trend, a yearly trend will be calculated as $T_{\{1,2,\ldots,i\ldots,n\}}$. In our research, the latest year trend value T_n will be used to forecast future weight.

Other than trend value, seasonal indices component also has been adjusted to overcome non-fixed seasonal issue. As aforementioned, the non-fixed seasonal could appear in different season, thus a conventional seasonal component could not help as it does not consider about the fluctuation that caused by the special event that happened in different season. The fluctuation that caused by non-fixed festive season need to be calculated and it will be included into adjusted trend-seasonal index model.

In addition, in the research we found the fluctuation of MSW generation is high, meaning the latest cycle data could provide a wrong impact to the forecast result. To reduce the fluctuation impact from the latest cycle, we assign different coefficient to the latest seasonal indices and non-fixed festive season variation. In the experiment phase, we found historical seasonal indices and non-fixed festive season variation own 0.7 coefficient, and latest seasonal indices and non-fixed festive season variation own 0.3 coefficient will provide the best forecasting result.

Figure 2 shows the blueprint of adjusted trend seasonal index model to forecast MSW generation volume. There are three main components in the flowchart which is Trend, Seasonal, and Non-Fixed Seasonal Component. Time series data need to be split into yearly before it can be used in three components.

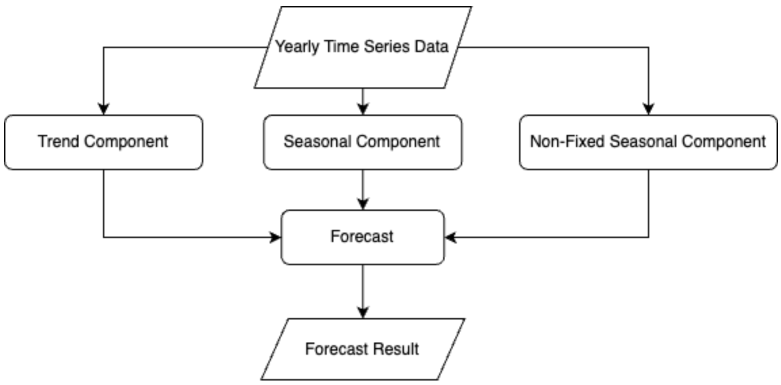

Fig. 2. Adjusted trend seasonal index model blueprint.

First, in the trend component, the yearly trend value can be found by applying trend equation. The latest year's trend value can be used to forecast new cycle MSW weight and historical trend value can be used for elimination to get detrended data. Once we have the yearly detrended data, we can extract the latest year's seasonal index. The latest seasonal indices will be assigned a coefficient of 0.3, while historical seasonal indices will be assigned a coefficient of 0.7 to obtain the final seasonal indices. These final seasonal indices will also become the historical seasonal indices for the next cycle.

In the non-fixed seasonal component, the objective of it is to identify non-fixed seasonal variations in MSW weight to address the issue of non-fixed festive seasons. Let's denote $NFSV_{nfs}$ as the variation of a particular non-fixed festive season. In our study, we have chosen Chinese New Year as the non-fixed festive season due to its occurrence on different dates each year and its significant impact on MSW generation. In our research, we have calculated the variations for five non-fixed seasons, including Chinese New Year, as well as one and two weeks before and after Chinese New Year.

Once we have the $NFSV_{nfs}$ values, we apply the same coefficients as mentioned earlier, with a coefficient of 0.3 assigned to the latest $NFSV_{nfs}$ and a coefficient of 0.7 assigned to the historical $NFSV_{nfs}$. Finally, once we have obtained the latest trend value, seasonal indices, and non-fixed seasonal variation, we can simply multiply them to obtain the forecasted result.

Additionally, we replace the forecasted weight for the non-fixed festive season with the calculated variation. The Table 1 shows the date of non-fixed season that we used in the study.

Table 1. 2012-2022 Chinese New Year date.

