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Demand Forecast Model and Route Optimization to Improve the Supply of an SME in the Bakery Sector

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Abstract

This research employs the Lean Six Sigma DMAIC methodology to address enhancing product distribution efficiency in a bakery chain. Following the diagnostic phase, demand forecasting models were developed using ARIMA and Holt Winter methods, with ARIMA demonstrating higher prediction accuracy. Furthermore, route mapping was conducted using the Clark-Wright algorithm. Key performance indicators (KPIs) such as delivery time, distance traveled, and MAPE (Mean Absolute Percentage Error) will be established for process control. Implementing these improvements aims to achieve more efficient product distribution management within the bakery chain.

Keywords

Supply Management Improvement, Demand Forecasting, Clark-Wright, Route Optimization, ARIMA

1. Introduction

In recent years, the implementation of Industry 4.0 has transformed and improved the connection systems between different entities. The digital transformation of the supply chain arises to communicate and coordinate situations in real time to increase the organization's competencies. These technological advances have a positive impact on the economy of organizations since the management of the supply chain is optimized, and demand has exponential growth due to globalization [1]. At the same time, supply chains have developed with greater complexity among their processes, which now consider the diversification of their portfolios, customer preferences, internal demand situations, multiple collaborations of suppliers, different geographical areas to be served, and a variety of intermediaries [2]. Interruptions in the distribution processes of SMEs happen very often, often due to a lack of production control according to the most inefficient and traditional supply method: supply to order. Since this strategy is not standardized, it is very likely to incur a production error, which generates unnecessary costs [1].

Having good transportation logistics and final delivery of finished products generates great value in the customer experience; however, this can be affected by high transportation costs such as gasoline. In 2022, gas prices have become 28% more expensive in Peru [3]. On the other hand, if you do not have good routing, this can delay established delivery times. In Peru, the increase in cars has a continuously growing trend of 6.49% yearly [4].

For the most part, small and medium-sized enterprises (SMEs) usually try to satisfy specific and focused needs of society and industry, which is why their distribution systems are generally based on small quantities, exact frequencies to supply their customers, and unique transport conditions. Considering those markets in

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which SMEs supply and their billing levels, they limit their investment in the necessary resources to plan and keep distribution activities under control; the situation is repeated if we talk about their levels of innovation, which directly affects their competitiveness and profitability in the long term [5].

Ensuring the availability of a product by satisfying consumer demand in a set period has proven to be a competitive advantage for retail chains. However, the inefficiency in the programming of routes of the distribution center vehicles causes delays in deliveries and many times culminates in shortages, so optimizing routes in the product distribution process can be considered a fundamental factor in customer demand satisfaction [6]. In addition, the planning of delivery routes through traditional methods needs to be improved since they only focus on reducing transportation costs between two locations. Therefore, Tsang includes in his investigation other factors such as food quality, arrival time windows, and even incidents or violations of driving requirements during delivery [7].

For all these reasons, the purpose of this research is the joint application of the projection of the demand of an SME in the bakery sector through triple exponential smoothing (Holt-Winters) and the Arima model and the optimization of routes for optimal replenishment. of their stores.

2. State of art

2.1 Forecast Models

The demand forecast is independent of the sector where you want to apply. It is an essential component for good management of your resources. It can be used in any industry that has a demand. We have Time series, regression, and machine learning models among the main demand forecast models [8]. Within the time series models, we have the ARIMA Model and Exponential Smoothing [8]. The ARIMA model is a derivative of the ARMA model, a moving average autoregressive model used to understand and predict future points in a time series, and the integration variable is added [8]. On the other hand, the Exponential Smoothing method is a more focused method for data with seasonal trends [8].

Among the most used techniques for demand forecasting is the Monte-Carlo Method, which consists of generating random events through sampling and thus calculating the probability of an event occurring. The value "0" is assigned to the event that did not happen, and the value "1" to the event that does occur. Finally, the accumulated frequencies are recorded; the more significant the simulation, the there is the probability that the event will occur. In 2021, Cui et al. applied the Monte-Carlo Method to estimate the required demand for the replacement of aircraft parts subject to different guarantees, correctly achieving control and planned replacement of inventories [9].

