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Event Index Computation for Forecasting Case Study: Car Sales in Thailand

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Abstract Due to the impact of special events, both positive and negative, on the sales data, the ordinary Time-series Decomposition (TSD) forecasting model cannot merely capture these effects, even with the added seasonality and trends. Therefore, in this research, a new method for computing the event indices, representing the unusual fluctuations for a certain period in the time series, is proposed in order for it to be incorporated into TSD, alongside the conventional trend, seasonal, and cyclical components. A case study of subcompact car sales monthly data in Thailand during the years 2011-2018 is examined as for that time period contains the 2011 nationwide big flood reflecting the negative impact, as well as the nation's tax-incentive first-car buyer scheme reflecting the positive impact on the dataset. The mean absolute percentage error (MAPE) is used as an accuracy measure of the proposed forecasting model and it illustrates the promising results in the end.

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1. Introduction

Thailand's automotive industry has been an important foundation for the nation's economic boost for many years. The government policies are always the key mechanisms for the industry to increase and improve the vehicle production capacities to replace the import volumes [1]. Since the government's liberalization policy on drawing in oversea investment for the industry development in 1991, Thailand has continuously expanded her production sizes for engine part making, automotive assembly, and other associated industries. As a result, automotive-related figures continued to grow in every segment including manufacturing, marketing, employment, and technology development, among others. Thanks also to the state's successful push on stimulating the domestic demand, Thailand became one of the global automotive manufacturing bases as well as the world's leading manufacturer of pickups and motorcycles [2]. Moreover, in the years 2014 and 2015, Thailand has achieved the highest production capacities in ASEAN [3] as shown

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in Table 1. From 2014 to 2015, ASEAN's total car production volume went down from 3.98 million to 3.89 million units. However, not only did Thailand manage to remain ASEAN's top car producer in both years, but also the production figure went up from 1.88 million units in 2014 to 1.91 million in 2015. Among these 1.91 million, 1.15 million cars were for commercial use while 0.76 million cars were for private use. Lagged behind Thailand in the ASEAN's car producer list, Indonesia and Malaysia were the numbers 2 and 3, each of which had roughly half the predecessor's production size.

TABLE 1. ASEAN's car production capacities from 2014 to 2015. (units: cars)

Country	Private Car	Commercial vehicles	2015	2014	Percent Change (%)
Thailand	760,688	1,152,314	1,913,002	1,880,007	2
Indonesia	824,445	274,335	1,098,780	1,298,523	-15
Malaysia	563,883	50,781	614,664	596,418	3
Vietnam	99,052	72,701	171,753	121,084	42
Philippines	36,395	62,373	98,768	88,854	11
Total	**2,284,463**	**1,612,504**	**3,896,967**	**3,984,877**	**-2**

Ref. : ASEAN Automotive Federation [3]

The monthly car sales figures in Thailand [4] for 8 years, ranged from January 2011 to December 2018 are shown in Figure 1. Based on this historical sales record, when looked closely, it revealed that the sales figures were very fluctuate, especially during the years 2011-2012. In that time, two major incidents occurred. First, the national big flood in the second half of the year 2011 severely damaged the country, the people, and obviously, many businesses. Even though, the flood lasted for about 5-6 months but the aftermath carried on for at least another year. The second coincident was the government policy on the intensive tax refund for the first car buyers who bought or reserved to buy their first subcompact car during the period of September 2011-December 2012 [5].

FIGURE 1. Thailand's monthly car sales (in Million Baht) from January 20011 to December 2018.

Previous work regarding this research in various aspects has been reviewed and concluded here as follows.

Ludvigson (1998), showed that the government financial policies concerning bank loans for car purchase affected car sales figures. Inversely, increasing interest rates had a negative impact on car sales figures [6]. The proportion of car ownership from 26 countries in the Organization for Economic Co-operation and Development (OECD) group, between the year 1960 and 1992 was relatively high in the industrialized member countries [7] including Portugal, Greece, and Ireland, based on their own expectation that they would be able seek higher income growth in the future. Vice versa, in China, India, and Pakistan, the growth of car ownership followed the growth of per-capita income of the countries.

As a result of the household expenses survey from 1970 to 1995, Dargay (2001) found that car ownership tended to increase with increasing revenue and negative correlation when revenue decreased [8]. Moreover, the research by Shahabudin (2009) showed a regression model incorporating all important predictive variables such as income levels, interest rates, financial aggregate and unemployment rates, that affected domestic and foreign car sales figures [9]. Wirotcheewan P. et al. (2011), used linear programming to find an accurate forecasting model for predicting advanced demand in exported automotive to foreign market and calculate the optimal quantity for export [10]. Muhammad et al. (2012) revealed that the GDP variables were positively correlated with car sales figures in five ASEAN countries, namely, Malaysia, Indonesia, Singapore, Philippine, and Thailand [11]. This indicated that national income was really one of the important factors to the automotive industry, presumably as well as many other industries. On the other hand, inflation unemployment rates and interest rates had a negative impact on car sales figures.

