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Rendayu Jonda Neisyafitri[1], Pornthipa Ongkunaruk[2,*]
[1] Department of Agro-Industrial Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia
[2] Department of Agro-Industrial Technology, Kasetsart University, Bangkok, Thailand

**) Correspondence email: pornthipa.o@ku.ac.th*

The Use of Intervention Approach in Individual and Aggregate Forecasting Methods for Burger Patties: A Case in Indonesia

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ABSTRACT

The Indonesian beef consumption increases sharply during Ramadan and made a difference between supply and demand. The research aimed to study the demand pattern of burger patties and determine a suitable forecasting method compared between quantitative and intervention forecasting methods. The actual demand was intervened by experts based on reasons such as supply shortage, holidays, promotion, and government projects. The daily sales of burger patties were collected for a year. Then, the data were divided into training and testing data. Later, time-series forecasting was performed by software. Then, the best forecasting method for daily data was selected between Individual forecasting and Top-Down forecasting. Similarly, for weekly data, the best forecasting method was compared between aggregate forecasting and Bottom-Up forecasting. Then, repeat the process for the intervened sales data. The result revealed that the mean absolute percentage error was improved after intervention by about 3.64%-58.83%. The combination of quantitative and qualitative approaches improved forecast accuracy. In addition, the aggregate level or weekly sales forecast had higher forecast accuracy than the disaggregated level. The Bottom-Up forecast performs better than the aggregate forecast. Hence, we recommended the company plans based on weekly data and implement Every Low Price to reduce the demand fluctuation.

Keywords: Aggregate forecasting; Burger patties; Individual forecasting; Intervention; Time-series forecasting

INTRODUCTION

Indonesia is one of the largest beef markets in Asia with a whole expenditure expected to grow 9% by 2022. Beef is the third most consumed protein in Indonesia after chicken and fish with a mean of meat consumption of 2.72 kg per capita per year (Agus, Budisatria, & Ngadiyono, 2014). Currently, there is a difference between the supply and the demand for beef. Where domestic production can cover around 45% of the requirement. To fulfill the unsatisfied demand, the Indonesian Government has been importing frozen meat and live cattle from Australia (Nendissa, Anindita, Hanani, Muhaimin, & Henuk, 2019). Beef consumption mostly increases sharply during some occasional events, such as Ramadan and

Eid Al-Fitr. Ramadan dates are established on a lunar calendar and change every season. Therefore, the timing for beef demand always changes every year (Australia, 2018).

The food supply chain sustainability depends on accurate future demand prediction (Petropoulos & Carver, 2019). Forecasting is one of the important activities in planning. It helps to estimate the demand and resources for production and service and control the planning to fulfill that level of activities (Lewis, 2012). It can act as a tool to enhance the performance of the supply chain management process to fulfill customer requirements. For the company, forecasting is important because it helps to manage the production, inventory, and planning decisions (Pennings & van Dalen, 2017). According to Fong, Li, Dey, Gonzalez Crespo, and Herrera-Viedma (2020), a forecast from one model is not enough. It has to be from a selection of several models. In addition, it is a challenge to create the most perfect forecasting model with only limited data available when using data mining (Cantón Croda, Gibaja, & Caballero, 2018).

There are three standard approaches to building a forecast model from a small-scale dataset. First, to increase the training dataset by increasing further data onto the existing data. Second, to use a collection of data to construct a forecast model, then the smallest error is chosen. Third, to focus on a particular projection algorithm which frequently happens with various parameters to be modified (Fong et al., 2020). However, according to Chopra and Meindl (2016), the facts of forecasts are always incorrect and they should contain the expected value and the error of the forecast. The short-term forecast is usually more accurate than long-term forecasts because the short-term forecast has a smaller standard deviation of error compared to that of the long-term forecasts. Also, the aggregate forecast accuracy is usually more than the disaggregate forecast accuracy since it has a smaller coefficient of variation (Athanasopoulos, Hyndman, Kourentzes, & Petropoulos, 2017). According to Li, Yin, Manrique, and Bäck (2021), when aggregation is achieved using adequate product sales data, the aggregated model could give a better forecast than other aggregated models. Wolters and Huchzermeier (2021) mentioned that no forecasting method can accurately predict the mixture of seasonal sales variations and promotion-stimulated sales heights over forecasting horizons of many weeks or months. Mor, Jaiswal, Singh, and Bhardwaj (2018) mentioned that forecasting accuracy is very important because the existing demand patterns are volatile, and it is affected by the dynamic market.

