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Forecast Methods and Periodic Review Inventory Model for Supply Planning to Reduce Food Waste

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Authors' contributions

This work was carried out in collaboration among all authors. Authors LNCP, ABNJ, SOCM and PCO designed the study, managed the literature review, selected the appropriate methods for implementation of the integrated approach, performed the statistical analysis, and wrote the first draft of the manuscript. Authors LNCP and ABNJ managed the implementation on the case study. Authors SOCM and PCO provided additional feedback for the revised manuscript. All authors read and approved the final manuscript.

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Case Study

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ABSTRACT

Food waste is an important economic and resource problem in all countries around the world. Particularly, the restaurant sector highly contributes to food waste and limited efforts or studies have been performed to overcome this problem. In this context, the present study addresses an alternative to improve the supply planning for perishable products in the restaurant sector through the application of specific forecasting methods and a stochastic inventory control model. For this purpose, a real enterprise within this economic sector was considered. Our findings support that monthly forecasts can be more appropriate for accurate demand estimation and supply planning of perishable products, which is important to reduce unnecessary products. Also, the periodic review inventory control model can lead to a more appropriate supply scheme to reduce the waste of surplus food. These findings and the proposed techniques can be used for other economic entities to reduce product waste due to poor supply planning.

Keywords: Food waste reduction; variable demand; periodic review; inventory control.

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1. INTRODUCTION

One third of food produced for human consumption, which is equivalent to approximately 1.3 billion ton per year, is lost or wasted along the entire food chain, from initial agricultural production to the place of final consumption [1]. In high- and middle-income countries, food is significantly wasted at the consumption stage, meaning that it is discarded (thrown away) even if it is still fit for human consumption. In low-income countries, food is mainly lost during the early and intermediate stages of the food supply chain and far less food is wasted in the consumption stage [2].

According to a study published by Rethink Food Waste [3], the United States currently spends more than $218 billion on growing, processing, transportation and disposing of unconsumed food. In this aspect, the restaurant sector generates 11.4 million tons of food waste annually (7.3 million tons of full-service restaurants and 4.1 million tons of limited-service restaurants), which represents a total cost of more than $25 billion [3]. Another implication of food waste is associated to emissions of CO_2. It is well known that significant CO_2 emissions are generated by the meat industry, and the waste of animal-containing food contributes to unnecessary CO_2 emissions [4].

Food waste can be categorized as edible, naturally inedible, industrial residue, inedible due to natural causes (pests), and inedible due to ineffective management [5]. Here, surplus food is frequently associated to waste of edible food, and waste due to ineffective management. These two conditions are observed in family restaurants and households which are the main generators of food waste [6]. In this context, unsuitable purchase planning of perishable products, poor tracking of the "preferably consume before" dates, and the carefree attitude of consumers about "allowing" edible food to be wasted, have been identified as management malpractices associated to food waste at the consumption stage [2]. Thus, efficient management of food supply is required to reduce the waste of edible food at these stages.

Based on this background, the restaurant sector is identified as a main generator of food waste due to management malpractices associated to supply planning. The purpose of this work is to propose an alternative to minimize the waste of edible and perishable food in this industry. This proposal is formulated by the integration of two main tasks: (a) forecasting of future demands of food ingredients to reduce the uncertainty for supply planning, and (b) an appropriate supply method to reduce the risk of surplus food while keeping a high service level.

Thus, the hypothesis for this work is defined as follows:

Ho: Forecasting and inventory control can reduce food waste in restaurants

Ha: Forecasting and inventory control are not useful to reduce food waste in restaurants

The hypothesis to test the suitability of the proposed alternative was evaluated through a case study. For this, we implemented the proposed method in a restaurant with a large use of perishable and edible food ingredients. The findings of this work are presented as follows: in Section 2 we present an overview of similar works which have used quantitative tools to optimize food supply within the restaurant industry, and in Section 3 we present the technical background of the quantitative tools used in this work. Then, in Section 4 we describe our methodology to integrate the proposed method within the context of the case study to reduce food waste. Finally, in Section 5 we present the results of the proposed method and in Section 6 we present our conclusions and future work. The development of this work supported the validation of the null hypothesis.

2. LITERATURE REVIEW

Many studies have been performed to understand the problem of food waste in order to know what is being done to solve the problem. Organizations within the food supply chain have implemented various logistical solutions to reduce food waste, among these the following can be mentioned: collaborative forecasts, optimization of delivery times to avoid affectation of the expiration date of food products, maintaining of low levels of safety inventory, tracking of service levels, and price reduction of near-to-expire food [7].