2.2 Impact of the application of demand forecast models in perishable products

Each demand projection model has its particularities. For a demand for baked goods in a supermarket, the ARIMAX model was applied, combining the ARIMA model with exogenous variables; they are not related to the time series but can influence the prediction [10]. For this case, both methods were compared, surpassing ARIMAX in terms of MAPE, thereby achieving greater precision in predicting and detecting replaceable items [10].

In another research for a German bakery that makes bread, they benchmarked their performance using various forecasting models, including S-Naïve, S-Mean, S-Median, ETS, and LSTM. The evaluation was based on several indicators: the target service level, fill rate, surplus rate, and loss. The results revealed that the LSTM model consistently showed higher precision than the other models. A significant difference was also observed between the ETS model and the baseline methods. Furthermore, it was concluded that operational performance is closely related to the accuracy of the forecasts provided. In summary, the results highlighted the superior performance of the LSTM model and its positive impact on the quality of operational decision-making [11].

2.3 Programming models for the optimization of distribution routes

Vehicle Routing Problems (VRPs) maintain simple structures, so they often appear to be basic optimization problems through discrete combinatorics. In the real world, the practicality of VRPs is significant, which is why they are used to validate the optimization performance of different algorithms, which ultimately helps develop efficient algorithms (Li et al., 2022). On the other hand, other authors mention that the VRP is naturally a complicated problem, and its modeling demands a statistical analysis of the speed and congestion of vehicles on different routes. In addition, travel time measurement strategies are fundamental and consist of several aspects, including simple, discrete, continuous, and stochastic [12].

In the study by Lugo, an algorithm model was used in a real case for the distribution of beauty products in 2 areas of Metropolitan Lima. This study used models such as Savings Algorithms, Petal Algorithms, and Insertion Algorithms. Managing to reduce 10.90 km of travel on the newly designed route and S/196.20 per year in each district [13].

The research carried out in previous years about product distribution management indicates that it is required to transport perishable foods through a refrigeration system. Therefore, an infrastructure suitable for long-term trips is required. Added to this is the importance of accelerating the distribution process to maximize the useful life of the products and not impair their quality and freshness. This situation can be achieved through adequate temperature control and the application of IoT technology for optimal route selection [14].

On the other hand, it highlights that the route optimization models that are given through IoT not only reduce the distribution and transportation time but also lead to a reduction in costs and an increase in the level of satisfaction for the client part [15]. His research tested the model's validity for optimizing vehicular routes through simulation, starting from a distribution center to 15 different customer destinations.

3. Methodology

The Lean Six Sigma DMAIC methodology will be employed to manage this project in Table 1. This methodology will assist us in identifying the root causes of the case study. Throughout each phase of the DMAIC process, we will gather crucial information essential for developing the proposed solutions.

Table 1: **Project Phases**

Project Phases	Tools
Define	Data Analysis
Measure	Pareto Analysis
Analyse	Ishikawa Diagram
Improve	Demand Forecasting Models and Route Distribution Model
Control	KPIS

a. Define

As a case study, we will focus on small and medium-sized enterprises (SMEs) in the food sector. This SME operates a chain of bakeries and has established itself as one of the leading traditional bakeries in the northern area of Lima and Callao. Their value proposition is based on improving the quality of their products and services and continuously innovating their facilities to meet the needs of their customers.

Currently, the distribution center and manufacturing plant are located at the Covida premises, and they have nine stores (8 legal entities) that sell their products. The process that will be improved within the bakery is product distribution to the branches. This process involves forecasting the demand, confirming the orders, and having the store managers sign an acknowledgment stating the reception of the products.

Objective: To improve the efficiency of product distribution to the stores, reducing transportation costs and ensuring that products arrive fresh and in line with the projected demand.

b. Measure

A virtual interview was conducted with the current engineer who supervises the factory at Covida SME. The interview aimed to gather general information about the distribution process and identify the main problems. The interview lasted for 1 hour, and the following data was collected regarding the initial situation:

- Average time spent on product dispatch: 1 hour and 30 minutes.
- Departure times from the factory to the stores: 10 am and 3:30 pm.
- Distribution cycle time to stores: 3 hours per vehicle.
- Number of transports: 2 non-refrigerated cars and one refrigerated car.
- Maximum number of stores per transport: 3.
- Monthly fuel expenses: No information available.
- Shifts per day: 2.
- Days per week: 7.
- Quantity of products to distribute: an average of 620.
- Quantity of containers to distribute: an average of 260.
- Staff: 3 Drivers,2 Dispatchers., 3 Product packing and sorting, 1 Supervisor

Additionally, a visit was scheduled for Saturday, November 19, 2022, during which evidence was collected from the SME's dispatch areas and shipping vehicles, Table 2.