Forecasting is sometimes complicated because the downstream supply chain stakeholders cannot share the information to support the forecast. Many industries such as food, retail, mining, rail, energy, tourism, and cloud computing need to generate more accurate forecasts to provide a better foundation for determining short-term, medium-term, and long-term corporate targets (Bandara, Hewamalage, Liu, Kang, & Bergmeir, 2021). One of the forecasting methods is the qualitative forecasting method which relies on personal judgment, intuition, and subjective evaluation (Chopra & Meindl, 2016). This method is appropriate when the historical data is limited or there is a change in the demand pattern. The forecast models with limited data will create different demand scenarios (Lee & Chiang, 2016). Other than that, qualitative forecasting which relies on professional modification or

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intervention is suitable for the demand that is responsive to sales promotion (Pradita, Ongkunaruk, & Leingpibul, 2020). The Top-Down forecast approach is based on the aggregate or family product, then dispersed to the particular items in the family based on the past proportion (Mirčetić, Nikoličić, Stojanović, & Maslarić, 2017).

Meanwhile, the Bottom-Up forecast approach summarizes the individual item time series forecast to generate the aggregate forecasts. According to Mirčetić et al. (2017) research in a beverage supply chain, it is found that the Bottom-Up forecasting generated more accurate forecasts. The forecasting method requires control and feedback to derive the best result. The principle for controlling forecasting is the forecast error must be normally distributed with a mean equal to zero ($\varepsilon_i \sim NID\ (0,\sigma^2)$). The forecasting method can be evaluated by measuring the forecast accuracy. The mean absolute percentage error (MAPE) is used to measure a difference between actual and forecast demand especially for a different type of data (Ha, Seok, & Ok, 2018). Forecast accuracy is critical to a firm's effectiveness in planning and inventory control (Davydenko & Fildes, 2013). The combination of both quantitative and qualitative approaches helps to increase forecast accuracy. The qualitative approach involves individual perception to figure out the unusual data points and adjust them before the data were processed quantitatively (Pradita et al., 2020). Kharfan, Chan, and Efendigil (2021) studied a data-driven methodology to improve the demand forecasting procedure for fashion retailers for recently launched products without historical data in a vigorous market situation. The results showed that the three-step model delivers visibility of core factors that influence demand through clustering and classification. The customized prediction is applied to provide the greatest results based on product characteristics such as life span length, sales quantities, retail price, and store location.

This research was conducted in an abattoir located in Bogor, West Java. Based on the previous investigation, it was found that the order cancellation affects demand planning in the abattoir. The problem of the burger patties demand is the order cancellation from the traders that affects demand planning in the abattoir. When a trader cancels the order to the abattoir, the scheduled time for producing the burger patties will be canceled. So, the worker will be idled. However, this situation is a loss for the abattoir since they have unutilized paid workers. Moreover, the company loses the chance to serve another trader. Demand planning is important for the company to protect from losing the chance to serve another customer. This research objectives were to study the demand pattern and determine the best forecasting method to improve forecast accuracy by comparing quantitative and intervention forecasting.

RESEARCH METHOD

The daily sales of burger patties were collected from the past year's abattoir and trader data (September 2018 – August 2019) because this company is just entering the industry. The data is split into two data including training and testing. The training data will be used to construct the forecasting model while the testing data will be used to verify how good the forecasting method is. There is no mandatory rule for the proportion of training and data. The common strategy is to split the data to 80% of the data into the training set and the rest for the testing set (Joseph & Vakayil, 2021).