Moreover, some researches revealed that significant increase in fuel price could also negatively impact the car sales [12],[13],[14]. This factor was found to induce uncertainty in operation costs that could affect the total car production costs. This, in turn, impacted the investment value and the consumer demand. The same finding was shown by Lee and Ni (2002) [15] in their research on 14 industrial countries. The hike in fuel prices was found to disrupt supply by the industrial sector, while at the same time, influenced consumer demand for industrial products, especially motor vehicles.

Rattanametawee W., Leenawong C. and Netisopakul P. (2016) [16] proposed multiple linear regression that incorporated seasonality and special events into the regression model. Their dependent variable was the car sales figures in Thailand while the independent variables were the nation's GDP and the car loan rates with dummy variables for handling the seasonality and the irregular events. Among all their three regression models, it turned out, as expected, that the model with the seasonal variables and the dummy event variables proved to be most useful according to the relevant high adjusted R-square.

Other research focusing on the time series forecasting methodology is presented in the following. The research by Apiwattanachai T. and Pichitlamken J. (2008) [17] used the three exponential smoothing technique or the Holt-Winter's forecasting model to estimate the customer demand in automobile. Both the multiplicative and the additive models with all three constants, , , and were used due to the presence of the trend and seasonality components. The result showed in their work that the additive model had a lower MAPE and hence a better model.

Chaimongkol W. and Tansathit C. (2010) [18] proposed a modification on the Decomposition and the Holt-Winter's forecasting models. The new model combining the additive decomposition with the additive Holt-Winters was applied to the passenger car demand data. The results was then compared to those from the original Decomposition and the Holt- Winter's models by their mean absolute percentage error (MAPE). The combined model exhibited better accuracy.

This paper proposes a new computation method for event indices to be use in the time series forecasting with a case study of the subcompact car sales data in Thailand due to the two special incidents, the national big flood and the tax-incentive car buyer program. In the next section, the proposed methodology for computing the event indices is explained, followed by the experiments and their results in Section 3. Then, this research is summarized and concluded in Section 4.

2. The Methodology

The Time-Series Decomposition (TSD) Method is a widely used model for forecasting when the forecast is based only on one factor, namely, time [19]. Typically, the four components of a time series are composed of the Trend (T), Seasonal (S), Cyclical (C), and Irregular (I) components. In this research, a multiplicative decomposition model is assumed and expressed as

$$y = T * S * C * I.$$

In addition to the four typical components above, one additional aperiodic component is added into the above formula, which is subsequently called the special event component (E), and thus the multiplicative model becomes

$$y = T * S * C * I * E.$$

The special event component accounts for some untypical occurrence that really affects, for some period, the time series, ether positively or negatively. For example, a marketing campaign could contribute to a sharp peak of the sales figure, thus the positive effect whereas a tsunami could cause a sharp drop in the sales for some particular product, thus the negative effect. In the proposed methodology, both marketing campaign and the tsunami will be called special events.

To describe the proposed computation for event indices more understandably, a case study of Thailand's subcompact car sales figure over an 8-year period starting from year 2011 up until 2018 was examined. Accordingly, two special events were found to have occurred during this 8-year monthly time-series sales data. One was the national big flood in Thailand in the late 2011, supposedly causing negative effects on many industries including this passenger car industry. While the other event was the government's tax-incentive first-car buyer program being officially in effect for those who purchased or made a reservation to purchase their first car from September 2011 to December 2012, supposedly producing positive effects on this particular car industry.

However, as the effective periods of the two special events overlapped, they classify the sales data into four distinctive events to reflect the effects of both special events. Furthermore, these four distinctive events to be flagged in the monthly sales periods do not have to be in compliance with the official time frame mentioned above. It is focused more on the real actions of the buyers whether or not to buy their first cars. The four classified events along with their event flag values as well as related parameters and notations are defined as follows.

Let $X^k_{y,m}$ refers to the original monthly car sales data of year y, months m, with the assigned event flag k, where $y = 1, 2, ...$ refers to the year 2011, 2012, and so on, $m = 1, 2, ..., 12$ refers to the month January,February,..., December. Finally, the event flag k takes one of the values $0, 1, 2, 3$ where flag $k = 0$ (the base flag) refers to the regular sales period when there is no effect from neither the big flood nor the incentive program, flag $k = 1$ refers to the period where buyers' decisions are affected mainly by the flood, flag $k = 2$ refers the period where buyers' decisions are affected by both the flood and the incentive program, and flag $k = 3$ refers to the sale period after the incentive program ends.

