Development of a Forecasting Tool to Address High Percentage of Breach in Delivery Times in a Local Food Delivery Service

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Abstract

Online Food Delivery Services (FDS) have increased in popularity in the past few years. Timely delivery of food is crucial as it affects the quality of food and customer attitude towards the service. This study aims to address the orders that fail to deliver within the target lead time (breach orders) due to the non-optimal assignment of riders. This study proposes a method for determining the riders to assign per area from the demand through a simple forecasting tool. Current studies have already identified the factors that contribute to rider output. This study analyzes these factors to make a formula to calculate the rider output. In addition, the researchers will investigate the effect of new products and seasonal promotions on demand through a review and statistical analysis of historical data. This study contributes simple program that calculates the number of riders to assign based on user input.

Keywords
Food Delivery Service, Delivery Riders, Demand, Breach Orders and Forecasting.

1.Introduction
The insurgence of Covid-19 cases in 2020 prompted a government response of implementing a nation-wide lockdown. The pandemic caused many businesses and restaurants to impose a closure to their physical stores due to the threat of transmission of Covid-19 and have opted to avail of third-party food delivery services. **Food Delivery Service** is a courier service in which independent stores and restaurants deliver food to their customers. Delivery can be through in-store delivery or through third party delivery. Food delivery services is still seen as a major trend in various demographic categories and continues to evolve in the means of providing the service. The annual growth rate (CAGR 2020- 2024) of the Food delivery industry (platform - customers) is projected to a 7.0% increase which will reflect on a forecasted revenue of 51,514 (in million US dollars) for the year 2020 alone. (Li, Mirosa, & Bremer, 2020)

A local Online Food Delivery Hub in the Philippines offers a variety of restaurants through a mobile app. The riders come from a third-party hiring company which can provide the labor force requirement as dictated by the company. The company established a Service Level Agreement (SLA) — the standard lead time for each process in the food delivery service. The process starts with Create to Preparing which involves the time it takes to process the order and establish the needed ingredients. Once the order is processed, the next activity is the Preparing to Ready wherein the stores will prepare the ingredients, cook the food, have the order packed, and ready for transit. The next activity Ready to In Transit is the time it takes for the order to be received by the rider. This ends with Delivery Rider to Customer Handover which is the total time between the arrival of the rider to the location and the customer receiving their order.

The historical data shows that the number of breach orders have significantly increased during the month of June and July 2020 due to the strict policies during the peak of the Covid-19 pandemic. This remained consistent for the remaining 5 months of 2020 with an average of 54.6% still averaging at 52.50% in 2021. Breach orders are observed from all the stores affiliated with Company A during the first few months of 2021. The biggest contributor to which is the Ready to In Transit process which should only take 5 minutes as per the SLA, but data shows that the actual process takes an average of 19.42 minutes varying between 6 to 40 mins.

Figure 1. Created to Preparing
Process Lead Time

Figure 2:Preparing to Ready
Process Lead Time

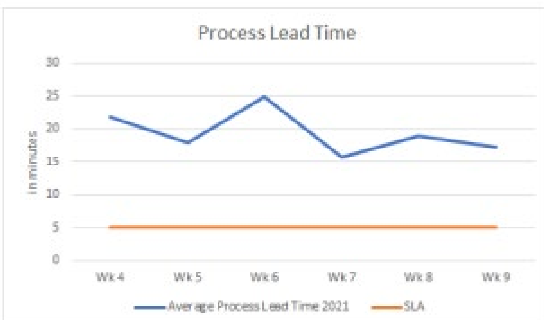


Figure 3. Ready to In-Transit
Process Lead Time

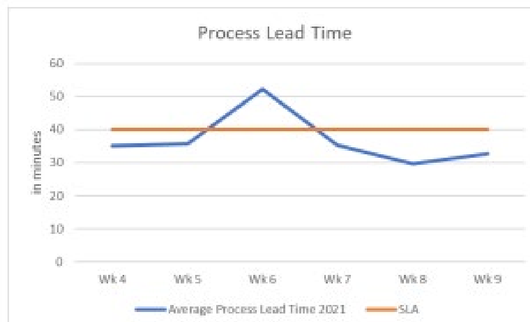


Figure 4. In-Transit to Delivered & Delivery Rider
to Customer Handover Process Lead Time