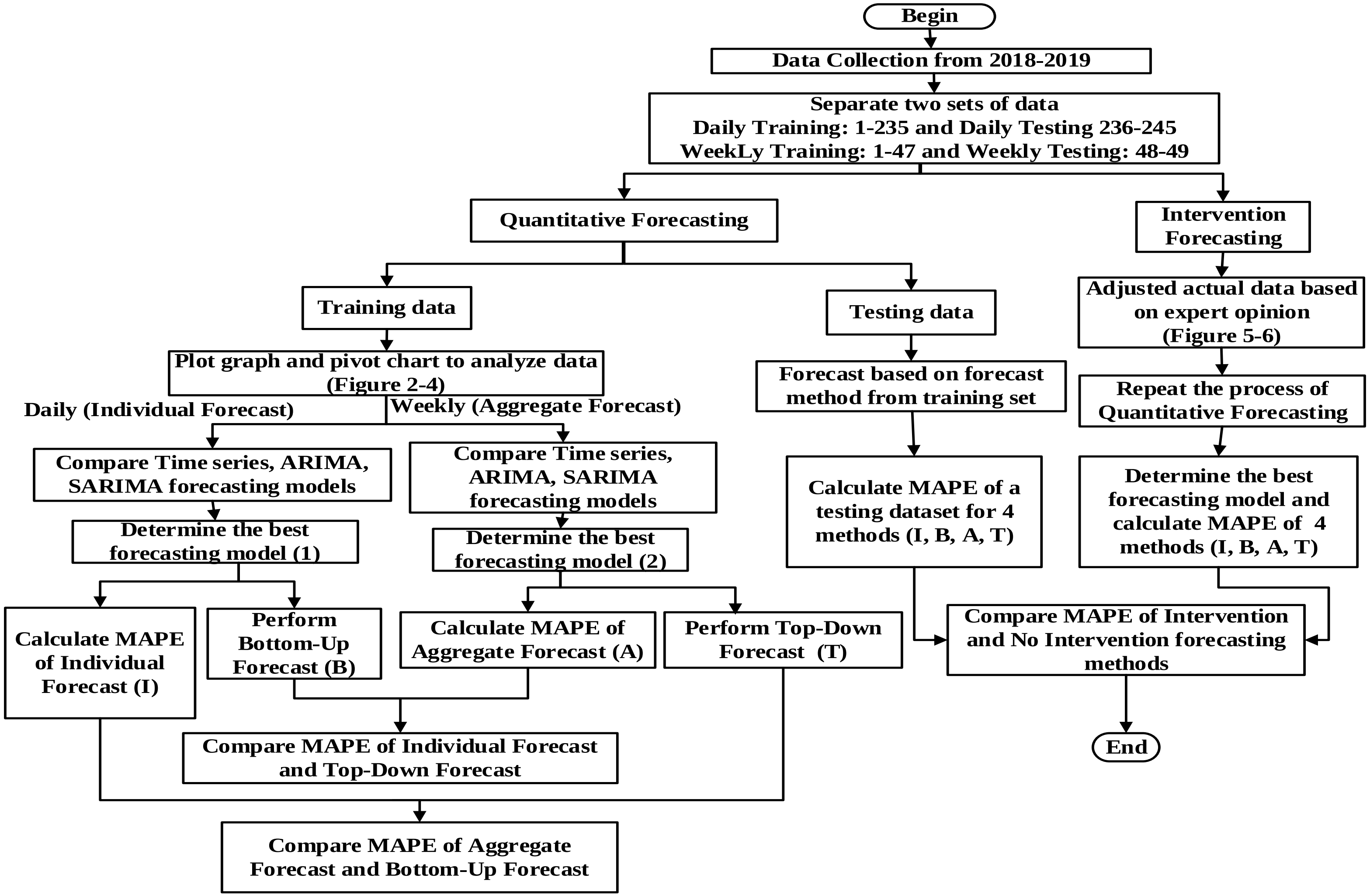

FIGURE 1. FLOWCHART OF COMPARISON THE FORECAST ERROR OF 4 FORECASTING METHODS BEFORE AND AFTER INTERVENTION

Several factors need to be considered by the decision-maker including characteristics, data type, and size of data. Most researchers divide the data based on the rule. In our case study, the training daily data is between Day 1^{st}-235^{th} and the testing daily data is Day 236^{th}-245^{th}. Similarly, the aggregate forecast of weekly data will be performed. The training weekly data is between Week 1^{st}-47^{th} and the testing weekly data is Week 48^{th}-49^{th}. Next, the historical data was analyzed whether there was a trend or seasonal. Then, the intervention forecast will be performed by adjusting the actual demand based on an in-depth interview with the abattoir manager and production supervisor considering the internal and external factors that affected the demand for burger patties. In the training data, the time-series forecasting methods were compared by using Crystal Ball software with the Predictor function. The optimal forecasting method will be selected to use in the testing data. In addition, for an individual level or daily data, the Individual forecasting will be compared with the Top-Down forecasting. Top-Down forecasting is from the multiplication of the proportion of daily data and the aggregate forecast. For an aggregate level or weekly data, the aggregate forecasting will be compared with the Bottom-Up forecasting. Bottom-Up forecasting is the sum of the Individual forecasting to become the weekly sales forecast. For the intervention forecasting, the forecast can be adjusted according to the event on that day such as adding 20% to the forecast value if there is a promotion. The summary of our method could be visualized as in Figure 1.

