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THE FORECAST ON THE NUMBER OF MOTORCYCLE ACCIDENTS IN CHONBURI

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Abstract. *Chonburi's accident forecasting project is designed to analyze accident data from the past 3 years, (2016 to 2018), to create statistics and predict the number of accidents that may occur in the future, so that those involved in the safety process, such as hospital or rescue agencies, will abruptly prepare to deal with emergency situations. In fact, this project also allows those interested in the statistics of accidents to learn about such information collected using time series: trend, moving average, seasonal and unusual variables, all of which have already been calculated and kept in Microsoft SQL Server, and regression analysis in forecasting. After that, the data is connected to Weka program to predict the number of accidents with linear regression function, and display the value and model of the forecast. Then it uses values from the forecast to create a line graph for a dashboard, using Microsoft Power BI. Thereafter, the results of the analysis and forecast provide information on various statistics related to the accidents. The numeric forecasting result is also revealed inexact and varied in each region. The result of the forecast of the number of accidents has an average RMSE error of approximately 3.5, analyzed by the incident location in Chonburi Province, which after obtaining the forecasting value of the number of accidents. However, there is a kind of data which cannot be analyzed and forecasted because there are few or no routes in some areas. Thus, there is no information about the accident in those regions or, there is so little that the data lacks continuity. In terms of forecasting, it is divided into 3 levels depending on the continuity of data, which means there is a weekly forecast, when the data consistently continues, monthly forecast when the data moderately continues, and quarterly forecast when the data is less consistent. It was detected that the accident had an RMSE error value of approximately 3.5 from the site inspection in Chonburi Province. The results of the examination of the number of accidents have been concluded. Then, all values from the forecasts are illustrated in the form of a dashboard to be more easily and conveniently understood by those who want to obtain the information.*
Keywords: Forecasts, Time series, Trend, Moving average, Seasonal variation, Motorcycle accidents

1. **Introduction.** Nowadays, there is widespread use of motorcycles since many commuters tend to choose them as the best choice of transport due to their small size, expedited travel time through a traffic, and cheaper price compared to cars. All the factors mentioned have led to the increasing number of motorcyclists each year, causing a higher rate of accidents as a consequence. This is because some commuters use the wrong type of vehicle, some are careless or still not ready to ride a motorcycle. Worst of all, this may result with some commuters losing their finances or dying in an accident. The location data of this incident was observed by Road Accident Victims Protection Co., Ltd., who collected this information on the website http://www.thairsc.com. The data used in this

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research will consider only the data that occurred in Chonburi province which is the center of industry, education, and tourism, with the statistical data gathered during the last three years show that most accidents are caused by motorcycles. Most of the population in the area is in the teenage years, popular to travel by motorcycle. Motorcycle accidents are the top ranking in Thailand, resulting in a large amount of losses. The research team realizes the benefits of using these accident data to be analyzed and forecasted for the relevant departments, such as hospital or rescuers, to readily prepare themselves to handle unexpected accidents. From the problems mentioned, there is an idea to create a website, that can show the statistics to predict number of future accidents. Chonburi, for example, has a large number of accidents. This information is allocated in order to provide a guide on how to cope with accidents. This is, of course, unless it would be a waste of time to take actions on immediate situations. On the other hand, if there is preparation in advance, it will, of course, make it safer to help the wounded from the accidents. For example, the relevant authorities can prepare to add more surveillance spots or increase the duration of work, when they know which areas have many accidents, or they can send more personnel from less-accident areas to the areas with higher accidents. These strategies will help save time to rescue the victims because time is very important in saving lives and taking instant control on the situation when an accident really takes place according to the actual forecast. Accident data is divided into two data: latitude and longitude data. Accidents have a fragmented pattern, so it needs to be adjusted to find the field of the area to achieve the incidence of accidents in different areas, and to be able to analyze and forecast accidents in each area accurately and reliably. Multiple accident prediction studies provide the principles of time series forecasting data mining. In this study, time series components were extracted from accident data and linear regression forecast in research to obtain a lower RMSE error model. In the analysis, the data is separated into 3 classes according to the consistency of the data. The continuous data will be forecasted weekly to foresee the number of accidents probably happening in the following weeks. Likewise, the moderately continuous data will be forecasted monthly, and the less continuous data will be forecasted quarterly [1,2]. And the prediction models were used in web application development in presenting accident data and forecasting incidents in important incident areas in order to allow the work involved to monitor and prepare for further prevention.