1.1. Objectives

This primary objective is to reduce the high percentage of breach orders of Company A service through application of various industrial engineering tools and concepts and through the use of a programming software. Based on historical data, it has been determined that non-optimal assignment of delivery riders per area causes the high percentage of breach. Therefore, the study aims to answer the following questions:

- What is the best approach to determine the number of riders to be assigned per area?
- What are the variables that affect the number of riders to be assigned per area?
- How will the demand affect the number of riders to be assigned per area?
- How will the rider output affect the number of riders to be assigned per area?

2.Literature Review

The prominence of online delivery services in the Philippines continues to flourish with more companies entering the market. Restaurants offering food takeaways traditionally hire drivers to deliver the food to its customers but new solutions emerged as online platforms were able to provide a new system to these restaurants which involved outsourcing FDS (Susskind and Curry, 2016). The most important thing to monitor in an FDS is the time it takes to deliver food to the customers. (Liu et al., 2016). Food orders should be delivered optimally in less than an hour and minutes after the food is ready. (Reyes et al. 2018). Achieving such urgency could be achievable without suffering from high cost of delivery equipment and manpower (Mladenow et al., 2016).

The convenience that comes with ordering items online is the main selling point of the service (Chai and Yar, 2019). As such, time-saving functions and consumers' time-consciousness are positively related to the use and adoption of online shopping (Saad, 2020). This is achieved through accurate demand forecasting and proper utilization of available resources (Mattia et al., 2017). Being out of capacity due to overflowing orders especially in challenging times would be a huge problem for the service and its customers.

Many FDS companies experience problems in the delivery process time (Ulmer et. al., 2020). Negative customer experiences because of breach in the delivery time of their orders may lead to customers being frustrated and perceiving the food-delivery service as untrustable and unreliable. When orders arrive late, not only are customers less likely to use the delivery service again, but they are also likely to give negative comments and bad ratings that would reflect badly on the service quality (Maze, 2016). The frustration experienced by the customers related to such breaches are expressed when time of delivery exceeds the estimated delivery time (Furunes, T., & Mkono, M. 2019).

This study demonstrates the application of the theory of constraints by Goldratt (1990) in food delivery services. A constraint, as defined in the theory, is the factor that limits the performance of the entire system. It is crucial to dissect the entire process into subprocesses to see the whole operation in a bird's eye view. After which, each subprocesses is to be associated their respective lead time. Yildiz and Savelsbergh (2019) found that the there is a significant improvement in the entire food delivery process by improving Ready to In-Transit process. This process is improved by having the right number of riders at the right time.

The use of forecasting tools has been seen in various studies across multiple industries. In call centers, workforce management (WFM) is a common response to staffing and scheduling. WFM is split into a sequence of steps, which involve forecasting: determining the number of workers needed at each time period to ensure that the desired level of service is met and shift scheduling: defined as the assignment of workers to certain shifts. The most common theoretical and algorithmic approaches include integer programming algorithms, which can only be used when the number of staff is indicated, while results from standard queuing models are very different from actual results. The easiest approach, albeit most practical, are simulation models that compute staffing requirements that achieve the desired level of service. (Mattia et al., 2017)

3.Methods

This study will mostly use a predictive research design. Currently, the company uses a naive forecasting approach that uses the previous month's deployment as the basis for the assignment of delivery riders per area for the next month. This study proposes a three-stage approach that involves forecasting the demand per area cluster in four-time windows during specific days of the week, determining the estimated output per rider during the time window, and assigning the number of riders based on demand over output.

Stage 1. This study will take an in-depth analysis of the relationship between demand and New Product and Seasonal Promotions. The independent variables are demand per area during time window ($X_{i,j}$) – previous demand per area in a specific time window during a certain day of the week expressed in the number of orders; Seasonal and New product promotion (ρ) – expected increase in demand due to a release of a new product based on averages from historical data and/or special occasion (e.g., Holidays, Company events, etc.) based on averages from historical data. The dependent variable is demand forecast – expected volume of demand during a specific time window during a certain day of the week expressed in the number of orders.