The time-series decomposition algorithm incorporating special events is proposed and explained here. The steps for computing the event indices and removing them from the original data resulting in the de-evented data are described in Steps 1 through 5. Then, from Step 6 onward, the conventional decomposition of the seasonal and cyclical components is incorporated into the de-evented data so that the subsequent data obtained in Step 11 is left with the trend component only, and hence called the de-all data. Finally, the forecasted data can be predicted in last two steps. First of all, let us start with finding the centered moving averages of the original monthly data.

The Event Decomposition Algorithm

Step 1: Finding the Centered Moving Average (CMAs).

Let $\bar{X}^k_{y,m}$ refer to the CMA of $X^k_{y,m}$ when the number of periods to average is 12. Obviously, $\bar{X}^k_{y,m}$ starts at $\bar{X}^k_{1,7}$ and ends at $\bar{X}^k_{8,6}$. For example,

$\bar{X}^k_{1,7} = \text{CMA}(X^k_{1,7}) = (X^k_{1,1} + X^k_{1,2} + ... + X^k_{1,12})/12$,

$\bar{X}^k_{1,8} = \text{CMA}(X^k_{1,8}) = (X^k_{1,2} + X^k_{1,3} + ... + X^k_{1,12} + X^k_{2,1})/12$,

$\bar{X}^k_{1,9} = \text{CMA}(X^k_{1,9}) = (X^k_{1,3} + X^k_{1,4} + ... + X^k_{1,12} + X^k_{2,1} + X^k_{2,2})/12, \ldots,$

$\bar{X}^k_{8,6} = \text{CMA}(X^k_{8,6}) = (X^k_{8,1} + X^k_{8,2} + ... + X^k_{8,11} + X^k_{8,12})/12$.

Then, each $X^k_{y,m}$ as well as its corresponding $\bar{X}^k_{y,m}$ is assigned a flag k where $k = 0, 1, 2,$ or 3 represents each of the four special events previously mentioned above.

Step 2: Computing the Mean Base-flagged CMAs.

For each month m, take only the $\bar{X}^k_{y,m}$ having flag $k = 0$ or the base flag, and compute the mean of the average of these data. In terms of notation, it can be expressed as

$$\bar{\bar{X}}^0_m = avg\bar{X}^0_{y,m} \tag{2.1}$$

Step 3: Finding the Event Factors.

Let $EF^k_{y,m}$ represent the event factor of year y, month m, which also contains the same flag k, as in $\bar{X}^k_{y,m}$. The event factor is obtained by dividing its corresponding CMA by the Mean Base-flagged CMA, $\bar{\bar{X}}^0_m$. Therefore,

$$EF^k_{y,m} = \frac{\bar{X}^k_{y,m}}{\bar{\bar{X}}^0_m} \tag{2.2}$$

Step 4: Computing the Event Indices.

Let E^k represent the event index for flag k, where $k = 0, 1, 2, 3$. This index can be obtained by, for each k, taking the average of all the event factors $EF^k_{y,m}$ having the same flag k across all the data. That is,

$$E^k = avgEF^k_{y,m}, \tag{2.3}$$

Step 5: Removing the Event Effect from the Data (De-eventing).

Let $D^k_{y,m}$ along with the common three parameters year y, month m, and flag k, represent the data after the event effect is removed or de-evented. Since this model is multiplicative, $D^k_{y,m}$ is obtained by taking the initial data, $X^k_{y,m}$, and dividing it by the event index, E^k, of the same flag k, as illustrated below

$$D^k_{y,m} = \frac{X^k_{y,m}}{E^k} \tag{2.4}$$

Because the event indices have been taken out, for less complicated notations, the superscript k can be discarded. That is, from here on, $D_{y,m} = D^k_{y,m}$ and the data is now left only with the seasonal and cyclical components. The remaining steps are to remove the effects of these two components from the current de-evented data. More precisely, seasonal indices are obtained through Steps 6 to 8 while cyclical factors are obtained through Steps 9 to 10.

Step 6: Finding the CMAs of the De-evented Data.

Let $\bar{D}_{y,m}$ refer to the CMA of $D_{y,m}$ when the number of period to average is 12. Therefore $\bar{D}_{y,m}$ starts at $\bar{D}_{1,7}$ and ends at $\bar{D}_{8,6}$, for instance

$$\begin{aligned}
\bar{D}_{1,7} = \text{CMA}(D_{1,7}) &= (D_{1,1} + D_{1,2} + \ldots + D_{1,11} + D_{1,12})/12, \\
\bar{D}_{1,8} = \text{CMA}(D_{1,8}) &= (D_{1,2} + D_{1,3} + \ldots + D_{1,11} + D_{1,12} + D_{2,1})/12, \ldots, \\
\bar{D}_{8,6} = \text{CMA}(D_{8,6}) &= (D_{8,1} + D_{8,2} + \ldots + D_{8,11} + D_{8,12})/12.
\end{aligned}$$

Step 7: Computing the Seasonal Factors.