2. Literature Review.

Objective of this research is to use data mining techniques to prepare and adjust data to suit the forecasting of accidents by studying forecasting techniques, preparing data and checking relational data to enter the forecasting process and displaying the dashboard report in different perspectives. A time series study by Zhou and his colleagues researches and improves forecasting by time-series clustering in F-measure method to solve the quality problem of online video service, measurement and guidance systems for online video services [3]. There is the study of the time series method by finding various elements in the data and calculation formulas from trend values, moving average, seasonal variation, cyclical variation, variation and Irregular variation. The component values were then used as factors in the multiple linear regression equation. The models of accident data from many countries were found to be very interesting [4-7].

2.1. Analysis of traffic accident using data mining techniques.

Analysis of traffic accidents by Hwa and Lee found that traffic accidents happened to children around the school. Using data mining techniques and GIS, it found patterns of child traffic accidents, patterns of time and incidents resulting in children's traffic safety management to be aware of the incident point and plot coordinates on maps using car accident data by QGIS and data collection by PostgreSQL and using R language to analyze the correlation of accidents and display on the map [8,9].

2.2. **Time series forecasting from a comparison of traditional and Box-Jenkins methods in a case study of the number of accidents in Thailand.** The Bureau of Highway Safety, Department of Highways, Ministry of Transport (2011) [1] studied the prediction of the number of accidents on highway in the form of the decomposition approach. In the study, the database has been assembled from the Bureau of Highway Safety, Department of Highways and the Royal Thai Police (from 1993-2002) to analyze and design a model using the decomposition approach to predict the number of accidents. This statistical research's process began with time-series-data distribution plan: both linear and non-linear, to determine the trend of the number of accidents in the time series. From the test results, it was revealed that there was a high rate of data volatility, and when performing a moving average to find seasonal components, it was found that the seasonal components in April were the highest, followed by January and December, all of which are the times in which the prevalence of accidents was due to driver behavior influenced by national's annual festivals in the country [10-13].

2.3. **The use of decomposition approach to create time series forecasting model.** Since road accidents are the leading cause of injury and death to people around the world, the establishment of driving-accident forecasting can help prevent and reduce the number of accidents on the road. Therefore, this study uses a seasonal time-series model in predicting the number of road accidents based on the incidence-data of patients sent to the hospitals. It was found that the highest accident rate was influenced by heavy traffic during annual holidays, including New Year's Day period, summer travels, and religious pilgrimages. Moreover, the forecast also shows an increase in potential accidents in the future, and the information found can then be used to plan to deal with further accidents in the upcoming future [2,11,14]. However, motorcycle accidents might be inaccurate because some of the accidents reported to the municipality do not have a specification of their causes because those who report the accidents are afraid, and they could have conflict with the police. Along with this, the analysis conducted as far as the accident data reported to the municipality: the causes of accidents from animal and car-backward collisions. Furthermore, from the analysis, it has been found that the trend of motorcycling into many regions and the motorcycle accidents has risen from the past. It is thus recommended that the Road Safety Board proposed a campaign to reduce accidents in the future [15]. Likewise, in Iran, the researchers there have conducted observational research to examine trends of road accidents and anticipate the accidents in the next year using a time-series model in 2007, in the assessment process of fatality likelihood from accidents in the previous years in order to predict the accidents that will occur in the next 4 years. This research has also acknowledged that the median age of deaths is 37.22 year-old, comprising 77.5% male, 22.5% female [14,16].

Since the quantitative data is collected to be used in the analysis, in order to make accurate predictions, other factors are required for the analysis, so the research study for time series forecasting models using time series decomposition is employed in various research studies including quantitative forecasts for solving various production planning allocation problems, for example, a research aimed at determining time series forecasting models to forecast animal feed exports by using time series decomposition that used data output forage from January 2011 to December 2014 to find out the least squares methods, which were three methods: linear, parabola and cubic polynomial. After that, the trend values of each method were used to find the relative values of seasons (S), relativistic cycles (C) and the relative values of irregular events (I), and then created the forecasting equations and tested the discrepancies. The result showed that the predictive model of the parabolic equation had the lowest errors [10].