The forecast accuracy was assessed by MAPE for training and testing data both actual and adjusted data or the intervention method.

$$MAPE=\frac{\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right|*100}{n} \quad (1)$$

The forecast error for period t is expressed in E_t, which comes from the formula:

$$E_t = F_t - D_t \quad (2)$$

Where F_t is the forecast at time t, D_t is the demand at time t, and n is the number of data. Finally, the MAPE of each method was compared to figure out which method performs the best. The forecasting method can be evaluated by measuring the forecast accuracy. Forecast accuracy is critical to a company's efficient planning and inventory control (Box, Jenkins, Reinsel, & Ljung, 2015).

RESULT AND DISCUSSIONS

The Historical Sales Data for Burger Patties

The historical sales data for burger patties were collected from a trader during September 2018 – August 2019. Normally, there are 5 days in a week for a sales order. However, we separated two more days i.e. holidays and promotion days. The holidays have no sales while the promotion day will have high sales data. There were some days with peak orders without any reason due to fluctuated orders from the trader. It is quite difficult to check whether there is a trend or seasonal from Figure 2. and Figure 3.

The ovals indicated the peak sales order which is far away from the average sales. According to the previous research by Huber and Stuckenschmidt (2020) about the daily demand forecasting in retail, one of the challenges is to forecast the demand on the special days since it has a different demand pattern than the regular day. Hence, we use a pivot chart to show the average, standard deviation, maximum, minimum, and the number of data so that the data could be simply analysed as in Figure 4.