Year\NFS	CNY-2	CNY-1	CNY	CNY+1	CNY+2
2012	2012-01-09	2012-01-16	2012-01-23	2012-01-30	2012-02-06
2013	2013-01-27	2013-02-03	2013-02-10	2013-02-17	2013-02-24
2014	2014-01-17	2014-01-24	2014-01-31	2014-02-07	2014-02-14
2015	2015-02-05	2015-02-12	2015-02-19	2015-02-26	2015-03-05
2016	2016-01-25	2016-02-01	2016-02-08	2016-02-15	2016-02-22
2017	2017-01-14	2017-01-21	2017-01-28	2017-02-04	2017-02-11
2018	2018-02-02	2018-02-09	2018-02-16	2018-02-23	2018-03-02
2019	2019-01-22	2019-01-29	2019-02-05	2019-02-12	2019-02-19
2020	2020-01-11	2020-01-18	2020-01-25	2020-02-01	2020-02-08
2021	2021-01-29	2021-02-05	2021-02-12	2021-02-19	2021-02-26
2022	2022-01-17	2022-01-24	2022-02-01	2022-02-08	2022-02-15

4. Study Material and Experiment

This study was conducted in Kuching, Sarawak, Malaysia, with waste weight data collected by the local waste management company - Trienekens (Sarawak) Sdn. Bhd. The specific collection area chosen for this study is located under the jurisdiction of Kuching MPP (Padawan Municipal Council). The selection of this area is based on its predominantly Chinese residential population, allowing for the examination of the impact of non-fixed festive seasons. Chinese New Year is chosen as the non-fixed festive season in this study.

Data on waste weights (kg) for the area were collected from 2012 to 2022. Given that the data is recorded only when a collection is completed, and with two collections per week, thus the data has been grouped into weekly datasets. In addition, the dataset was further divided into a training set and a testing set. The training set spans from January 1, 2012, to December 31, 2018. The testing set covers the period from January 1, 2019, to December 31, 2022.

As mentioned earlier, Chinese New Year will serve as the non-fixed festive season parameter. In this study, we recorded the week of Chinese New Year, as well as one and two weeks before and after Chinese New Year, as the non-fixed festive season parameters. Thus, there will be 5 NFS in this study. Table 1 shows the date of the parameter.

In addition, our study involved comparing results obtained using different coefficient ratios. We discovered that employing a ratio of 0.7 for historical data and 0.3 for the latest data produced the most accurate forecasts. This observation suggests that municipal solid waste (MSW) volume exhibits significant fluctuations, with recent data showing considerable variance. However, leveraging a combination of historical data provides a more stable and robust result. To evaluate the performance of various coefficient combinations, we utilized metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The results, as shown in the Table 2, clearly indicate that the 0.7:0.3 ratio yields the lowest error rates, highlighting its effectiveness in forecasting MSW volume for waste collection planning.

Table 2. Results of different coefficient ratios.

Coefficient [historical: latest]	MSE	RMSE	MAE
0.3:0.7	7088743.980	2662.469	1833.596
0.4:0.6	6331744.221	2516.295	1748.423
0.5:0.5	5722591.778	2392.193	1675.105
0.6:0.4	5333259.442	2309.385	1625.144
0.7:0.3	5324021.918	2307.384	1620.110

5. Result and Comparison

In the study, we compared the SARIMA model, the Trend-Seasonal-Index model, and the proposed adjusted Trend-Seasonal Index model with non-fixed festive seasonal variable.

Figure 3 shows the waste volume forecasting from January 1, 2019, to December 31, 2022, using the Adjusted Trend-Seasonal Index model with a non-fixed festive season variable, Conventional Trend-Seasonal Index model and SARIMA model. The red line represents the actual results from the testing dataset, the blue line represents the forecasted results from the proposed Adjusted Trend-Seasonal Index model, the orange line represents the conventional Trend-Seasonal Index model, the green line represents the SARIMA model, and the red vertical lines mark Chinese New Year.