According to a 10-year analysis of transport-risk rates from 2000 to 2009 in which multivariate linear regression was used in modeling and forecasting the transport accident fatality-rate, the age of deaths in Thailand has increased: more male than female in the age-range between 20-29 years old. The other method is the multiplication and reversal frequently used to model mortality and the number of deaths with the modulation of models such as geographic variables, regional rates comparing only age and sex, which consider age and time areas, and the population. In several developing countries, road accidents are a serious problem, so there has been the development of models to predict accident possibility like the research on road accidents in Malaysia which has adopted an unchangeable structured time-series method that has been improved from the original one. It also has the model's accuracy validation with the mean absolute percentage error (MAPE). From the process, the linear trend model provides the value of MAPE of 0.082% indicating that the accident trends have been lowered, which makes the model satisfactory to be used for more highly efficient accident prediction [10,17-20] and the research on road accidents in Nigeria uses the data between 1989 to 2008 to analyze a number of accidents on time by time series method [21].

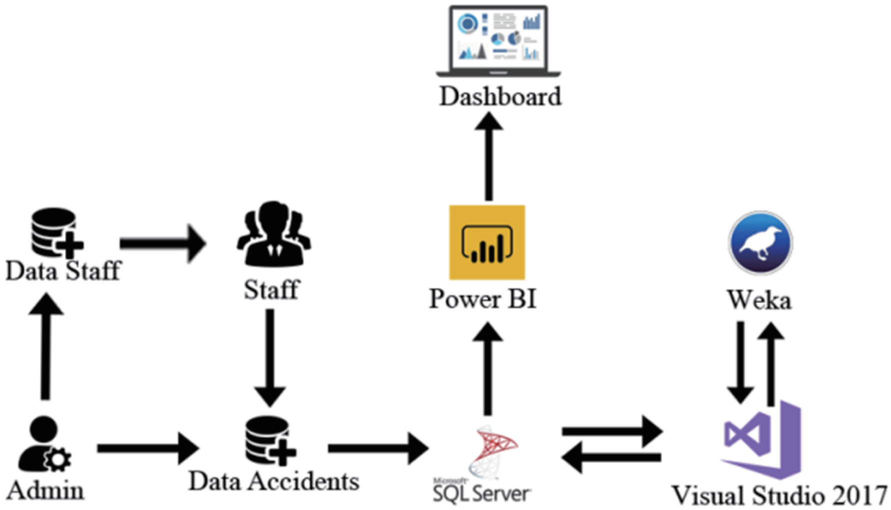

FIGURE 1. System work flow

3. Methodology.

3.1. A preparation of accident data for forecasting.

3.1.1. *Area zoning.* The accident information is a kind of raw data which cannot be used immediately since there are a lot of details required to be adapted: the date, time, province – where the accident occurred (only Chonburi in this case), district, sub-district, scene, latitude and longitude, nature of incident, type of vehicle, symptoms, and sex and age of the wounded. In addition, since incident data has no frequency of information, it is necessary to define the area of Chonburi Province by dividing it into a total of 181 areas; each area is set 5 square kilometers. Unfortunately, there are only 120 available areas because the other 61 areas have very little continuous data or no data at all since there is no route going through these locations. Hence, the entire 61 areas are taken out of the observations, while the rest of 120 areas are coded and named following the center of that area, and defined the forecast state based on the continuity of the data as a number: 1 is a monthly forecast, 2 is a quarterly forecast, 3 is a weekly forecast, and 4 is non-predictable [6].

3.1.2. *A preparation of relevant data values.* The analysis of time series data requires the preparation of relevant data values prior to analyzing them with Weka. There are 5 necessary values in the process: trend, moving average, seasonal variation, cyclical variation and irregular variation. The methods will be as follows [3,7,13,18,22,23].