Stage 2. This study will provide a calculation for the estimated output per rider within a time window through a forecasting tool. The independent variables are total working time (Peak and Non-peak) – the total number of working hours per rider in a specific time window during a certain day of the week; Rider Efficiency – the ideal efficiency of delivery riders is based on theories expressed in percentage. Estimated total delivery time – the total time of delivery per order expressed in minutes. Distance from the store to the customer – the total number of travel distances from the store to the customer is expressed in kilometers (km). Number of Drops - the number of drops that a rider will make during a single trip. The dependent variable is Rider Output – refers to the total number of orders that a rider can deliver during a specific time window.

Stage 3. This study contributes a new formula for the number of riders to be assigned per area during a time window using the forecasted demand and output per rider.

4.Data Collection

The data is acquired by conducting an interview on Company A. This study gained historical data for analysis using various industrial engineering concepts One of the variables concerning the riders to be assigned per area is identified to be the demand in an area during an assigned period. As such, it is important to give an accurate forecast of the demand for the assigned period. The weekly data were classified under regular demand (regular week) or seasonal demand (seasonal week).This study defines regular weeks as weeks with no ongoing seasonal promotion or new product releases that may affect the demand during the week. In 2021, 19 of 29 (65%) of the total weeks were considered regular weeks. The most regular weeks were identified approaching Q3 accounting for 10 of 19 regular weeks. This study defines regular weeks as weeks with an ongoing seasonal promotion or new product releases that may affect the demand during the week. These consist of weeks that encompass national holidays, commemorations, or special days (e,g, Mother's Day, Father's Day, Payday Blowout, Monthly Sale). In 2021, 10 of 29 (35%) of the total weeks were considered seasonal weeks.

Forecasting Tool for Rider Output

The variables needed to forecast the rider output per area was found through process analysis and review of previous studies (Das and Yadav, 2020; Zambetti et al., 2017; Liu et al., 2016; Reyes et al., 2018). These were identified to be maximum total delivery time, distance from the store to the customer, and demand. Specifically, this tool requires the following information: demand (in number of orders), the average speed of riders (in km/h), total working time (in minutes), rider efficiency (in %), Delivery Rider to Customer Handover (in minutes), Ready to In-transit time (in minutes), number of drops (single or multiple), and maximum distance from customer A to customer B.