In the case of food waste from restaurants, several recommendations associated to proper management of resources have been proposed. Some of these recommendations consist of qualitative practices such as: adoption of a “zero food waste” vision, first in - first out (FIFO) consumption of goods, review of menus to have better control of food products with less movement (and thus, prone to be wasted due to not being consumed), adequate refrigeration and freezing techniques to prolong the freshness of products and make donations of leftover food to organizations and / or food banks [8]. Another study proposed the use of Material Flow Cost Accounting (MFCA) to quantify the flow of material in the production process in unitary and monetary terms. Within the context of restaurants, this tool is applied in the storage, production and service processes with the objective of reducing the quantity and costs associated with food waste [9].

Something that is common to these works is the implicit aspect of planning. Note that food products with less movement must be ordered in sporadic and smaller lots. The way to identify these products is by performing a continuous tracking of consumption rates. Then, forecasting is important to support future requirement planning. The success of any supply strategy depends on how well the future requirements can be estimated to prepare the most suitable plan [10]. By using effective forecast methods, the supply chain can be strengthened by reducing uncertainty. To achieve an adequate forecast within the supply chain, the type of information and the quality of information shared between producers and traders must be considered [11].

By having an appropriate estimation of the future requirements, the use of an adequate supply strategy is needed. This to define the most suitable lots size and supply frequency to ensure two important aspects: (a) minimum holding and ordering costs associated to inventory management, and (b) high service level, which can be understood as the ability of the restaurant to provide the required food product at the time when it is needed by the consumer [12].

Thus, an integrated approach of forecasting and inventory control can provide the needed tool to reduce food waste in the restaurant industry. This approach can support the effectiveness of other tools and managerial practices as those reported in [7,8,9].

3. TECHNICAL BACKGROUND

In this section, we present the details of the forecast and inventory control tools considered to formulate the proposed method to reduce food waste.

3.1 Forecasting

Forecasting methods can be classified into four groups: (a) qualitative methods, which are characterized by being subjective and based on human judgement, (b) time series methods, which are based on historical demand information and serve as an indicator to predict demand behavior, (c) causal methods, which assume a correlation of certain factors in the environment with future demand behavior, and (d) simulation forecasting methods, which mimic customer choices that give rise to demand (these methods can combine time series and causal methods to simulate different possible scenarios) [13].

These methods have been tested in different sectors to evaluate their suitability to different scenarios and conditions. In example, time series methods are very suitable to forecast demand within the tourism sectors [14], hotels [15], restaurants [16], and cold chains for perishable goods [17] among others.

Specifically, the most well-known forecast methods used to estimate demand patterns are the following: Linear Regression (LR), Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (Brown's Method), Exponential Smoothing with Trend (Holt's Method), and Exponential Smoothing with Trend and Seasonality (Winter's Method). These methods consider the terms described in Table 1.

Table 1. Terms of forecast methods

Term	Description
L_t	Estimated value at the end of period t
T_t	Estimated trend at the end of period t
S_t	Estimated seasonal factor for period t
F_t	Demand forecast for period t (from period t-1)
D_t	Real demand observed at period t
E_t	Forecast error at period t
W_t	Weight assigned to period t
I_t	Seasonal index at period t

Then, the forecast methods are described as follows:

a) Linear Regression (LR): This method is used when demand *D* has no observable trend or seasonality. If we consider the average demand from the previous period, the forecast *F* for the next period *t* is estimated with support of two coefficients α and β as follows:

$$F_t = \alpha + \beta * D_{t-1} \tag{1}$$

b) Simple Moving Average (SMA): This method is used when demand *D* has no observable trend or seasonality. If we consider the average demand from the previous (most recent) *n* periods, the forecast *F* for the next period *t* is estimated as:

$$F_t = \frac{D_{t-1}+D_{t-2}+\cdots+D_{t-n}}{n} \tag{2}$$

c) Weighted Moving Average (WMA): This method uses the same dynamics of the SMA method, but a higher weight is assigned to the most recent periods and a lower weight to the most distant periods to calculate the forecast *F* for period *t*:

$$F_t = W_1 * D_{t-1} + W_2 * D_{t-2} + \ldots + W_n * D_{t-n} \tag{3}$$

d) Simple Exponential Smoothing (Brown's Method): This method is the most appropriate when demand data *D* does not present an observable trend or seasonality. To perform the forecast, three pieces of information are required: the most recent forecast F_t, the actual demand during the forecast D_t, and a smoothing constant α:

$$F_{t+1} = \alpha * D_t + (1-\alpha) * F_t \tag{4}$$

e) Exponential Smoothing with Trend (Holt's Method): This method is suitable when demand presents a level and trend without seasonality. For this method, two smoothing constants α and β are used to update the level and trend estimates:

$$F_{t+1} = S_t + T_t \tag{5}$$

where

$$S_{t+1} = \alpha * D_{t+1} + (1-\alpha) * (S_t + T_t) \tag{6}$$

$$T_{t+1} = \beta * (S_{t+1} - S_t) + (1-\beta) * T_t \tag{7}$$

f) Exponential Smoothing with Trend and Seasonality (Winter's Method): This method is suitable when demand presents a level with trend and seasonality. For this method, the variable *p* is used to indicate the number of periods within each seasonal space. α, β, and γ are used as smoothing constants to update the level, trend, and seasonality estimates respectively:

$$F_{t+1} = (S_t + T_t) * I_{t-p+1} \tag{8}$$

where:

$$S_{t+1} = \alpha * (D_t + 1/I_{t-p+1}) + (1-\alpha) * (S_t + T_t) \tag{9}$$

$$T_{t+1} = \beta * (S_{t+1} - S_t) + (1-\beta) * T_t \tag{10}$$

$$I_{t+1} = \gamma * (D_t + 1/S_{t+1}) + (1-\gamma) * I_{t-p+1} \tag{11}$$

As previously mentioned, some methods may be more suitable for other demands than others. This is measured by specific error metrics such as MAD (Mean Absolute Deviation), MSE (Mean Squared Error) and MAPE (Mean Absolute Percent Error). MAD measures the size of the error in units and it is computed with the average of the difference between the actual demand and the forecast in absolute values. MSE maximizes the MAD error (MAD^2) to make the error more evident in the periods where there is a greater difference. Finally, MAPE computes the percentage of the forecast error as MAD/(actual value of the demand). Thus, these metrics can guide the appropriate application of the forecast method in accordance with the characteristics of a specific problem.

3.2 Inventory Control

When future demands can be accurately estimated through the appropriate forecast method, the estimated data can be used for other processes. As inventory management is considered to reduce the surplus of food and thus, reduce the food waste, an appropriate inventory control model must be considered.

The formulation of an inventory model may consider the following aspects [18]: (a) product type/use (perishable products, substitute products or products which are durable over time), (b) number of required products, (c) deficit is allowed or not, (d) delivery times (anticipation times) under deterministic or non-deterministic demand patterns, (e) fixed or variable inventory management costs, (f) periodic or continuous revision (tracking of re-order point), (g) instantaneous or continuous replacement of products if they are ordered or produced, and (h) the planning horizon which may include a single or several periods.

Particularly, the selection of the inventory model depends on the demand pattern of the required products. If demand is deterministic, then models which assume certainty regarding the future demand patterns is recommended. On the other hand, if demand is stochastic, then models which assume uncertainty regarding future demands is recommended. Because all supply operations involve a certain degree of uncertainty, it is recommended to consider stochastic or non-deterministic models [12].

In this context, a periodic review model presents advantages in time and costs for the companies. It also provides greater flexibility in its initial implementation and follow-up processes [19]. In the periodic review model, which is also known as the *P* model, fixed interval reorder system, or periodic reorder system, the inventory of a product is reviewed periodically and not continuously. Such a system can simplify the scheduling of deliveries because it establishes a routine. New orders are always placed at the end of each revision and the time between orders has a fixed value of *T*. Demand is a random variable, so the total demand between revisions is variable. In a *P* model, the lot size of the required products *Q* can change from one order period to another, but the time between orders is fixed [12].

The mathematical formulation of the *P* model can be expressed as:

$$Q = d * (T + LT) + z\sigma_d * \sqrt{T + LT} - I \qquad (12)$$

where *Q* is the required product quantity to supply the inventory, *d* is the average daily demand, *T* is the time between orders, *LT* is the length of the delivery time, σ_d is the standard deviation of the daily demand through the delivery time, *z* is the number of standard deviations associated to a required service level, and *I* is the available inventory level at the time of revision [12].

An example of a periodic review system is the case of a soft drink supplier who visits grocery stores weekly. Each week, the vendor reviews the store's carbonated soft drink inventory and replenishes it with sufficient article volume to meet both demand and safety inventory requirements until the following week. When the predetermined time *T* has elapsed since the last revision, a new order is placed for the inventory item to return to the target inventory level [20].