1) *Trend* is T derived from

$$T = a + bx \tag{1}$$

When the equation has

$$a = \frac{\sum y}{n} \tag{2}$$

and

$$b = \frac{\sum xy}{\sum x^2} \tag{3}$$

y is actual data value, n is number of datasets, and x is data's central value that has been set.

The value of x is obtained by counting the total number of data sets to determine if all data sets are even or odd. If the number of data sets is even, put $1, 2, 3, \ldots, n$ where the data set is greater than the central value of the data and put $-1, -2, -3, \ldots, -n$ where the data set is less than the central value of the data. On the contrary, if the number of data sets is odd, put 0 for the central value of the data, and put $1, 3, 5, \ldots, n$ where the data set is greater than the central value of the data and $-1, -3, -5, \ldots, -n$ where the data set is less than the central value of the data.

When the values of trend for each area are different due to different data, the number of data sets will change after inserting new data sets, affecting the trend values to change as well.

2) *Moving Average* is MA derived from

$$MA = \sum_{i=1}^{n} y \tag{4}$$

The determination of MA is different in many ways because the obtained data is recorded daily with 3 types of the forecast.

2.1) A monthly forecast is a method in collecting data once a month, in which there are 36 data sets over 3 years when n stands for 12 months. The sum of y is calculated from the first to twelfth month in 2016, divided by n and put into the middle of the data set: the seventh month of 2016. Then, the method will be repeated to find the next MA by calculating the sum of y from the second month in 2016 to the first month in 2017, and dividing the sum with n again. The whole process will continue as a loop until it has reached the total number of data sets.

2.2) A weekly forecast is a count of the total data on a weekly basis over 3 years, which there are about 144 data sets with n as the number of weeks. The sum of y is calculated from the first week of the first month to the fourth week of the first month in 2016 divided by n and put into the middle of the data set: the third week of the first month in 2016. The next set's MA is obtained by taking the sum of y from the second week of the first month to the first week of the second month in 2016 to be divided by n, and the loop will continue until it meets the total number of data sets.

2.3) A quarterly forecast is similar to the weekly one but the number of data sets of the quarterly forecast is less than the weekly forecast because there are only 12 data sets collected over 3 years with n as the number of quarters. The sum of y is calculated from the first to the fourth quarter in 2016 divided by n and put into the middle of the data set: the third quarter of 2016. The value of MA in the next set is obtained by taking the sum of y from the second quarter of 2016 to the first quarter of 2017 to be divided by n, and the loop will continue until it meets the total number of data sets.

3) *Seasonal Variation.* Seasonal variation, S, is obtained by applying the moving average to the average again. It is the sum, divided by 2, of the current MA and the next MA which keeps repeating to meet the total amount of data. The actual data will be divided by the existing mean and multiplied by 100 to acquire the resulting values to put in order. Then, the values in each row are added together and divided by the multiplied number, and then provide the unadjusted value of seasonal variation which must be brought to count the exact total number of data sets, multiplied by 100: $12 \times 100 = 1200$, multiplied again by 1200 and divided by the sum of the unadjusted data. After that, S values are adjusted and sorted in chronological order, looping repeatedly until all the data sets have been completed.

TABLE 1. An example of quarterly moving-average insertion

Year	Month	y	MA	Year	Month	y	MA	Year	Month	y	MA
2016	1	27	–	2017	1	44	53.833	2018	1	52	61.25
	2	35	–		2	68	55.583		2	41	60.917
	3	41	–		3	76	57.583		3	46	60.833
	4	24	–		4	52	59.583		4	59	59.75
	5	22	–		5	47	60.25		5	62	59.75
	6	30	–		6	79	63.083		6	56	58.833
	7	45	38.25		7	66	65.417		7	62	60.167
	8	40	39.667		8	64	66.083		8	63	–
	9	46	42.417		9	70	63.833		9	57	–
	10	53	45.333		10	61	61.333		10	61	–
	11	47	47.667		11	81	61.917		11	70	–
	12	49	49.75		12	77	63.167		12	93	–