Let $SF_{y,m}$ represent the seasonal factor of year y and month m. Therefore, the seasonal factors are obtained from dividing the de-evented data by its CMA counterparts as follows

$$SF_{y,m} = \frac{D_{y,m}}{\bar{D}_{y,m}}. \tag{2.5}$$

Step 8: Computing the Seasonal Indices.

Let S_m represent the seasonal index for month m. Then, this index is found by taking the average of the same month-m seasonal factors data across the years. That is,

$$S_m = avgSF_{y,m}. \tag{2.6}$$

Before removing the seasonal effects from the de-evented data, steps for obtaining the cyclical factors are carried out in the following Steps 9 to 10. Subsequently, both seasonal and cyclical factors will be removed simultaneously in Step 11.

Step 9: Obtaining the Trend Line Equation of the De-evented Data.

Let $TD_{y,m}$ refer to the year y, month m data obtained from the linear trend equation of the CMAs of the de-evented data, $\bar{D}_{y,m}$, from Step 6. The general formula for this trend line depending on time t is as follows

$$TD_{y,m} = b_0 + b_1 t. \tag{2.7}$$

where b_0 is the y-intercept and b_1 is the slope of the trend line. After getting all the data from the trend line equation, the next step is to find the cycle factors.

Step 10: Finding the Cycle Factors.

A cycle factor is just a division of the CMA of the de-evented data and its trend-line counterpart and when $CF_{y,m}$ represents the cycle factor of year y and month m,

$$CF_{y,m} = \frac{\bar{D}_{y,m}}{TD_{y,m}}. \quad (2.8)$$

Step 11: Removing the Seasonal and Cyclical Components from the De-evented Data.

The de-all data, $DA_{y,m}$, refers to the data whose all three main components, namely, event, seasonal, and cyclical components, have been removed; therefore, divide the de-evented data from Step 5 by its corresponding seasonal index from Step 8 and also the cycle factor from Step 10 as follows

$$DA_{y,m} = \frac{D_{y,m}}{S_m * CF_{y,m}}. \quad (2.9)$$

Step 12: Obtaining the Trend Line Equation of the De-all Data.

Now, the only component left in the de-all data is the trend component. Let $TDA_{y,m}$ refer to the year y, month m data obtained from the linear trend equation of the de-all data in the previous step. The general formula for this trend line depending on time t is as follows

$$TDA_{y,m} = c_0 + c_1 t. \quad (2.10)$$

where c_0 is the y-intercept and c_1 is the slope of the trend line.

Step 13: Incorporating the Three Main Components Back to the Forecasted Data.

Using the trend line equation of the de-all data in (2.10), forecasted data in year y, month m, or $TDA_{y,m}$, can all be obtained. Then, by the multiplicative approach, the final forecasted data, denoted by $TF_{y,m}$, becomes

$$TF_{y,m} = TDA_{y,m} * S_m * CF_{y,m} * E^k. \quad (2.11)$$

This proposed algorithm will be applied on the Thailand's car sales data in the next section. In the meantime, during the development of this algorithm, it is found that the event index of the base flag case or the normal case is always 1 as shown in the following Theorem.

Theorem 2.1. *Let E^k represent the event index for flag $k, k = 0, 1, 2, 3,$ and be defined as in (2.3), i.e., $E^k = avgEF^k_{y,m}$, then $E^0 = 1$.*

Proof. Let n^0_m be the total number of data of month m across all years having flag $0; m = 1, 2, \ldots, 12$.

From Step 4, we know that the event index for the base flag is

$$E^0 = avgEF^0_{y,m},$$

which can be expressed as

$$E^0 = avgEF^0_{y,m} = \frac{\sum EF^0_{y,m}}{n^0_1 + n^0_2 + \ldots + n^0_{12}}.$$

By the formula (2.2) in Step 3, we obtain

$$E^0 = \frac{\sum\left(\frac{\bar{X}^0_{y,m}}{\bar{\bar{X}}^0_m}\right)}{n^0_1 + n^0_2 + \ldots + n^0_{12}},$$

which can be decomposed into

$$E^0 = \frac{\sum\left(\frac{\bar{X}^0_{y,1}}{\bar{\bar{X}}^0_1}\right) + \sum\left(\frac{\bar{X}^0_{y,2}}{\bar{\bar{X}}^0_2}\right) + \ldots + \sum\left(\frac{\bar{X}^0_{y,12}}{\bar{\bar{X}}^0_{12}}\right)}{n^0_1 + n^0_2 + \ldots + n^0_{12}}.$$