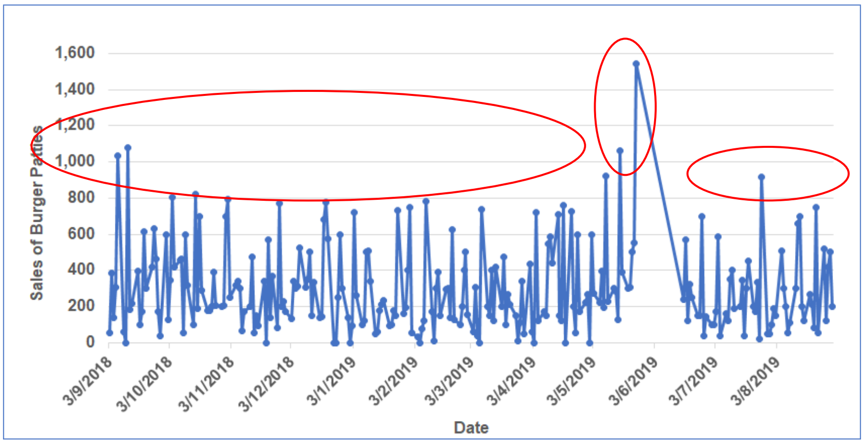

FIGURE 2. THE HISTORICAL DAILY SALES DATA FOR BURGER PATTIES

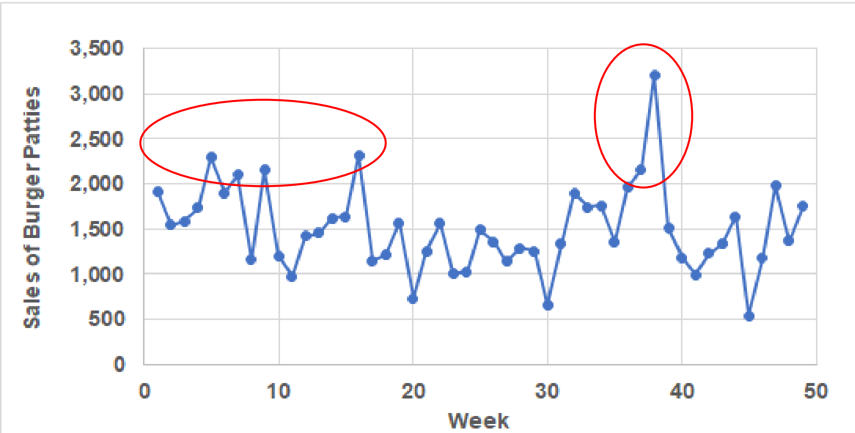

FIGURE 3. THE HISTORICAL WEEKLY SALES DATA FOR BURGER PATTIES

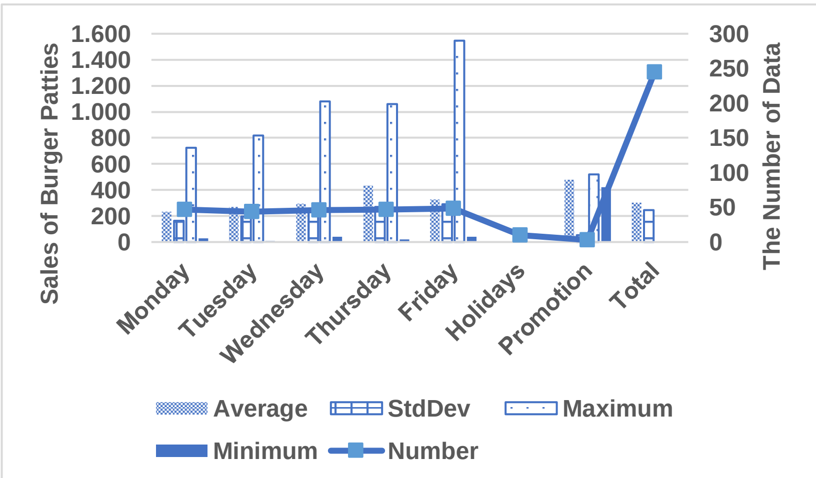

FIGURE 4. THE ANALYSIS OF DAILY SALES OF BURGER PATTIES

The results showed that the daily sales were seasonal on weekdays. There were higher sales on Thursday and Friday than those on Monday to Wednesday. The demand in May was increasing because of the Ramadhan and Eid Al-Fitr. However, the demand between May and June was not plotted because it is the Eid Al-Fitr holiday, and the abattoir had to stop the operation according to the government regulation for 3 weeks. In addition, there might have a trend in daily data. The variances of weekdays sales were very high, and this resulted in high forecast error.

The Intervention of Daily Sales Data

The in-depth interview was conducted with the experts to justify the unusual pattern of the data. Then, the intervention was performed to adjust the abnormal data back to normal. This implied that the data will be reduced if the data was too high. Otherwise, the data will be increased if it was too low. Hence, the expert should be able to justify when these two events happened. Two major factors affect the unusual pattern in the supply chain called internal and external supply chain factors. The internal factors could be the supplier, the company's condition, and customers. Meanwhile, the external factors could be government regulations and policies, economic conditions, social trends, and natural disasters that affect the buying power of the customers.

The data adjustment was done according to several events in the abattoir. On 7 September 2018, the abattoir started the project and sponsorship to increase the market coverage. Hence, the sales data on this day will be deducted by 15%. Besides, on 12 September 2018, there was an accumulated order as the effect of the Islamic New Year holiday. During this holiday the abattoir was closed. Then, the adjustment of decreasing the demand should be pursued because this event did not happen every week. On 12-16 November 2018, a huge flood happened in several areas in Jakarta. Therefore, the number of customers who are mainly hotels, restaurants, and caterers were decreasing. The adjustment was performed by increasing demand by 10%. On 22 December 2018, there was a tsunami in *Sunda* Strait that happened because of an explosion and fractional breakdown of the Anak Krakatau volcano. Several coastal regions in Banten and Lampung Province were struck. This strait connects Java and Sumatera Island. The cattle from the feedlot need to be transported through this strait and there is no other way to transfer these cattle. During this situation, the harbor was closed because it was not safe for the ship to pass through the straits. Therefore, the feedlot was unable to send the cattle to the abattoir. This situation was affecting the supply shortage on 14-18 January 2019, since the raw material is the chilled beef that has already passed the aging time. Therefore, the demand was increased in that period. After that, on 18-20 March 2019, the company signed a new contract with a big retailer to give a sponsorship to their events. Hence, the sales were adjusted by decreasing it. At the end of the month, there was a generator set breakdown. So, the abattoir only has limited capacity to produce the burger patties. Hence, the sales were adjusted by increasing it by 5%.

On 1-5 July 2019, the sales were decreased due to supply shortages during the Eid Al-Fitr holiday. During this period, the government prohibited cargo shipping activity for 3 weeks. Therefore, the abattoir was unable to do the operation activities normally. The materials that the abattoir used were just only the available stock in the warehouse. Since it has a limited capacity, the sales were not high enough. Hence, the sales were adjusted by increasing it. On 26 July 2019, the company signed a new project with the retailer to produce a huge quantity for the retailer. Therefore, there was an irregular pattern. Then, the data was adjusted by decreasing it. From the end of July until the beginning of August, the customer's buying power was decreasing due to the economic condition. The sales were dropped and there were a lot of stocks in the warehouse. So, the demand in this period was adjusted by increasing it. Two weeks later, there was a special occasion celebrated by Muslims which is the Eid al-Adha. During these days, the Muslims in the country will slaughter either cattle, buffalo, or sheep. Since the abattoir provides the service to process the raw meat from the customer to produce a burger patty. The customers use this service, and it makes the sales increase. Hence, the sales were adjusted by decreasing it. At the end of August, the sales of the burger patties were decreased since the customers still have their meat from the Eid Al-Adha. Therefore, the abattoir and the trader make promotions to push the sales. During this period, the sales were increased and need to be adjusted by decreasing it. On 27 and 30 August 2019, the sales were decreased due to supply shortage and need to be adjusted. The summary of the adjustment in the training data is shown in Table 1. The contrast between the daily and weekly actual and the adjusted data of burger patties demand is shown in Figure 5 and Figure 6.