Table 2: **Distribution Locations of the Company under Study**

Business Name	Locations	Address
Industria Alimentaria D'Julia S.A.C.	Vivanco	Av. General Manuel Vivanco N°400 - Pueblo Libre
Inversiones Tipequi E.I.R.L.	Megaplaza	Av. Alfredo Mendiola N°3698, Interior M4 - Independencia
Inversiones Maricela Peralta E.I.R.L.	Centro Cívico	Av. Inca Garcilazo de la Vega N°1337 Int. 1102 - Cercado de Lima
Inversiones Yuri Peralta E.I.R.L.	Covida	Urb. Covida Av. Antúnez de Mayolo N°1223 - Los Olivos
Maricela Peralta E.I.R.L.	Covida Snack	Urb. Covida Av. Antúnez de Mayolo N°1217 - Los Olivos
Maricela Peralta Quintanilla	Sucre	Jr. Cusco 400 - Magdalena del Mar
Inversiones Cariza E.I.R.L	Bolívar	Av. Simón Bolivar N°1097 - Pueblo Libre
Ysmael Peralta Quintanilla	Palmera	Av. Carlos A. Izaguirre N°948 - Urb. Las Palmeras - Los Olivos

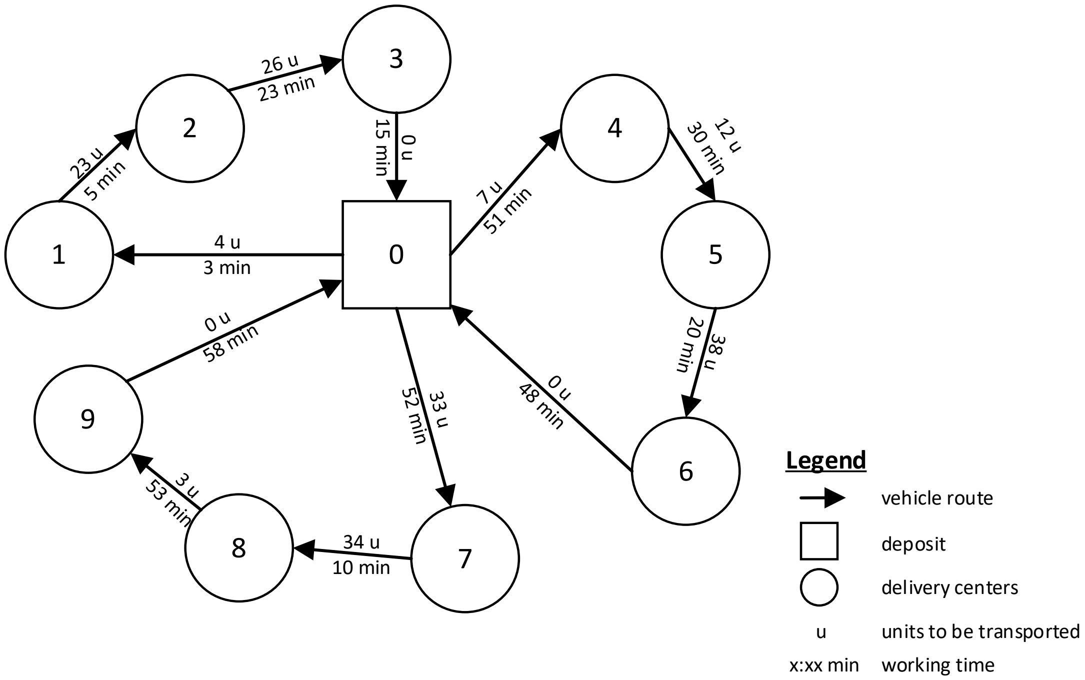

Figure 1: Initial Routing Diagram of 1 vehicle

c. Analyse

A Pareto diagram in Figure 2 y Table 3 will be developed to identify the main problems in the product distribution process based on the drivers' interviews, visits, and tracking of distribution trips over 30 days.