By formula (2.1) in Step 2, we have

$$\begin{aligned} E^0 &= \frac{\sum\left(\frac{\bar{X}^0_{y,1}}{avg\bar{X}^0_{y,1}}\right) + \sum\left(\frac{\bar{X}^0_{y,2}}{avg\bar{X}^0_{y,2}}\right) + \ldots + \sum\left(\frac{\bar{X}^0_{y,12}}{avg\bar{X}^0_{y,12}}\right)}{n^0_1 + n^0_2 + \ldots + n^0_{12}} \\ &= \frac{\left(\frac{\sum \bar{X}^0_{y,1}}{\left(\frac{\sum \bar{X}^0_{y,1}}{n^0_1}\right)}\right) + \left(\frac{\sum \bar{X}^0_{y,2}}{\left(\frac{\sum \bar{X}^0_{y,2}}{n^0_2}\right)}\right) + \ldots + \left(\frac{\sum \bar{X}^0_{y,12}}{\left(\frac{\sum \bar{X}^0_{y,12}}{n^0_{12}}\right)}\right)}{n^0_1 + n^0_2 + \ldots + n^0_{12}}. \end{aligned}$$

Then,

$$E^0 = \frac{\left(\frac{\sum \bar{X}^0_{y,1}}{\sum \bar{X}^0_{y,1}}\right)n^0_1 + \left(\frac{\sum \bar{X}^0_{y,2}}{\sum \bar{X}^0_{y,2}}\right)n^0_2 + \ldots + \left(\frac{\sum \bar{X}^0_{y,12}}{\sum \bar{X}^0_{y,12}}\right)n^0_{12}}{n^0_1 + n^0_2 + \ldots + n^0_{12}}.$$

Hence, $E^0 = 1$. ■

3. The Experimentals and the Results

In this section, the proposed time-series decomposition algorithm incorporating special events from the previous section is applied to the Thailand's monthly car sales figures ranged from January 2011 to December 2018. Due to the two major incidents being the national big flood and the tax incentive program and the definitions of the four flags previously stated in Section 2, the following flag assignment to the monthly car sales data is obtained:

Flag 1 referring to the sales period where car buyers' decisions are affected mainly by the flood, is assigned to months Oct 2011 - Jan 2012,

Flag 2 referring the period where car buyers' decisions are affected by both the flood and the incentive program, is assigned to months Feb 2012 - Sep 2013,

Flag 3 referring to the aftermath period, is assigned to Oct 2013 - Sep 2014,

Flag 0 referring to the normal sales period, is assigned to the remaining months.

Table 2. Results from the event decomposition algorithm Steps 1 to 5.

Month	Time	Car sales	flag	$\bar{X}^k_{y,m}$	$\bar{\bar{X}}^0_m$	$EF^k_{y,m}$	E^k	$D_{y,m}$
Jan-11	1	24,812.31	0		27,239.87		1.00	24,812.31
Feb-11	2	24,856.65	0		27,410.99		1.00	24,856.65
Mar-11	3	28,944.01	0		27,592.34		1.00	28,944.01
Apr-11	4	17,675.21	0		27,739.47		1.00	17,675.21
May-11	5	15,471.06	0		27,899.45		1.00	15,471.06
Jun-11	6	22,160.50	0		28,048.28		1.00	22,160.50
Jul-11	7	26,003.30	0	20,795.62	24,954.96	0.83	1.00	26,003.30
Aug-11	8	25,601.39	0	20,490.56	24,979.90	0.82	1.00	25,601.39

Month	Time	Car sales	flag	$\bar{X}^k_{y,m}$	$\bar{X}^0_m$	$EF^k_{y,m}$	E^k	$D_{y,m}$
Sep-11	9	27,763.89	0	20,159.89	25,010.45	0.81	1.00	27,763.89
Oct-11	10	12,813.77	1	20,102.19	26,840.77	0.75	0.80	16,030.14
Nov-11	11	8,403.67	1	21,020.13	27,131.00	0.77	0.80	10,513.07
Dec-11	12	17,787.90	1	22,328.01	27,469.30	0.81	0.80	22,252.84
Jan-12	13	19,319.96	1	23,450.14	27,239.87	0.86	0.80	24,169.46
Feb-12	14	23,027.61	2	24,510.31	27,410.99	0.89	1.32	17,464.63
Mar-12	15	22,836.78	2	25,751.72	27,592.34	0.93	1.32	17,319.89
Apr-12	16	22,397.63	2	27,851.60	27,739.47	1.00	1.32	16,986.83
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jul-13	31	34,043.82	2	34,521.43	24,954.96	1.38	1.32	25,819.55
Aug-13	32	37,534.01	2	33,504.01	24,979.90	1.34	1.32	28,466.59
Sep-13	33	37,879.10	2	32,434.55	25,010.45	1.30	1.32	28,728.30
Oct-13	34	29,906.23	3	31,558.23	26,840.77	1.18	1.05	28,464.52
Nov-13	35	27,857.49	3	30,862.94	27,131.00	1.14	1.05	26,514.55
Dec-13	30	28,153.73	3	30,181.07	27,469.30	1.10	1.05	26,796.52
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jul-14	43	25,633.96	3	26,585.74	24,954.96	1.07	1.05	24,398.21
Aug-14	44	24,377.96	3	26,616.19	24,979.90	1.07	1.05	23,202.76
Sep-14	45	27,720.11	3	26,461.53	25,010.45	1.06	1.05	26,383.80
Oct-14	46	23,767.18	0	26,250.17	26,840.77	0.98	1.00	23,767.18
Nov-14	47	26,852.59	0	26,186.28	27,131.00	0.97	1.00	26,852.59
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Sep-18	93	33,901.57	0		25,010.45		1.00	33,901.57
Oct-18	94	31,710.03	0		26,840.77		1.00	31,710.03
Nov-18	95	34,267.79	0		27,131.00		1.00	34,267.79
Dec-18	96	33,409.57	0		27,469.30		1.00	33,409.57