TABLE 1. DETAILS ON THE ADJUSTMENT OF TRAINING DATA

Date	Quantity	Reason
07 September 2018	-15%	Sales increased due to project/sponsorship
12 September 2018	-10%	Sales increased due to accumulated orders from Islamic New Year Holiday
12 - 16 November 2018	10%	Sales decreased due to floods in several areas in Jakarta
14 - 18 January 2019	20%	Sales decreased due to supply shortage effect from *Sunda* Strait Tsunami
18 - 20 March 2019	-5%	Sales increased due to project/sponsorship
25 - 29 March 2019	5%	Sales decreased due to machine breakdown
24 May 2019	-50%	Sales increased due to the accumulated sales in Eid Al-Fitr
1 - 5 July 2019	15%	Sales decreased due to supply shortage
26 July 2019	-10%	Sales increased due to project/sponsorship
29 July - 2 August 2019	25%	Sales decreased due to low market demand/low buying power
13 - 14 August 2019	-20%	Sales increased due to Eid al-Adha
26, 28-29 August 2019	-20%	Sales increased due to promotion
27, 30 August 2019	20%	Sales decreased due to supply shortage

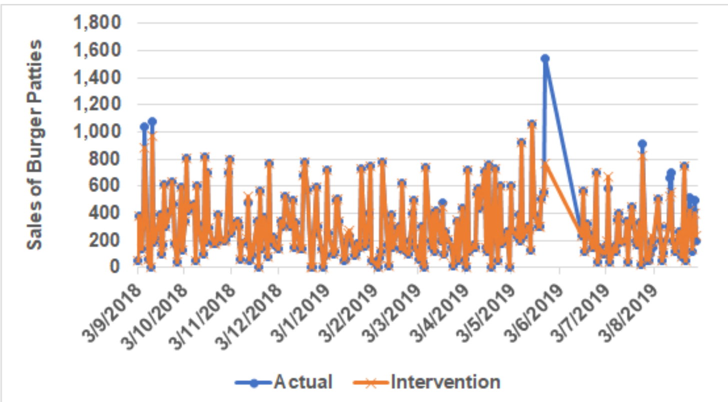

FIGURE 5. COMPARISON OF ACTUAL AND ADJUSTED (INTERVENTION) DAILY SALES DATA FOR BURGER PATTIES

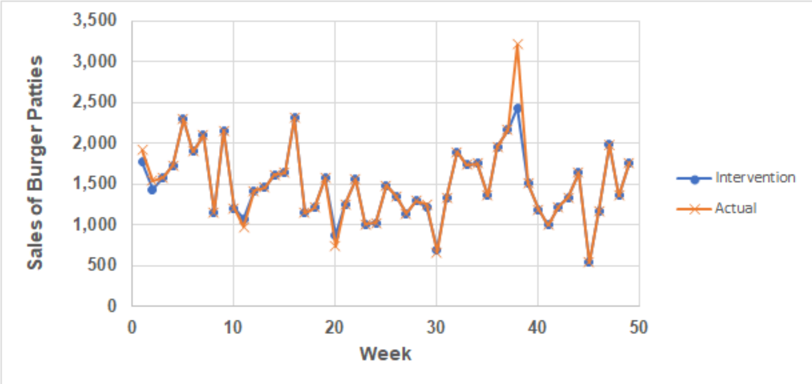

FIGURE 6. COMPARISON OF ACTUAL AND ADJUSTED (INTERVENTION) WEEKLY SALES DATA FOR BURGER PATTIES

Comparison demand characteristics before and after intervention

The descriptive analysis of daily sales data showed that the average sales on weekdays were 234.02-433.32 pieces per day while there was no order on holidays and the average on promotion day was 480 items with lower variance compared to weekdays. The most fluctuation on orders was on Friday and the highest average of sales was on Thursday. The major performance indicators most frequently employed in forecasting literature are coefficient of variation (CV) and MAPE (Sevlian & Rajagopal, 2018). The CV of daily data was quite high due to the fluctuation of sales data and ten national holidays. After adjusting the data, the average sales on weekdays were 235.19-437.77 pieces per day. Moreover, the variance after intervention could be reduced by 1.13-18.81%, especially on Friday which has a very high variance. On weekly basis, the CV could be reduced by 62.01% and 63.64% compared between daily and weekly data for before and after the intervention, respectively. In addition, the intervention could reduce CV by 9.68% as shown in Table 2. It implied that the aggregate forecast is more accurate and the intervention could increase the forecast accuracy. Posch, Truden, Hungerländer, and Pilz (2021) pointed out that most researchers on forecasting are focused on aggregate forecasting, which forecast on weekly sales rather than forecast individual item per day. Hence, the company should require the trader to order on weekly basis.

TABLE 2. COMPARISON OF SALES ORDER BEFORE AND AFTER INTERVENTION FOR BURGER PATTIES BY PIVOT TABLE

Day/Week	# of Data	Actual Data			Intervention Data			% CV Reduction
		Average	CV	Range	Average	CV	Range	
Monday	47	234.02	0.706	695	235.19	0.698	695	1.13%
Tuesday	44	269.52	0.73	810	268.52	0.711	810	2.60%
Wednesday	46	292.7	0.787	1,040	289.32	0.749	932	4.83%
Thursday	47	433.32	0.625	1,040	437.77	0.617	1,040	1.28%
Friday	48	326.25	0.888	1,505	307.96	0.721	840	18.81%
Holidays	10	0	-	0	0	-	0	-
Promotion	3	480	0.11	100	384	0.11	80	0.00%
Total	245	301.18	0.816	695	296.68	0.77	695	5.64%
Week	49	1,505.88	0.310	2,607	1,489.61	0.280	1,897.5	9.68%

Comparison of Actual and Intervention Forecasting Methods