4. METHODOLOGY

This work validates a proposed quantitative approach through its application in a case study. For this work, the application was performed in a restaurant in the city of Puebla in Mexico. This business unit has a large demand of different perishable food products and a high rate of food waste (all purchases are empirically estimated with a high degree of speculation). Its background is described in Table 2.

On this company, the proposed approach which integrates forecasting and inventory control was applied. For this purpose, we followed the methodology described in Table 3. The results obtained at each step are described in the following sections.

4.1 Data Collection and Selection of the Most Important Products

Data regarding the demand of all perishable food products was obtained during the period of January to August 2019. For this data, all purchase invoices of raw materials during this period were reviewed. Note that non-food products, or non-perishable products such as cleaning items, kitchen utensils and beverages, were discarded from the analysis.

Then, selection of the most important products was performed by using the ABC classification method. This method allows the selection of the most representative products in terms of value and frequency of purchase. From a total of 354 perishable food products, a set of 10 products were considered as the most value-representative for the restaurant. These products were avocado, onion, mushroom, tomato, melon, papaya, chicken, pineapple, green tomato and tortilla.

Table 2. Background of the case study company

Lifetime	> 30 years
Branch	10 branches within Mexico and 1 outside
Specialty	Seafood, including other options such as meat and poultry
Certifications	Distinctive "H" (high strict hygiene standards) which is the maximum recognition granted by the Mexican Secretariat of Tourism (obtained since 1991).

Table 3. Methodology steps for the application process

Step	Description
Data Collection	A database was elaborated considering the demand of all the food products used by the restaurant.
Selection of the Most Important Food Products	The most representative products were selected by using the ABC method which consists of selecting the products which account for the 50% of the inventory's value.
Demand Analysis	The demands of the selected food products are analyzed to determine their characteristics of trend, seasonality and variability to determine the most appropriate forecasting method. The analysis was carried out on a monthly, fortnight and weekly basis.
Evaluation of Forecast Methods	The forecast models were applied on the demand data and the errors were computed (MAD, MSE, MAPE) to determine which forecast model is more suitable for each of the selected products.
Forecasted Demand	Once the most adequate forecast methods have been selected, these are applied to estimate the forecast demand for the next periods. This serves as a reference for planning the supply of the next periods.
Implementation of the *P* Inventory Control Model	A periodic review inventory model is implemented with the forecasted demand information to determine the optimal quantity to order, considering the expiration times of the perishable food products.

5. RESULTS

5.1 Demand Analysis

The historical data of the selected 10 products was reviewed on a monthly, fortnight and weekly basis to determine its behaviour and detect its trend and seasonality. Table 4 shows the average, standard deviation and coefficient of variation of the demand for each product.

When reviewing the data in Table 4, it was observed that the coefficient of variation is lower in the monthly data, as opposed to the weekly data which has a higher coefficient of variation. This means that there is not much variation in demand on a monthly basis. Thus, a forecast model for stable demand such as the moving average method, or the weighted moving average method, can be used. On the other hand, the variation of demand on a weekly basis is greater, so it is not advisable to use forecast models for stable demand. In these cases, it is preferable to use models that adapt to the level of variation of demand to try to reduce the forecast error. In this case, methods such as Holt and Winter can be used.

Particularly, the coefficient of variation of the pineapple is very high compared to other products. This is due to a sudden drop in demand in the last month. Therefore, the demand for pineapple is not useful to make a forecast objectively. For this reason, it has been decided not to consider pineapple at the time of making the forecasts.

5.2 Evaluation of Forecast Methods

Table 5 presents the best forecasting methods for each evaluated product, based on the MAD, MSE and MAPE error metrics. This is presented for monthly, bi-weekly, and weekly forecasts.

Table 4. Comparison of the coefficient of variation of the demand patterns of the selected food products

Period		Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Pineapple	Green tomato	Tortilla
MONTHLY											
	AVERAGE.	134.47	263.71	62.62	837.28	308.14	384.18	252.80	318.43	242.92	508.06
	STD. DEV.	16.78	31.88	4.95	96.86	44.20	33.63	28.11	102.41	34.77	57.78
	COEF. VAR.	0.12	0.12	0.08	0.12	0.14	0.09	0.11	0.32	0.14	0.11
FORTNIGHTLY											
	AVERAGE.	67.23	131.86	31.31	418.64	154.07	192.09	126.40	159.22	121.46	254.03
	STD. DEV.	12.00	22.33	6.76	54.42	30.09	26.72	24.92	55.00	21.33	46.96
	COEF. VAR.	0.18	0.17	0.22	0.13	0.20	0.14	0.20	0.35	0.18	0.18
WEEKLY											
	AVERAGE.	30.74	60.28	14.31	191.38	70.43	87.81	57.78	72.78	55.52	116.13
	STD. DEV.	10.75	10.66	4.64	45.39	22.97	18.93	16.50	27.66	13.95	31.85
	COEF. VAR.	0.35	0.18	0.32	0.24	0.33	0.22	0.29	0.38	0.25	0.27