TABLE 2. An example of ordering seasonal variation values on the actual data

Year	Month	y	S	Year	Month	y	S	Year	Month	y	S
2016	1	27	81.809	2017	1	44	81.809	2018	1	52	81.809
	2	35	92.666		2	68	92.666		2	41	92.666
	3	41	101.807		3	76	101.807		3	46	101.807
	4	24	91.680		4	52	91.680		4	59	91.680
	5	22	89.334		5	47	89.334		5	62	89.334
	6	30	107.267		6	79	107.267		6	56	107.267
	7	45	106.680		7	66	106.680		7	62	106.680
	8	40	96.846		8	64	96.846		8	63	96.846
	9	46	107.079		9	70	107.079		9	57	107.079
	10	53	105.236		10	61	105.236		10	61	105.236
	11	47	111.680		11	81	111.680		11	70	111.680
	12	49	107.915		12	77	107.915		12	93	107.915

4) *Cyclical Variation* replaced by C can be derived from

$$C = \frac{Y}{T} \tag{5}$$

where Y is the actual data, and T is the trend value.

5) *Irregular Variation* replaced by I can be derived from

$$I = \left(\frac{Y}{T \times S}\right) \times 100 \tag{6}$$

where S is the seasonal variation.

All precedent values are necessary for the analysis. The forecasting in each area always needs to prepare data in advance. The information will vary depending on the area and forecasting state.

The last part of the data preparation is to highlight the actual data in the next forecast, represented by $y + 1$, which can be seen that the $y + 1$ column contains the value of the last row as null or no value. Thus, the blank space is the predicted value using the linear regression function and cross validation folds = 10.

3.2. **The forecast of the number of accidents.** After readily preparing the information for the forecast of the number of accidents, the prepared data saved in SQL Server will be linked to Weka so that the program can generate a prediction model and forecast the number of possible future accidents using linear regression which uses the cross validation at 10. Consequently, the prediction result and model are represented. The model and the outcome of prediction about the number of accidents appear varied, and each area has different model in predicting the number of accidents, which are monthly, quarterly and weekly forecasts [5].

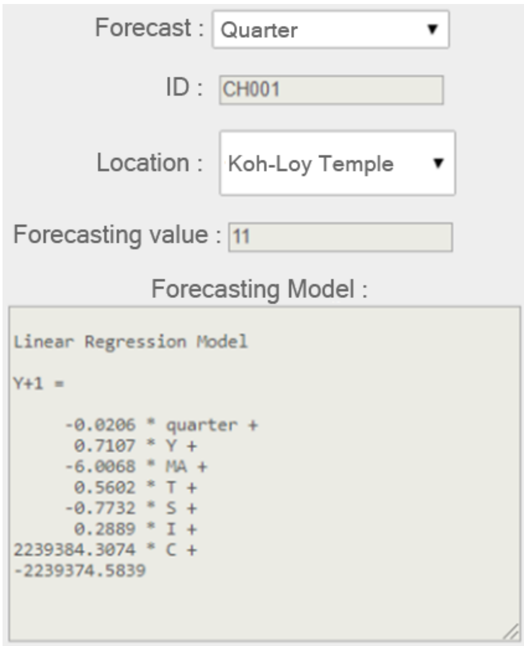

Figure 2. An example of quarterly forecast values and models

3.3. **Dashboard.** After the forecast value has been obtained, it will be recorded in a new table to create a line graph showing a comparison of the number of accidents between the actual and forecast data. All data will be saved in Microsoft SQL and connected to Microsoft Power BI to create a graph to display on web application.

4. **Results.** The results of this research that the data obtained after the forecast were similar to or different from the actual data, depending on the continuity of the data. If the accident data of a certain period occurs more frequently than others, the forecast results can be inaccurate, if the data in the same area is too different and in some areas, the accident period, but is not consistent or it occurs. One then never happened again. Occasionally, accidents occurred for a long time, so data from that incident could not be used to analyze the accident-site accident prediction model by using linear regression from time series factors. The results were as follows: For instance, for the monthly forecasting, the data displayed 181 incident sites, which only 39 sites were analyzed, and the average RMSE was 3.55. the total deaths were at the highest point (40 people) at Soi Lotte,