Table 3: **Problems Found in the Diagnosis**

Problems	Frequency	Percentage	Percentage Accumulated
Percentage Accumulated	14	82.4	82.4
Percentage Accumulated	2	11.8	94.1
Poor cargo organization	1	5.9	100

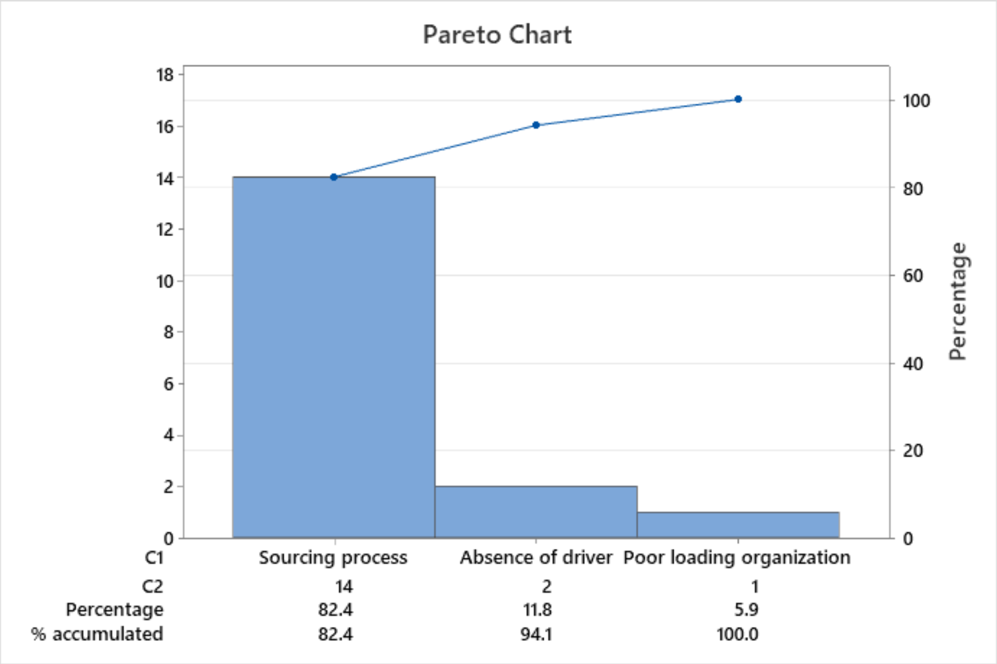

Figure 2: Pareto Chart

Considering the accumulated percentage of 94.1%, the main problems in the studied process are the delay in product delivery and driver absence.

Next, the Ishikawa diagram in Figure 3 will be developed for the main problem identified in the Pareto diagram to determine the root causes.