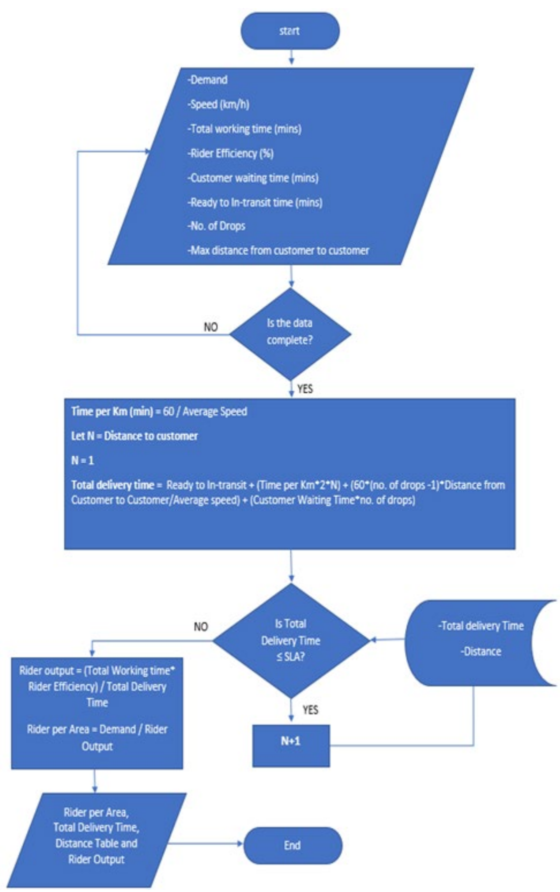


Figure 5: Program Flow Chart

The total delivery time is computed by the summation of the individual delivery process lead times. This includes the Ready to In-Transit time, driving time from store to the customer, Delivery Rider to Customer Handover A (the time it takes for customer A to get the order), estimated driving time from customer A to customer B, Delivery Rider to Customer Handover B (the time it takes for customer B to get the order), and driving time from customer to the store. The initial assumption is that the distance between the customer and the store is 1 kilometer. If the total delivery time is within the Service Level Agreement (SLA), the total delivery time and distance is saved, the distance between the customer and the store is increased by an additional kilometer, and the program recomputes given the new distance; otherwise, the loop ends. After finding the maximum allowable distance between the customers and the store, the rider output will be computed using the total working time (mins), rider efficiency (in %), and total delivery time. The final output of this tool is the total delivery time with respect to the distance from the store to the customer, rider per area, and serviceable radius.

5.Result and Discussion

Independent Samples T-Test

Table 1. Independent Samples T-Test Summary

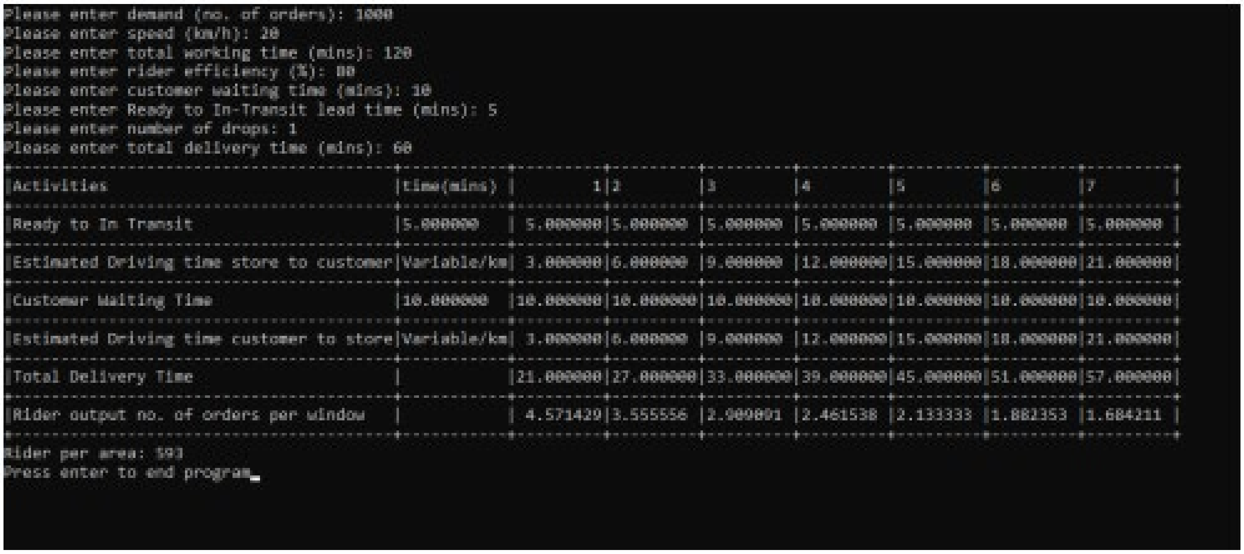
Store	α	p-value	Conclusion
1	0.05	0.000	Reject H_0
2	0.05	0.000	Reject H_0
3	0.05	0.000	Reject H_0
4	0.05	0.046	Reject H_0
5	0.05	0.272	Accept H_0
6	0.05	0.243	Accept H_0
7	0.05	0.000	Reject H_0
8	0.05	0.003	Reject H_0