Phan Thong District, and the lowest point at 0 at Huai Yai Mook, Banglamung District. Therefore, the highest RMSE in the analysis was 7.11 at the scene of Soi Khanam Seven, Sriracha District, and the lowest value was 1.54 at the scene on Nong Phlap Road – Sangkapiao Soi 6, Bang Lamung District. In terms of the quarterly forecast, there were 181 incident sites but only 62 could be used to analyze for the results, and it was shown that the average RMSE was 3.92, the highest number of deaths was 52 at the Pho Luang Rajthong Palace Shrine, Phan Thong District, and the lowest was 0 at Greenwood Golf Club, Ban Bueng District. Thus, the highest RMSE was 11.839 at the scene of Greenwood Golf Club in Ban Bueng District and the lowest RMSE was 1.009 at the scene of Khong Song Phi Nong, Phanat Nikhom District. Besides, from the weekly forecast from 181 incident sites, of which only 15 actual analysis results were obtained, and the average RMSE was revealed at 3.206, the highest number of deaths was 35 at Prachasuk Sawang, Muang Chonburi District and the least number was 0 at Ban Rong Po gas depot, PTT Public Company Limited, Bang Lamung District. Consequently, from the analysis, it was indicated that the highest RMSE value was 5.644 at the scene of Prachasooksawang, Mueang Chonburi District and the RMSE value was minimal at 0.38 at the scene of Mit Samphan Road, Mueang Chonburi. Visualization of time-series forecasts on web applications with dashboard with Microsoft Power BI, time series component analysis with SQL Script on Microsoft SQL Server and linear regression analysis on Weka Software, connected to a web application to use automatic prediction and display the result as shown in Figure 3. Figure 4 shows dashboard results, reporting of the number of accidents in Chonburi Province and the results of 3 types of accident prediction: monthly, quarterly and weekly. Figure 5 shows a linear graph comparing the y-values for the number of accidents at the actual scene, shows a solid linear graph with the $y+1$ value representing the number of accidents according to the forecast scene, and shows Line Graph Clip Art.