Table 5. Most appropriate forecasting methods based on the lowest error value

PRODUCT			**MONTHLY**			**FORTNIGHTLY**			**WEEKLY**	
		MAD	**MSE**	**MAPE**	**MAD**	**MSE**	**MAPE**	**MAD**	**MSE**	**MAPE**
AVOCADO	**METHOD**		**WINTER**			**LR**			**LR**	
	VALUE	3.69	24.62	2.71%	7.94	98.01	12.62%	8.23	101.84	32.65%
ONION	**METHOD**		**WINTER**			**HOLT**			**BROWN**	
	VALUE	23.72	632.79	8.91%	18.09	508.48	13.72%	9.21	128.59	14.89%
MUSHROOM	**METHOD**		**LR**			**LR**			**LR**	
	VALUE	3.63	21.40	5.95%	5.41	42.84	19.99%	3.78	20.90	35.62%
TOMATO	**METHOD**		**WINTER**			**WINTER**			**HOLT**	
	VALUE	37.04	1,467.12	4.54%	30.74	1,348.51	7.34%	28.24	1,594.33	16.64%
MELON	**METHOD**		**HOLT**			**LR**			**BROWN**	
	VALUE	19.39	548.25	6.06%	19.23	573.87	13.51%	21.39	733.22	29.29%
PAPAYA	**METHOD**		**WINTER**			**WINTER**			**BROWN**	
	VALUE	15.21	561.11	3.92%	20.63	656.28	11.19%	16.59	388.91	18.74%
CHICKEN	**METHOD**		**WINTER**			**LR**			**LR**	
	VALUE	14.39	324.57	5.50%	18.31	580.64	16.46%	12.88	262.28	24.65%
GREEN TOMATO	**METHOD**		**WINTER**			**SMA**			**LR**	
	VALUE	20.35	653.81	8.74%	10.78	239.22	8.91%	10.08	169.72	23.16%
TORTILLA	**METHOD**	**WMA**			**SMA**			**LR**		
	VALUE	34.79	3,501.82	7.71%	30.45	1,524.48	13.34%	26.84	972.65	25.84%

Table 6. Monthly forecast in kilograms (January-December 2019)

Monthly period	Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Green tomato	Tortilla
1	153.80	268.96	62.59	975.34	256.78	414.93	266.78	223.18	478.77
2	135.26	244.38	62.60	844.82	256.78	363.41	269.26	202.75	470.50
3	140.78	285.79	62.61	928.72	274.00	381.41	216.68	230.46	602.79
4	155.86	231.35	62.61	816.85	287.29	351.08	271.04	222.00	550.70
5	136.91	271.69	62.62	842.34	300.11	415.05	264.19	263.45	565.66
6	115.36	265.04	62.62	736.84	315.28	360.36	248.18	226.66	559.71
7	117.15	282.68	62.63	838.78	329.37	374.84	211.86	289.07	479.42
8	127.59	240.03	62.63	725.75	349.09	372.10	265.56	281.92	472.33
9	110.05	278.06	62.64	698.91	366.71	400.76	249.13	291.61	480.08
10	105.61	281.31	62.65	672.48	381.99	404.61	248.73	299.60	482.58
11	99.52	286.36	62.65	629.49	397.28	409.77	248.54	312.69	482.40
12	91.02	287.41	62.66	608.27	412.56	413.29	247.87	320.09	482.22

Table 7. Fortnightly forecast in kilograms (January-December 2019)