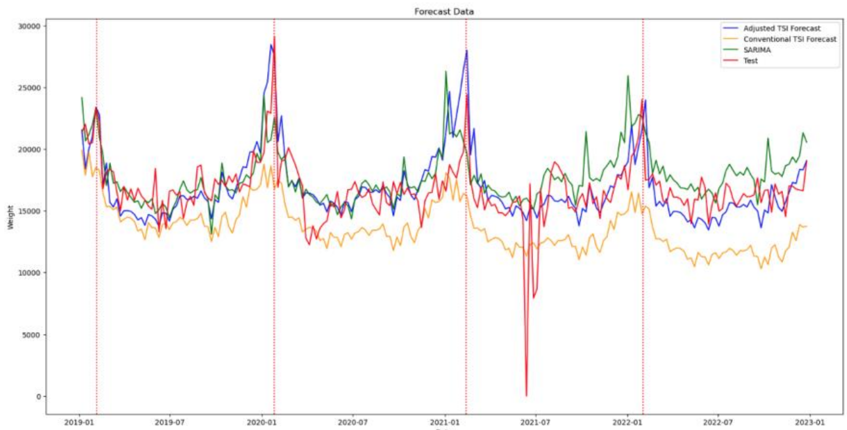

Fig. 3. Forecast result of adjusted trend seasonal index model, conventional trend seasonal index model, sarima model, and testing data.

The proposed Adjusted Trend-Seasonal Index model yielded the following metrics: MSE - 5,324,021, RMSE - 2,307, and MAE - 1,620. From the Fig. 4, we observe that the forecasted results closely follow the pattern of the actual testing dataset, except for the data collection error in the testing data during June 2021.

Fig. 4. Forecast result of adjusted trend seasonal index model and actual testing data.

In comparison, we also assessed the Conventional Trend-Seasonal Index model. The forecasting results of Conventional Trend-Seasonal Index model produced the following error rates: MSE - 13,943,775, RMSE - 3,734, and MAE - 3,280. The forecast result of Conventional Trend-Seasonal in Fig. 5 indicates that the forecasting results deviate significantly from the actual testing dataset when compared to the adjusted Trend-Seasonal Index model with a non-fixed festive season component.

Fig. 5. Forecast result of conventional trend seasonal index model and actual testing data.

Lastly, we applied the SARIMA (Seasonal Autoregressive Integrated Moving Average) model to the same dataset and compared it with the above two models. In this study, we employed SARIMA(2,1,1)(2,1,0) (52) for forecasting, as shown in the chart below. The error rates for this model were MSE - 6,775,833, RMSE - 2,603, and MAE - 1,834. This model exhibited better performance compared to the Conventional Trend-Seasonal Index model. However, in contrast to the proposed Adjusted Trend-Seasonal Index model with a non-fixed seasonal variable, this model fails to capture the weight variation of the non-fixed festive season. From the Fig. 6, we observe that the forecasted results of SARIMA model are not influenced by the Chinese New Year season.

Fig. 6. Forecast result of SARIMA model and actual testing data.

Lastly, we applied the SARIMA (Seasonal Autoregressive Integrated Moving Average) model to the same dataset and compared it with the above two models. In this study, we employed SARIMA(2,1,1)(2,1,0) (52) for forecasting, as shown in the chart below. The error rates for this model were MSE - 6,775,833, RMSE - 2,603, and MAE - 1,834. This model exhibited better performance compared to the Conventional Trend-Seasonal Index model. However, in contrast to the proposed Adjusted Trend-Seasonal Index model with a non-fixed seasonal variable, this model fails to capture the weight variation of the non-fixed festive season. From the Fig. 6, we observe that the forecasted results of SARIMA model are not influenced by the Chinese New Year season.

In Table 3, we can clearly see that the proposed Adjusted Trend-Seasonal Index model has lower MSE, RMSE, and MAE values compared to the Conventional Trend-Seasonal Index model and the SARIMA model, indicating it provides better forecasting results.

Table 3. Error rate of adjusted trend seasonal index model, conventional trend seasonal index model, and SARIMA model.

Model	MSE	RMSE	MAE
Adjusted Trend-Seasonal Index model with non-fixed festive seasonal variable	5,324,021	2,307	1,620
Conventional Trend-Seasonal Index model	13,943,775	3,734	3,280
SARIMA Model	6,775,833	2,603	1,834

6. Conclusion

Malaysia, being a multiracial country, people tend to celebrate their festive season. However, these celebrations often result in an unpredictable spike in the volume of municipal solid waste, posing challenges to MSW management. Thus, this study proposes an adjusted trend seasonal index model with a non-fixed festive seasonal variable, which aims to predict MSW volume by considering the effect of non-fixed festive seasons. Through the investigation, the proposed model has demonstrated superior performance compared to the conventional trend seasonal index model and SARIMA. Importantly, the proposed model extends beyond MSW management and can be applied to any problem related to time-series forecasting with non-fixed seasonal issues.

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