By following the steps of the proposed algorithm, Table 2 shows the results of undertaking Steps 1 through 5 for computing the event indices and de-event them from the sales data. The event indices for the four flags are shown in the second right-most column, E^k, more particularly, $E^0 = 1.00, E^1 = 0.80, E^2 = 1.32$ and $E^3 = 1.05$. These event indices really capture the essence of each of the four flags. The index for flag 0 or the base flag being exactly equal to 1.00 can truly represent the the normal sales period while the index for flag 1 is lower than that of the normal period because, during the flood period, people are naturally not in the mood for buying cars. Later, when the flood is going away and, to some people, with their cars, the index for flag 2 therefore gets higher than that of the normal period showing that the tax-incentive program is working effectively in people's minds. The event index for the last period flag 3 is roughly around 1.00 showing everything is coming back to normal. Note also that the base flag event index E^0 at 1.00 satisfies Theorem 2.1. After obtaining all the event indices, the de-evented data are shown in the right-most column, $D^k_{y,m}$ of Table 2.

Next, to obtain the seasonal indices, Steps 6 through 8 are carried out on the de-evented data $D^k_{y,m}$ from Table 2. The right-most column of Table 3 shows the resulted seasonal indices for each month, as also reported here as follows, $S_1 = 0.95, S_2 = 0.99, S_3 = 1.07, S_4 = 0.83, S_5 = 1.00, S_6 = 1.04, S_7 = 1.03, S_8 = 1.02, S_9 = 1.13, S_{10} = 0.97, S_{11} = 0.96$ and $S_{12} = 1.01$.

TABLE 3. Results from the event decomposition algorithm Steps 6 to 8.

Month	Time	Car sales	$D^k_{y,m}$	$\bar{D}_{y,m}$	$SF^k_{y,m}$	S_m
Jan-11	1	24,812.31	24,812.31			0.95
Feb-11	2	24,856.65	24,856.65			0.99
Mar-11	3	28,944.01	28,944.01			1.07
Apr-11	4	17,675.21	17,675.21			0.83
May-11	5	15,471.06	15,471.06			1.00
Jun-11	6	22,160.50	22,160.50			1.04
Jul-11	7	26,003.30	26,003.30	21,813.58	1.19	1.03

Month	**Time**	**Car sales**	$D^k_{y,m}$	$\bar{D}_{y,m}$	$SF^k_{y,m}$	S_m
Aug-11	8	25,601.39	25,601.39	21,478.79	1.19	1.02
Sep-11	9	27,763.89	27,763.89	20,686.45	1.34	1.13
Oct-11	10	12,813.77	16,030.14	20,173.43	0.79	0.97
Nov-11	11	8,403.67	10,513.07	20,535.97	0.51	0.96
Dec-11	12	17,787.90	22,252.84	21,149.11	1.05	1.01
Jan-12	13	19,319.96	24,169.46	21,515.35	1.12	0.95
Feb-12	14	23,027.61	17,464.63	21,799.96	0.80	0.99
Mar-12	15	22,836.78	17,319.89	22,204.31	0.78	1.07
Apr-12	16	22,397.63	16,986.83	23,254.44	0.73	0.83
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jul-13	31	34,043.82	25,819.55	27,767.76	0.93	1.03
Aug-13	32	37,534.01	28,466.59	27,432.41	1.04	1.02
Sep-13	33	37,879.10	28,728.30	27,115.93	1.06	1.13
Oct-13	34	29,906.23	28,464.52	26,898.34	1.06	0.97
Nov-13	35	27,857.49	26,514.55	26,764.16	0.99	0.96
Dec-13	30	28,153.73	26,796.52	26,678.26	1.00	1.01
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jul-14	43	25,633.96	24,398.21	25,668.26	0.95	1.03
Aug-14	44	24,377.96	23,202.76	25,807.48	0.90	1.02
Sep-14	45	27,720.11	26,383.80	25,776.12	1.02	1.13
Oct-14	46	23,767.18	23,767.18	25,676.21	0.93	0.97
Nov-14	47	26,852.59	26,852.59	25,710.33	1.04	0.96
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Sep-18	93	33,901.57	33,901.57			1.13
Oct-18	94	31,710.03	31,710.03			0.97
Nov-18	95	34,267.79	34,267.79			0.96
Dec-18	96	33,409.57	33,409.57			1.01

Table 4. Results from the event decomposition algorithm Steps 9 to 13.