Fortnightly period	Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Green tomato	Tortilla
1	77.12	150.60	31.49	476.03	127.08	197.09	128.48	89.94	161.62
2	75.80	127.66	31.46	500.94	130.68	200.90	128.21	140.57	317.15
3	74.49	125.10	31.44	418.07	134.28	201.73	127.93	77.72	287.31
4	73.17	129.45	31.41	426.54	137.88	171.40	127.65	102.74	255.36
5	71.85	128.29	31.39	419.41	141.47	202.66	127.37	103.32	262.55
6	70.53	129.10	31.37	484.47	145.07	195.21	127.10	92.91	259.60
7	69.21	129.88	31.34	395.85	148.67	185.68	126.82	108.80	261.99
8	67.89	127.54	31.32	404.59	152.27	146.27	126.54	113.39	296.69
9	66.57	126.78	31.30	433.44	155.87	180.61	126.26	123.68	285.81
10	65.26	126.90	31.27	451.93	159.47	207.14	125.99	123.66	275.53
11	63.94	132.17	31.25	385.55	163.07	195.10	125.71	132.25	275.53
12	62.62	131.50	31.22	400.65	166.67	176.61	125.43	131.46	245.46
13	61.30	129.78	31.20	402.58	170.26	199.45	125.16	135.32	239.01
14	59.98	133.67	31.18	433.03	173.86	215.69	124.88	139.09	232.46
15	58.66	136.42	31.15	357.14	177.46	209.11	124.60	139.92	241.60
16	57.34	135.43	31.13	344.92	181.06	172.40	124.32	140.81	244.91
17	56.02	135.95	31.11	354.11	184.66	203.03	124.05	129.74	233.71
18	54.71	136.61	31.08	353.19	188.26	203.03	123.77	126.22	240.65
19	53.39	137.26	31.06	354.84	191.86	202.99	123.49	121.76	236.13
20	52.07	137.92	31.04	354.41	195.46	202.73	123.21	125.91	236.83
21	50.75	138.57	31.01	363.67	199.05	201.33	122.94	124.63	237.87
22	49.43	139.22	30.99	363.67	202.65	201.33	122.66	124.10	236.95
23	48.11	139.88	30.96	363.67	206.25	201.33	122.38	124.88	237.22
24	46.79	140.53	30.94	363.67	209.85	201.33	122.10	124.54	237.35

Table 8. Weekly forecast in kilograms (January-December 2019)

Weekly period	Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Green tomato	Tortilla
1	36.16	55.30	14.62	128.70	50.24	81.26	60.20	48.10	122.16
2	35.84	55.30	14.60	222.65	50.24	81.26	60.06	48.54	121.81
3	35.52	55.70	14.58	221.34	49.52	80.92	59.92	48.97	121.45
4	35.20	56.12	14.57	223.11	52.52	83.27	59.77	49.41	121.10
5	34.88	56.16	14.55	231.49	54.55	85.25	59.63	49.85	120.74
6	34.56	56.34	14.53	222.36	53.89	84.54	59.49	50.28	120.39
7	34.24	56.82	14.51	210.60	55.53	85.53	59.35	50.72	120.03
8	33.92	56.67	14.49	208.94	55.45	84.98	59.21	51.16	119.68
9	33.60	57.65	14.48	206.53	54.86	84.71	59.06	51.59	119.32
10	33.29	57.39	14.46	206.24	57.21	84.98	58.92	52.03	118.97
11	32.97	57.66	14.44	207.95	57.39	84.29	58.78	52.47	118.61
12	32.65	58.35	14.42	211.40	57.86	83.34	58.64	52.90	118.26
13	32.33	58.37	14.40	206.48	57.90	83.69	58.49	53.34	117.90
14	32.01	57.92	14.39	204.71	56.81	83.34	58.35	53.78	117.55
15	31.69	57.32	14.37	200.07	57.82	84.21	58.21	54.21	117.19
16	31.37	57.17	14.35	199.20	56.98	83.36	58.07	54.65	116.84
17	31.05	56.45	14.33	197.45	57.94	83.34	57.93	55.09	116.48
18	30.74	56.90	14.31	199.37	58.32	84.27	57.78	55.52	116.12
19	30.42	56.64	14.30	194.28	58.94	83.73	57.64	55.96	115.77
20	30.10	57.21	14.28	192.48	60.38	84.50	57.50	56.40	115.41
21	29.78	57.27	14.26	189.87	60.51	84.83	57.36	56.83	115.06
22	29.46	58.36	14.24	188.75	62.17	85.97	57.21	57.27	114.70
23	29.14	59.02	14.22	196.15	60.72	85.21	57.07	57.71	114.35
24	28.82	58.80	14.21	193.10	60.85	85.68	56.93	58.15	113.99
25	28.50	58.59	14.19	184.36	61.17	86.87	56.79	58.58	113.64
26	28.19	58.56	14.17	183.05	63.34	87.38	56.65	59.02	113.28
27	27.87	58.36	14.15	180.67	63.36	85.85	56.50	59.46	112.93
28	27.55	59.66	14.13	183.42	64.51	86.44	56.36	59.89	112.57
29	27.23	60.07	14.12	177.33	65.56	87.94	56.22	60.33	112.22