The independent samples t-test results include a comparison of the Regular and Seasonal demand in each store. The test uses $\alpha = 0.05$ with a 0.95 confidence level. Store 1 has a p-value of 0.000, since $\alpha <$ p-value H_0 is rejected and there is a significant difference between the Regular and Seasonal demand. Store 2 has a p-value of 0.000, since $\alpha <$ p-value H_0 is rejected and there is a significant difference between the Regular and Seasonal demand. Store 3 has a p-value of 0.000, since $\alpha <$ p-value H_0 is rejected and there is a significant difference between the Regular and Seasonal demand. Store 4 has a p-value of 0.0046, since $\alpha <$ p-value H_0 is rejected and there is a significant difference between the Regular and Seasonal demand. Store 5 has a p-value of 0.272, since $\alpha >$ p-value H_0 is accepted and there is no significant difference between the Regular and Seasonal demand. Store 6 has a p-value of 0.243, since $\alpha >$ p-value H_0 is accepted and there is no significant difference between the Regular and Seasonal demand. Store 7 has a p-value of 0.000, since $\alpha <$ p-value H_0 is rejected and there is a significant difference between the Regular and Seasonal demand. Store 8 has a p-value of 0.003, since $\alpha <$ p-value H_0 is rejected and there is a significant difference between the Regular and Seasonal demand.

The results of the independent samples t-test show that there is indeed a significant difference between the Regular and Seasonal demand in most of the stores. Integration of the findings from this test may provide possible improvements to Das and Yadav's (2020) formulation of future demand where they failed to consider the effects of product promotions and seasonal offerings.

Output from the Forecasting Tool

This program made for the company requires the same assumptions from the tool to be input in a CMD window. The output includes a time-distance table for each respective distance from the store to the customer. The program also computes the number of riders to be assigned per area by dividing the demand with the rider output. This program will be provided for free, developed using the C++ programming language. The goal of this software is to provide a basis for the number of riders to be assigned that the company may use to address the high percentage of untimely deliveries.



```
Please enter demand (no. of orders): 1000
Please enter speed (km/h): 20
Please enter total working time (mins): 120
Please enter rider efficiency (%): 80
Please enter customer waiting time (mins): 10
Please enter Ready to In-Transit lead time (mins): 5
Please enter number of drops: 1
Please enter total delivery time (mins): 60
```

Activities	time(mins)	1	2	3	4	5	6	7
Ready to In Transit	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
Estimated Driving time store to customer	Variable/km	3.000000	6.000000	9.000000	12.000000	15.000000	18.000000	21.000000
Customer Waiting Time	10.000000	10.000000	10.000000	10.000000	10.000000	10.000000	10.000000	10.000000
Estimated Driving time customer to store	Variable/km	3.000000	6.000000	9.000000	12.000000	15.000000	18.000000	21.000000
Total Delivery Time		21.000000	27.000000	33.000000	39.000000	45.000000	51.000000	57.000000
Rider output no. of orders per window		4.571429	3.555556	2.909091	2.461538	2.133333	1.882353	1.684211

```
Rider per area: 593
Press enter to end program
```

Figure 6: Program Interface and Output

Serviceable Radius. Figure 6 shows the maximum allowable distance from the store to the customer given the set of assumptions in the forecasting tool.

Rider Output. Each distance would have its respective rider output based on the total delivery time, total working time, and rider efficiency.

Number of Riders to be assigned per area. The tool provides the number of riders to be assigned per area based on the demand (Xi,j) and the computed rider output.

6. Conclusion

Given that the company utilizes a third-party hiring service for their riders, the best approach was found to be a forecasting tool to help in the workforce management. The main cause of the high percentage of breach was found to be the Ready to In Transit process which, according to related literature, is solved by having the right number of riders per area at a given time. The forecasting tool is able to output the number of riders to be assigned given the variables that any typical Food Delivery Service will be able to provide based on their respective situation and context.

Demand and Rider Output was found to be the variables needed to identify the number of riders to be assigned per area. It was also found that the Regular and Seasonal Demand should be considered in forecasting the demand per area. This information provides a possible improvement to the way the company forecasts demand. This study has identified the variables affecting rider output relative to the distance from the store to the customer that will be used in the forecasting tool.

It is recommended to use the demand of the current week separated into peak and non-peak hours for a specific area to be input into the program before the beginning of the next week to be used for optimal rider assignments in the area of next week. It is recommended to deseasonalize the demand before having its input in the forecasting tool. This will remove seasonal patterns in the time-series data to provide more or less regular demand data as the basis of the rider to be assigned per area. It is recommended to gather data on the average distance of a customer to the store as a deterministic approach.

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