Month	**Time**	**Car sales**	$TD_{y,m}$	$CF_{y,m}$	$DA_{y,m}$	$TDA_{y,m}$	$TF_{y,m}$
Jan-11	1	24,812.31	23,517.25			23,240.68	
Feb-11	2	24,856.65	23,582.98			23,312.41	
Mar-11	3	28,944.01	23,648.71			23,384.14	
Apr-11	4	17,675.21	23,714.44			23,455.86	
May-11	5	15,471.06	23,780.17			23,527.59	
Jun-11	6	22,160.50	23,845.91			23,599.32	
Jul-11	7	26,003.30	23,911.64	0.91	27,725.66	23,671.05	22,149.41
Aug-11	8	25,601.39	23,977.37	0.90	27,978.55	23,742.78	21,675.44
Sep-11	9	27,763.89	24,043.10	0.86	28,583.80	23,814.51	23,078.10
Oct-11	10	12,813.77	24,108.83	0.84	19,662.31	23,886.23	15,566.47
Nov-11	11	8,403.67	24,174.56	0.85	12,883.34	23,957.96	15,627.53
Dec-11	12	17,787.90	24,240.30	0.87	25,163.53	24,029.69	16,986.40
Jan-12	13	19,319.96	24,306.03	0.89	28,877.34	24,101.42	16,124.71
Feb-12	14	23,027.61	24,371.76	0.89	19,664.13	24,173.15	28,307.88
Mar-12	15	22,836.78	24,437.49	0.91	17,844.66	24,244.88	31,027.48
Apr-12	16	22,397.63	24,503.22	0.95	21,570.40	24,316.60	25,249.14
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jul-13	31	34,043.82	25,489.20	1.09	23,053.40	25,392.53	37,498.09
Aug-13	32	37,534.01	25,554.93	1.07	25,960.68	25,464.26	36,816.28
Sep-13	33	37,879.10	25,620.66	1.06	24,044.24	25,535.99	40,229.18
Oct-13	34	29,906.23	25,686.39	1.05	27,898.58	25,607.71	27,450.50
Nov-13	35	27,857.49	25,752.12	1.04	26,558.24	25,679.44	26,935.70
Dec-13	30	28,153.73	25,817.85	1.03	25,584.76	25,751.17	28,336.86
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jul-14	43	25,633.96	26,277.98	0.98	24,295.43	26,253.27	27,699.66
Aug-14	44	24,377.96	26,343.71	0.98	23,186.81	26,325.00	27,677.36
Sep-14	45	27,720.11	26,409.44	0.98	23,944.96	26,396.73	30,558.42
Oct-14	46	23,767.18	26,475.17	0.97	25,152.79	26,468.45	24,952.74
Nov-14	47	26,852.59	26,540.90	0.97	28,856.90	26,540.18	24,639.87
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Sep-18	93	33,901.57	29,564.56	1.14	26,233.91	29,839.68	38,472.40
Oct-18	94	31,710.03	29,630.29	1.15	28,419.23	29,911.41	33,298.10
Nov-18	95	34,267.79	29,696.02	1.15	31,089.95	29,983.14	32,971.70
Dec-18	96	33,409.57	29,761.75	1.15	28,780.89	30,054.87	34,808.05

Then, Steps 9 and 10 for obtaining the cycle factors are performed. All of the event factors are revealed in column $CF_{y,m}$ of Table 4. Also, in Table 4, the de-all data whose all three time-series components, i.e., the event, the seasonal, and the cyclical components have been removed in Step 11 are shown in column $DA_{y,m}$. Furthermore, the final fitted car sales data obtained from Steps 12 and 13 having included back the three components are displayed in the last column, $TF_{y,m}$, of Table 4.

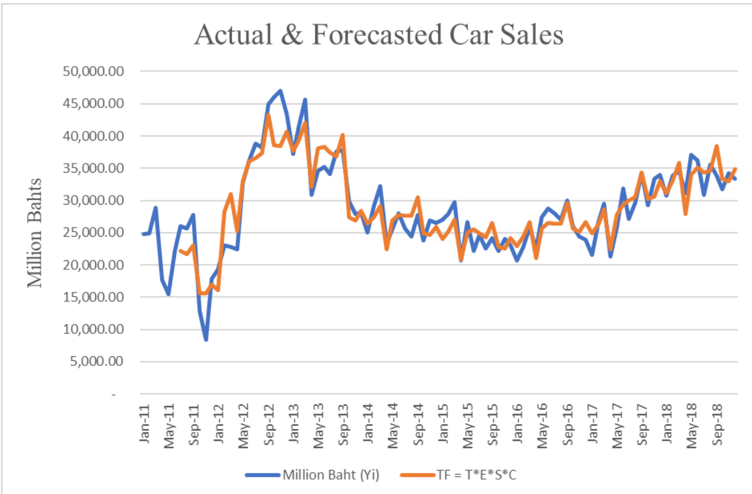

FIGURE 2. Actual Thailand's monthly car sales and their forecasts by the event decomposition.