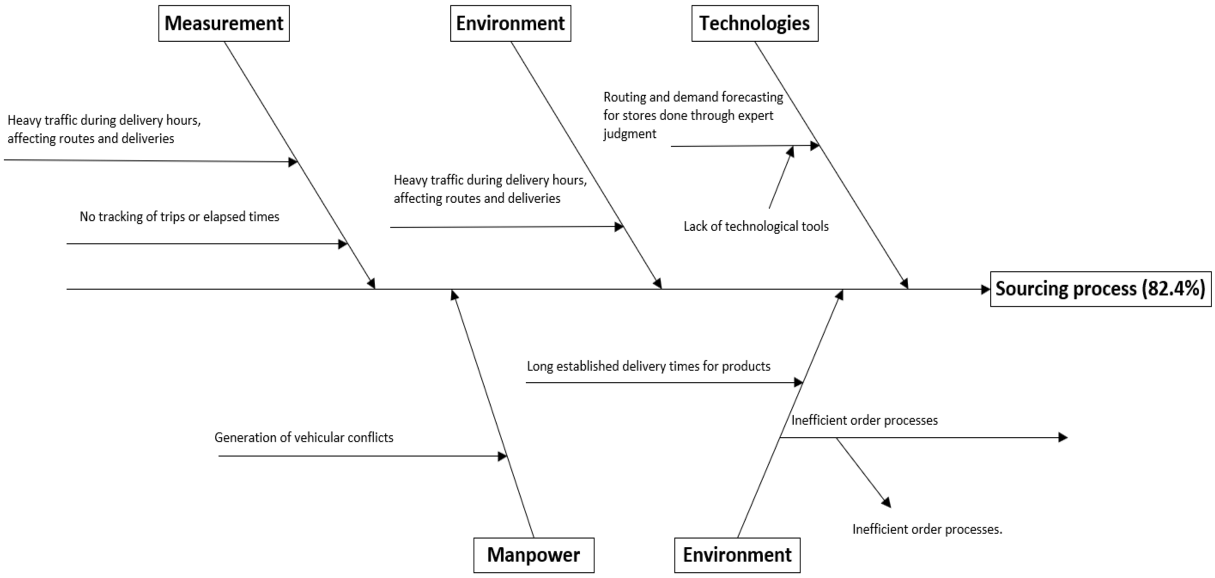

Figure 3: Ishikawa

d. Improve

To achieve better production management and have an accurate demand, we will compare two models:

• ARIMA (1)

• Holt Winter (2)

For both models mentioned, we will calculate the future values, compare the MAPE (Mean Absolute Percentage Error), and select the method with the lowest MAPE.

For both sets of data, the input will consist of 50 historical production values of the bakery's products, which will be evaluated using the equations of the two models.

$$I_t = \theta_1 * I_{t-1} + \theta * \in_{t-1} + \in_t \tag{1}$$

Where:

I_t : Integration variable differential

$\theta_1 * I_{t-1}$: Autoregressive term

$\theta * \in_{t-1}$: Autoregressive term

$\in_t$: Current error term

$$Y_{(t+h)} = L_{(t)} + h * T_{(t)} + S_{(t-l)} \tag{2}$$

Where:

$Y_{(t+h)}$: is the forecast for time t+h

$L_{(t)}$: is the level at time t

h: is the number of periods into the future.

$T_{(t)}$: is the trend at time t

$S_{(t-l)}$: is the seasonality factor from the previous period.

To optimize the delivery routes to the eight different stores, the Clarke and Wright (1964) logarithm for route optimization will be used:

$$S_{(ij)} = C_{(i0)} + C_{(j0)} - C_{(ij)} \tag{3}$$

Where:

$S_{(ij)}$: is the savings obtained by combining routes.

$C_{(i0)}$: is the cost of going from the depot to customer i.

$C_{(j0)}$: is the cost of going from the depot to customer i.

$C_{(ij)}$: is the cost of going from customer i to customer j.

e. Control

Carefully selected key performance indicators (KPIs) in Table 4 will be implemented to ensure efficient management. Two main KPIs used in this context are delivery time, distance traveled, and MAPE (Mean Absolute Percentage Error) for demand forecasting.

Table 4: **KPIs**

Indicator	Meaning	Formula	Objective
Delivery Time	The measure of the average time required to complete deliveries.	The sum of delivery times to each location/Total number of locations.	Reduce delivery time by 30%.
Distance Travelled	The measure of the average time required to complete deliveries.	The sum of kilometers traveled in a day.	Reduce distance traveled by 30%.
MAPE	The measure of the average absolute percentage difference	The sum of absolute percentage errors of all data points / Total number of data points.	Maintain MAPE below 50%.

4. Results

Regarding the demand forecasting model, the MAPE for two products in the store was analyzed for the two compared methods in Table 5. For product 1, the ARIMA method yielded a MAPE of 7.08%, indicating relatively high accuracy in the predictions. On the other hand, the Holt-Winters method obtained a MAPE of 9%, indicating slightly lower accuracy in the forecasts for this product. For product 2, the ARIMA method showed a MAPE of 23.9%, indicating moderate accuracy in the predictions. In comparison, the Holt-Winters method exhibited a MAPE of 35%, indicating lower accuracy in the forecasts for this specific product. Based on these results, the ARIMA method will forecast the demand for the products in the study.