Weekly period	Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Green tomato	Tortilla
30	26.91	60.56	14.10	176.35	65.54	87.79	56.08	60.77	111.86
31	26.59	61.35	14.08	173.92	66.57	87.33	55.93	61.20	111.51
32	26.27	60.85	14.06	170.52	68.84	88.55	55.79	61.64	111.15
33	25.95	60.86	14.04	168.01	70.90	89.64	55.65	62.08	110.80
34	25.63	60.23	14.03	164.62	71.07	88.59	55.51	62.51	110.44
35	25.32	60.82	14.01	164.08	71.88	88.09	55.37	62.95	110.08
36	25.00	60.09	13.99	153.81	71.69	87.12	55.22	63.39	109.73
37	24.68	60.13	13.97	151.05	71.91	87.17	55.08	63.82	109.37
38	24.36	60.18	13.95	148.30	72.12	87.23	54.94	64.26	109.02
39	24.04	60.23	13.94	145.55	72.34	87.28	54.80	64.70	108.66
40	23.72	60.27	13.92	142.80	72.55	87.33	54.66	65.13	108.31
41	23.40	60.32	13.90	140.04	72.77	87.39	54.51	65.57	107.95
42	23.08	60.36	13.88	137.29	72.98	87.44	54.37	66.01	107.60
43	22.77	60.41	13.86	134.54	73.20	87.49	54.23	66.44	107.24
44	22.45	60.45	13.85	131.79	73.41	87.55	54.09	66.88	106.89
45	22.13	60.50	13.83	129.03	73.63	87.60	53.94	67.32	106.53
46	21.81	60.54	13.81	126.28	73.84	87.65	53.80	67.75	106.18
47	21.49	60.59	13.79	123.53	74.06	87.71	53.66	68.19	105.82
48	21.17	60.63	13.77	120.78	74.27	87.76	53.52	68.63	105.47
49	20.85	60.68	13.76	118.02	74.49	87.81	53.38	69.07	105.11
50	20.53	60.73	13.74	115.27	74.70	87.87	53.23	69.50	104.76
51	20.22	60.77	13.72	112.52	74.92	87.92	53.09	69.94	104.40
52	19.90	60.82	13.70	109.77	75.13	87.97	52.95	70.38	104.04

Table 9. Quantity to be ordered in kilograms (Q)

Weekly period	Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Green tomato	Tortilla
1	44.48	73.95	17.42	287.40	94.91	106.76	72.10	85.65	146.65
2	35.74	55.27	14.60	129.28	50.20	81.17	60.01	48.09	121.70
3	35.42	55.25	14.58	220.62	50.16	81.15	59.87	48.52	121.34
4	35.10	55.67	14.56	219.28	49.35	80.73	59.73	48.96	120.99
5	34.78	56.11	14.54	220.70	52.50	83.27	59.59	49.40	120.63
6	34.46	56.14	14.52	227.92	54.62	85.30	59.44	49.83	120.28
7	34.14	56.32	14.51	219.55	53.90	84.59	59.30	50.27	119.92
8	33.82	56.82	14.49	208.83	55.61	85.59	59.16	50.71	119.57
9	33.50	56.66	14.47	207.17	55.50	85.04	59.02	51.14	119.21
10	33.19	57.69	14.45	204.86	54.84	84.76	58.88	51.58	118.86
11	32.87	57.42	14.43	204.44	57.31	85.04	58.73	52.02	118.50
12	32.55	57.69	14.42	205.80	57.47	84.33	58.59	52.45	118.14
13	32.23	58.40	14.40	208.61	57.96	83.31	58.45	52.89	117.79
14	31.91	58.42	14.38	204.04	57.97	83.67	58.31	53.33	117.43
15	31.59	57.96	14.36	202.24	56.79	83.27	58.17	53.76	117.08
16	31.27	57.33	14.34	197.93	57.83	84.21	58.02	54.20	116.72
17	30.95	57.16	14.33	196.95	56.87	83.25	57.88	54.64	116.37
18	30.64	56.34	14.31	195.19	57.86	83.19	57.74	55.07	116.01
19	30.32	56.81	14.29	196.57	58.22	84.20	57.60	55.51	115.66
20	30.00	56.47	14.27	191.90	58.83	83.53	57.45	55.95	115.30
21	29.68	57.07	14.25	190.08	60.34	84.37	57.31	56.39	114.95
22	29.36	57.07	14.24	187.56	60.43	84.71	57.17	56.82	114.59
23	29.04	58.31	14.22	186.31	62.18	85.97	57.03	57.26	114.24
24	28.72	59.02	14.20	192.04	60.51	85.08	56.89	57.70	113.88
25	28.40	58.77	14.18	188.98	60.54	85.59	56.74	58.13	113.53
26	28.08	58.50	14.16	181.35	60.73	86.90	56.60	58.57	113.17
27	27.77	58.42	14.15	179.83	63.09	87.42	56.46	59.01	112.81
28	27.45	58.03	14.13	177.42	62.96	85.73	56.32	59.44	112.46
29	27.13	59.62	14.11	178.96	64.13	86.39	56.17	59.88	112.10