In Figure 2, the original Thailand's monthly car sales as well as their final forecasted car sales data obtained from the proposed time-series event decomposition algorithm as shown in Table 4 are plotted together in Figure 2. The two curves appear closely next to each other as the calculated mean absolute percentage error (MAPE) of this forecast is relatively good at 8.17%.

4. Conclusion

In this article, a new time-series decomposition to incorporate the effects of special events is proposed. Thailand's monthly car sales figures from the years 2011-2018 demonstrates a good application due to the large affective two incidents, namely, the national big flood and the tax-incentive program for first car buyers. These two incidents create four distinctive events or flags for the proposed method. Each flag's event index obtained from the proposed computation method agrees well with the flag definition. Coupled with the seasonal, cyclical, and the trend components obtained, the final forecasts of the original car sales data prove very promising results with a low MAPE of just 8.17%. Ultimately, the event index computation proposed in this work can be beneficial to time-series decomposition forecasting when incidents having huge positive/negative impacts are present in the data.

References

[1] F.T.I Automotive Industry Club, The Federation of Thai Industries Automotive Industry Club. http://www.aic.or.th, 2016.

[2] S. Chantaburee. 2016. [Online]. Available: http://www.aseanthai.net/ewt_news.php?nid=5720 & filename=index. [Accessed 4 November 2018].

[3] ASEAN Automotive Federation. [Online]. Available: http://www. aseanautofed.com/statistics.html. [Accessed December 2017].

[4] Office of Industrial Economics 2018. [Online] Available:http:// www.oie.go.th/. [Accessed 31 May 2018].

[5] Thailand e-Government. [Online] Available: https://www.egov.go.th/th/e-government-service/190/. [Accessed 7 September 2018].

[6] S. Ludvigson, The channel of monetary transmission to demand: evidence from the market for automobile credit, Journal of Money, Credit, and Banking 30 (1998) 365–383.

[7] J.M. Dargay and D. Gately, Income's effect on car and vehicle ownership, worldwide: 19602015, Transportation Research Part A: Policy and Practice 33 (1999) 101–138.

[8] J.M. Dargay, The effect of income on car ownership: evidence of asymmetry, Transportation Research Part A: Policy and Practice 35 (2001) 807–821.

[9] S. Shahabudin, Forecasting automobile sales, Management Research News 32 (2009) 670–682.

[10] P. Wirotcheewan, A. Kengpol, K. Ishii, and Y. Shimada, Modelling and forecasting for automotive parts demand of foreign markets on Thailand, Asian International Journal of Science And Technology in Production and Manufacturing Engineering: AIJSTPME 4 (2011) 1–13.

[11] F. Muhammad, M. Yahya, M. Hussin and A. Ab Razak, Automobile sales and macroeconomic variables: A pooled mean group analysis for ASEAN Countries, Journal of Business and Management (IOSRJBM) 2 (2012) 15–21.

[12] J.D. Hamilton, A neoclassical model of unemployment and the business cycle, Journal of Politicial Economy 96 (1988) 593–617.

[13] R.S. Pindyck, and J.J. Rotemberg, Dynamic factor demands and the effects of energy price shocks, American Economic Review 73 (1983) 1066–1079.

[14] B.M. Barber, R.W. Click and M.N. Darrough, The impact of shocks to exchange rate and oil prices on U.S. sales of American and Japanese automakers, Japan and World Economy 11 (1999) 57–93.

[15] K. Lee, and S. Ni, On the dynamic effects of oil price shocks: a study using industry level data, Journal of Monetary Economics 49 (2002) 823–852.

[16] W. Rattanametawee, C. Leenawong and P. Netisopakul, The effects of special events on regression for subcompact car sales in Thailand, Jurnal Teknologi (Sciences & Engineering) 78 (2016) 161–165.

[17] T. Apiwattanachai and J. Pichitlamken, Time-Series forecasting model for automobile sales in Thailand, Operations Research Network of Thailand (2008) 298–303.

[18] W. Chaimongkol and C. Tansathit, Forecasting Model for Automobile Sale in Thailand, The 2nd International Conference on Logistics and Transport & The 1st International Conference on Business and Economics Ridges Lakeland Resort Queenstown, Queenstown, New Zealand Theme: Managing Risk and Finance in Global Supply Chain (2010) 16–18.

[19] B.L. Bowerman and R.T. O'Connell, Forecasting and Time Series : An Applied Approach, Wadsworth, Inc., USA, 1993.