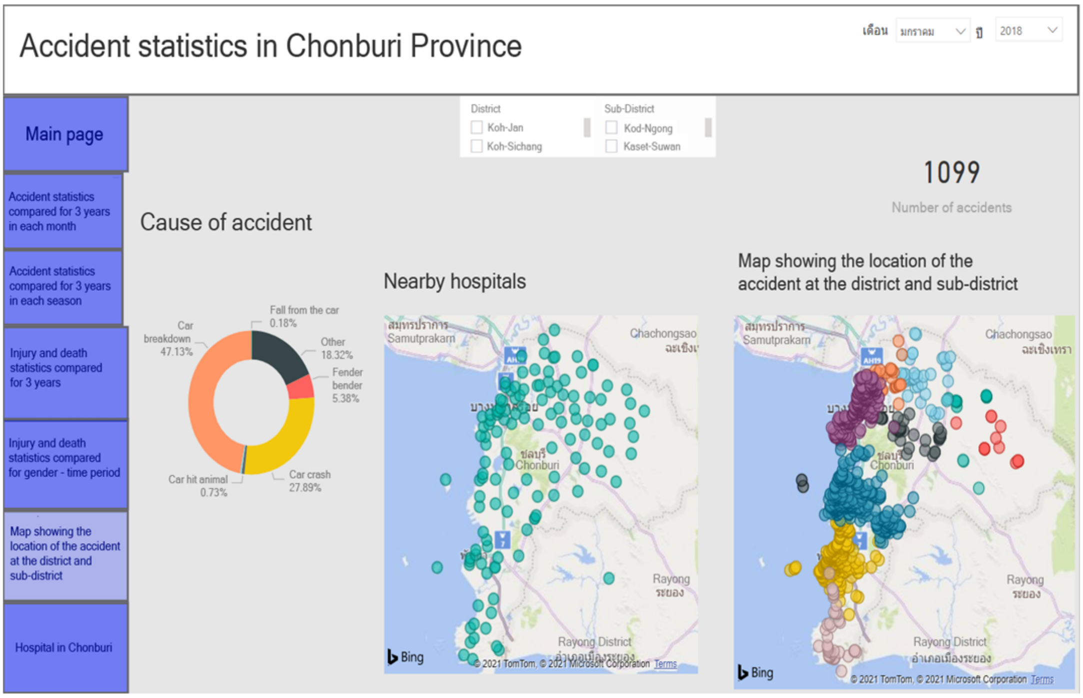

FIGURE 3. Map showing the accident at the district – subdistrict

5. **Conclusion and Discussion.** From the results of the research and analysis to predict the number of accidents at various incident locations in Chonburi Province using data on the 3-year accidents in Chonburi from 2016 to 2018, a time-series forecasting model was constructed using time-series separation method, separating the incident area and three