The forecasting methods were compared based on a daily and weekly basis to understand the demand pattern and to plan for procurement, production, and distribution. These daily and weekly data enable abattoirs to track, monitor, and display demand for the short term and offer the capability to recap for the longer term such as months, quarters, and years (Chase, 2009). From the analysis, the daily data had both trend and seasonal whereas the weekly data had a trend but no seasonal. However, the best forecasting methods for daily and weekly demand were autoregressive integrated moving average (ARIMA). ARIMA is the most common and fundamental entity for time series analysis. This method predicts the future demand values of a time series by calculating the future value's statistical likelihood (Ford, Nava, Tan, & Sadler, 2020). It implied that there was a trend in daily and weekly data. We did not accept the best method for daily data from the software since it contradicted our analysis. Hence, we overlayed the ARIMA with Seasonal Additive. For the intervention daily data, Damped Trend Non-Seasonal was chosen instead of ARIMA. This led to high forecast error in the training data, but lower forecast error in the testing data. The best forecasting methods for actual and intervention of daily data are not the same. It implied that after adjusting the data, the seasonal pattern was removed. According to Hamzah et al. (2021), the ARIMA method is more accurate and can be used to predict chicken-based food products on weekly sales data. Other than that, Li et al. (2021) develop research using a two-step product lifecycle forecast approach for consumer technology products with inadequate sales data. It is found that to predict the lifecycle of a new product, models based on aggregated products usually outperform the models based on an individual product. The best forecasting method for weekly data was the same regardless of intervention which implied there was a trend but not seasonal as shown in Table 3.

TABLE 3. BEST FORECASTING METHODS OF DAILY AND WEEKLY SALES DATA

Sales data	Pattern		Best forecasting method	
	Trend	Seasonal	Actual	Intervention
Daily Data	/	/	Seasonal Additive	Damped Trend Non-Seasonal
Weekly Data	/	x	ARIMA(1,0,0)	ARIMA(1,0,0)

Comparison of forecast error between the actual and intervention of daily sales data

In the Individual forecasting methods, the forecast errors of the training data without the intervention were 68.14%, and with the intervention was 60.91% while those of the testing data were 65.75% and 49.24%%, respectively. The intervention improved the forecast accuracy by 10.61% and 25.10% in the training and testing data, respectively. In the Top-Down forecasting method, the forecast errors of the training data without the intervention were 135.80%, and with the intervention was 128.93% while that of the testing data were 104.28% and 94.98%, respectively. The result showed that the training data forecast error was higher than that of the testing data which is not normal. The reason was that the best forecasting methods of the training data were overlayed by the other methods. After the intervention, there were some improvements in the training data for 5.06% and 8.92% which was lower than the Individual forecasting for the testing data as shown in Table 4. Individual forecasting performed better than the Top-Down forecasting method; however, the forecast accuracy was still very low. Besides, the intervention would not help to increase the accuracy up to the acceptance level. This implied that the daily data should not be used to perform the short-term planning. The Top-Down approach performed poorly due to the fluctuation of the proportion of daily sales.