Table 5: **Results of future values using the ARIMA method**

Day	Product 1	Product 2
1	1055	325
2	1042	325
3	1042	325
4	1042	325
5	1042	325

On the other hand, demand optimization. It yielded the optimal route with the Clark-Wright model in Figure 4. It achieved an average time of 5 hours and 19 min and a distance traveled of 59 km, which will be discussed in more detail in the discussion chapter.

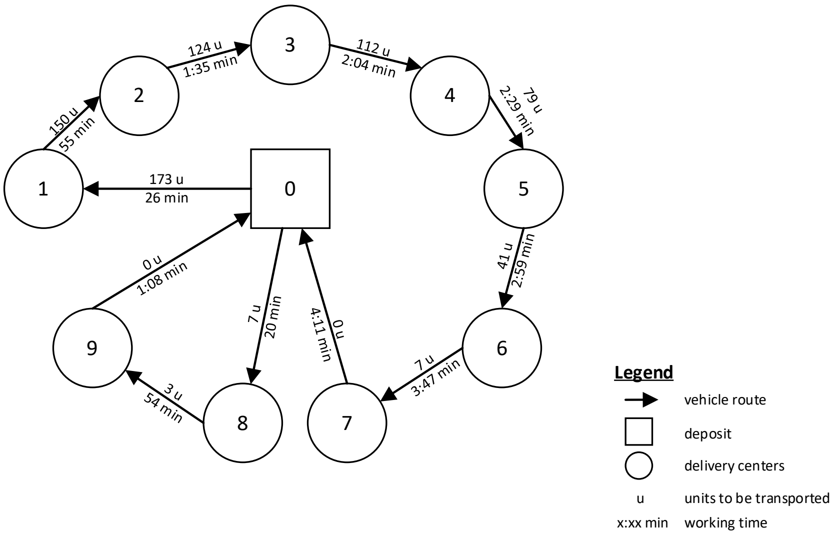

Figure 4: Finally Routing Diagram of 1 vehicle.

5. Discussion

The use of MAPE as an indicator of effectiveness is essential when forecasting and diagnosing future calculations; this statistic compares the results between 2 or more simulation models, granting the optimal result. This error indicator can also be interpreted as the amounts necessary to keep in the safety stock since it estimates the probability that the predicted value is far from the actual value; the lower its value, the more accurate the estimate is and, therefore, the required safety stock will be lower, and vice versa. Until now, the Holt-Winters and ARIMA models, among others, suggest and propose effective forecasts to project future values with different applications and consider additional criteria such as time series or seasonality. However, there is still no unanimous agreement that certifies that one is better than the other in general; it will always depend on the scenario in which it is applied.

On the other hand, the results obtained after the simulation using the Clark-Wright model are contrasted with the initial situation in Table 6.

Table 6: **Comparative table of situations**

	Initial situation	**Optimal situation**
Vehicles	Two without refrigeration 1 with refrigeration	One without refrigeration 1 with refrigeration
Times	3 vehicles x 3h = 9h	4h 11min + 1h 8min = 5h 19min
Distance	87.81 km	48.27km + 10.73km = 59km
Compliance to return before the 2nd shift (3:30 pm)	Each vehicle returns: V1 = 11:30 am V2 = 12:30 pm V3 = 12:53 pm	Each vehicle returns: V1 = 14:11 pm V2 = 11:08 am

As the ideal situation can be seen, it was possible to reduce the number of vehicles used in the initial situation; this would imply lower transportation and driver costs. It could even be used solely as a private vehicle for personalized deliveries, whose expense would be assumed by the consumer.

Regarding travel times, in the initial situation, a maximum of 3 hours was allocated to each vehicle since the route to be used was random and at the discretion of the distributors; unlike the optimal situation, the best option to distribute has been mapped products in up to 3 hours and 41 minutes. Likewise, it optimizes the conservation of the product since it remains in the vehicle for less time.

For the distances traveled factor, in the new situation, it was possible to reduce the distribution route by almost 30km; with this improvement, the level of destruction of the products increases since they would spend less time in motion, and therefore, the probability of accidents is minimized.

Finally, both situations meet the indicator of returning for the 2nd delivery turn, but this does not limit the optimal situation to not being implemented since it returns with more than one hour before starting the next turn.

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