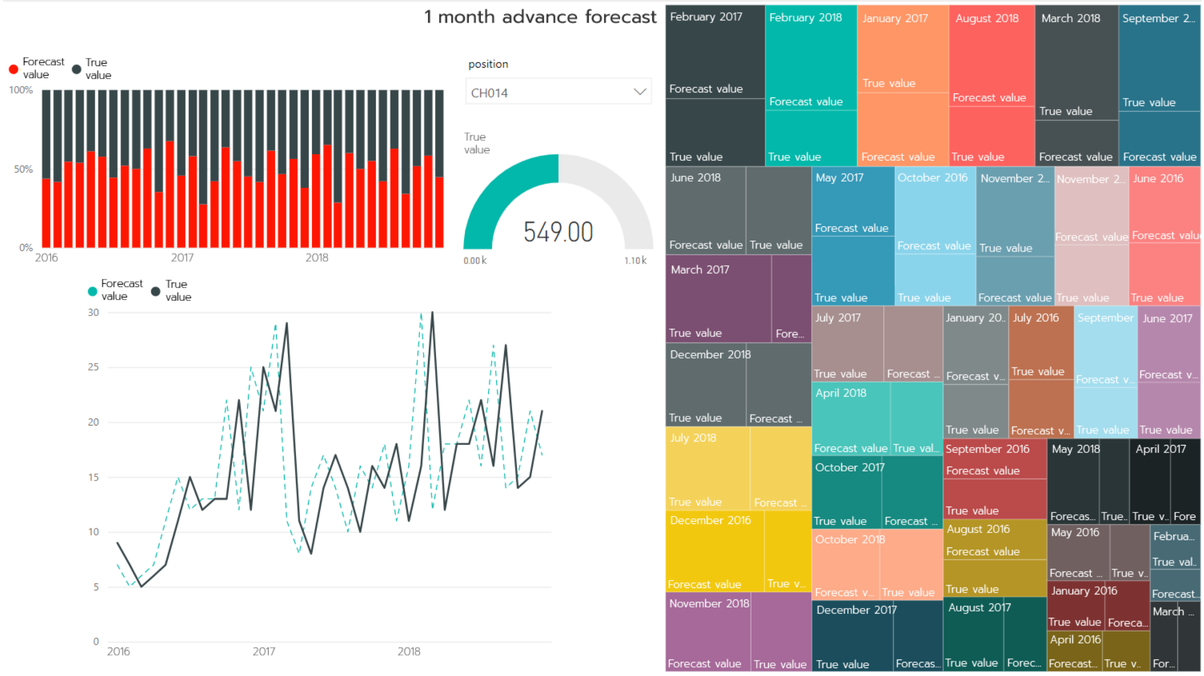

FIGURE 4. The forecast of the number of accidents dashboard

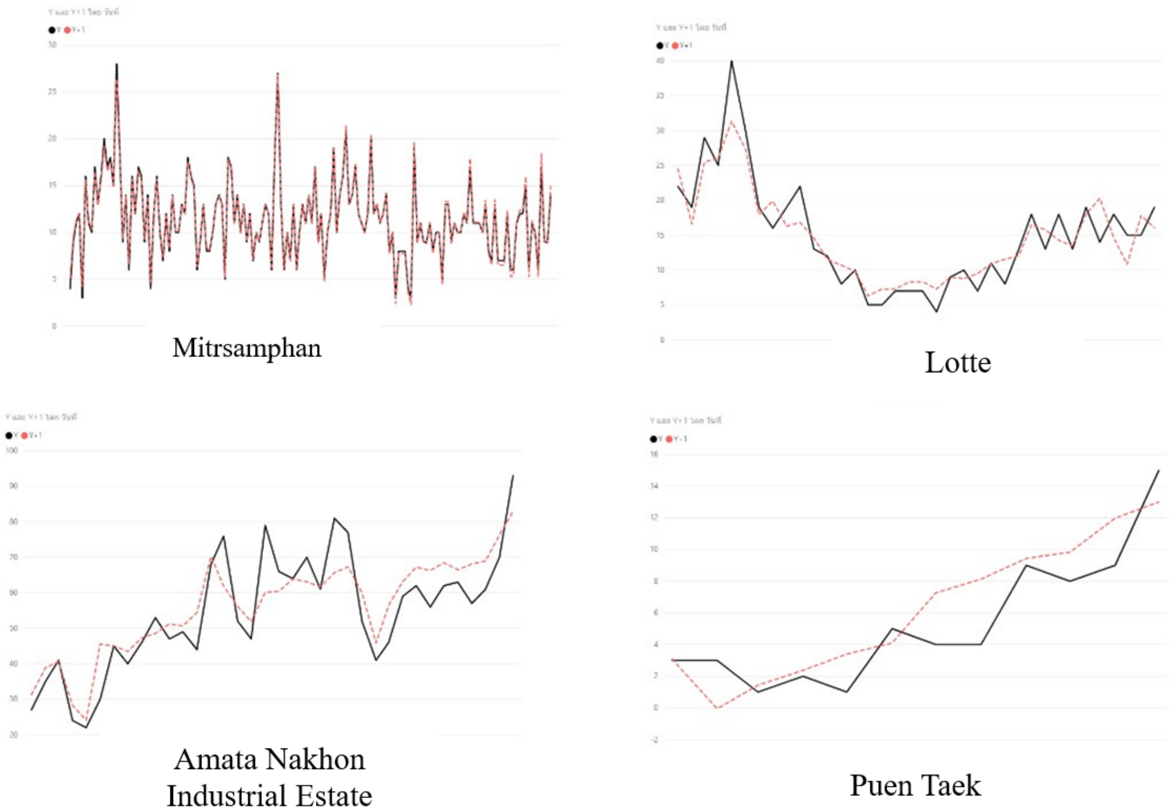

FIGURE 5. An example of line graph forecast values compared with actual values

periods of time: monthly, quarterly and weekly accident peaks, which can be concluded that the use of accident data to create a forecast model using the time series and linear regression, and make a forecast provide the outcome of the number of the incidents, close to the actual values, that are neither very high nor very low from the typical value of the data, and the root mean square error: RMSE is different due to the condition in each area. In terms of the accidental areas, if the number of accidents in any area varies greatly

TABLE 3. An example of quarterly forecast values compared with actual values

An example of quarterly forecast values					
Ban Khong Dara School		Wat Surasak Montri		Ko Lan	
Actual values	Forecast values	Actual values	Forecast values	Actual values	Forecast values
5	7.844	2	2.698	3	3.092
4	8.918	3	4.087	3	−0.051
11	9.710	3	4.524	1	1.436
11	6.483	5	4.480	2	2.378
5	6.347	6	4.655	1	3.403
9	2.547	4	4.550	5	4.096
2	2.876	4	5.781	4	7.264
3	4.272	5	4.338	4	8.129
6	1.251	4	5.340	9	9.438
3	5.075	7	2.195	8	9.834
3	3.678	2	6.353	9	11.981
2	3.232	6	3.958	15	13.006
RMSE	4.969+/−2.415	RMSE	2.579+/−3.547	RMSE	4.286+/−6.477
Micro average	5.983+/−0.000	Micro average	5.503+/−0.000	Micro average	7.231+/−0.000

at different times, it will lead to more in accurate predicting value than usual. As the forecasts mentioned above, it can inform those involved or responsible for each area to learn the number of accidents that could happen in the future so that they will be able to prepare to handle every unexpected accident appearing immediately.

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