TABLE 4. COMPARISON OF FORECAST ERRORS BETWEEN THE ACTUAL AND INTERVENTION OF DAILY SALES DATA

Forecasting Methods	Actual		With Intervention		Improvement	
	Training	Testing	Training	Testing	Training	Testing
Individual	68.14%	65.75%	60.91%	49.24%	10.61%	25.10%
Top-Down	135.80%	104.28%	128.93%	94.98%	5.06%	8.92%

Comparison of forecast error between the actual and intervention of weekly sales data

The weekly sales forecasts were compared between aggregate and the Bottom-Up forecasting methods. In the aggregate forecasting methods, the forecast errors of the training data without and with the intervention were 22.78% and 21.95%, respectively. The forecast errors of the testing data were 39.59% and 16.30%, respectively. According to Pradita et al. (2020), In general, a forecast error in testing data will be higher than that of the training data since the forecasting model is based on training data. A method can be said overfitting if its error is low on the training data but high in the testing data, and it is an underfitting if its error is high on both training and testing data (Ghasemian, Hosseinmardi, & Clauset, 2020). A model that can fit in multiple categories is more accurate when the fundamental data is adequate (Van Donselaar, Peters, de Jong, & Broekmeulen, 2016). Hence, if the gap error between training and testing data is small, it implied that the model fits the data well. After the intervention, there was an improvement in the forecast accuracy where 3.64% and 58.83% in the training and testing data, respectively.

In the Bottom-Up forecasting methods, the forecast errors of the training data without and with the intervention were 31.85% and 29.50%, while those of the testing data were 20.48% and 8.81%, respectively. This implied that the forecasting method was suitable for the testing data. Besides, the intervention could improve the forecast accuracy by 7.40% and 57.00% as shown in Table 5. Compared with the forecast errors of the daily data, it implied that the weekly data could increase the forecast accuracy. However, the error was still a bit high in the aggregate forecast while Bottom-Up was more suitable.

TABLE 5. COMPARISON OF FORECAST ERRORS BETWEEN THE ACTUAL AND INTERVENTION OF WEEKLY SALES DATA

Forecasting Methods	Actual		With Intervention		Improvement	
	Training	Testing	Training	Testing	Training	Testing
Aggregate	22.78%	39.59%	21.95%	16.30%	3.64%	58.83%
Bottom-Up	31.85%	20.48%	29.50%	8.81%	7.40%	57.00%

In summary, the Bottom-Up forecasting method performs the best. Hence, the company should plan based on weekly data. Besides, to reduce the daily sales order variance, Everyday Low-Price promotion should be implemented. The company may try to find the causes of high variance in sales data and remove them. The point of sales (POS) data sharing also could help to increase the forecast accuracy and reduce the bullwhip effect in the upstream supply chain.

CONCLUSION

Demand forecasting is an important activity in planning. This research determined the best forecasting method for burger patties products on a daily and weekly basis due to one-year data availability. This study compared the Individual and Top-Down forecasting methods for daily sales forecast and the Bottom-Up and Aggregate forecasting methods for the weekly sales forecast. The time series forecasting, and intervention method were performed and compared. The demand pattern was analyzed based on sales data due to no point of sales data (POS) being available. The results showed that the daily sales data highly fluctuated on weekdays. This resulted in lower forecast accuracy on daily sales forecasts. We found that the intervention forecasting improves the forecast accuracy by 3.64%-58.83%. In addition, the aggregate sales data on weekly basis can improve the forecast accuracy. The best forecasting method is the Bottom-Up forecast by using the ARIMA method. Hence, it is recommended to perform the weekly sales forecast rather than the daily sales forecast and implement the intervention by the experts who realize the past and future situation. In addition, this research can be applied in other industries that need to forecast their products to increase service level and reduce inventory.

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Author contributions: Rendayu Jonda Neisyafitri was responsible for data collection, literature review, forecasting analysis, and drafting the manuscript. Pornthipa Ongkunaruk was responsible for forecasting methodology, forecasting analysis, and editing the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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