Weekly period	Avocado	Onion	Mushroom	Tomato	Melon	Papaya	Chicken	Green tomato	Tortilla
30	26.81	60.08	14.09	173.54	65.20	87.96	56.03	60.32	111.75
31	26.49	60.58	14.07	172.07	64.91	87.82	55.89	60.75	111.39
32	26.17	61.17	14.06	169.42	65.83	87.37	55.75	61.19	111.04
33	25.85	60.81	14.04	166.03	68.46	88.47	55.61	61.63	110.68
34	25.53	60.81	14.02	163.25	70.87	89.03	55.46	62.06	110.33
35	25.22	60.24	14.00	159.81	71.02	88.35	55.32	62.50	109.97
36	24.90	60.77	13.98	158.08	71.92	88.00	55.18	62.94	109.62
37	24.58	60.09	13.97	150.18	71.68	87.12	55.04	63.37	109.26
38	24.26	60.13	13.95	147.43	71.90	87.17	54.89	63.81	108.91
39	23.94	60.18	13.93	144.68	72.11	87.23	54.75	64.25	108.55
40	23.62	60.22	13.91	141.93	72.33	87.28	54.61	64.68	108.20
41	23.30	60.27	13.89	139.17	72.54	87.33	54.47	65.12	107.84
42	22.98	60.31	13.88	136.42	72.76	87.39	54.33	65.56	107.49
43	22.66	60.36	13.86	133.67	72.97	87.44	54.18	65.99	107.13
44	22.35	60.41	13.84	130.92	73.19	87.49	54.04	66.43	106.77
45	22.03	60.45	13.82	128.16	73.41	87.55	53.90	66.87	106.42
46	21.71	60.50	13.80	125.41	73.62	87.60	53.76	67.30	106.06
47	21.39	60.54	13.79	122.66	73.84	87.65	53.61	67.74	105.71
48	21.07	60.59	13.77	119.90	74.05	87.71	53.47	68.18	105.35
49	20.75	60.63	13.75	117.15	74.27	87.76	53.33	68.61	105.00
50	20.43	60.68	13.73	114.39	74.48	87.81	53.19	69.05	104.64
51	20.11	60.72	13.71	111.63	74.69	87.87	53.04	69.48	104.28
52	19.49	60.73	13.68	106.22	74.70	87.87	52.77	69.50	103.59

It can be seen from Table 5 that, in general, monthly forecasts have a lower level of error than fortnightly and weekly forecasts. Weekly forecasts are those with a higher level of MAPE error. Hence, the most appropriate monthly forecast method for most products is Winter's method, however, there are exceptions for mushroom, melon and tortilla demand, where the methods with the lowest level of error were Linear Regression (LR), Holt and WMA, respectively.

For the fortnightly forecast, the most frequent method that yielded the lowest level of MAPE error is the LR method, which is shown as the best option for four of the evaluated products, followed by Winter's method as the best option for forecasting tomato and papaya demand, the SWA method for forecasting tomato and tortilla demand, and finally Holt's method for forecasting onion demand.

In the case of the weekly forecast, the method that gave the best results and appears most frequently to perform the forecast is the LR method, which is shown as the best option for five products, followed by Brown's method, which is shown as the best forecast option for three products. For the tomato demand forecast, the method with the lowest level of error is Holt's method.

A forecast is highly accurate when the MAPE error level is less than 10%, a forecast is good when the MAPE error level is between 11% and 20%, a forecast is reasonable when the MAPE error level is between 21% and 50%, and when the MAPE error exceeds 50% it means that the forecast is inaccurate [21]. For this work, monthly forecasts show a MAPE error value of less than 10%, which means that the forecast is highly accurate. In the case of the fortnightly period, the forecasts are good because the MAPE error level is less than 20%; even highly accurate forecasts are presented for tomatoes and green tomatoes. In the case of the weekly period, most reasonable forecasts are presented, located between 20% and 50% of the MAPE error, with exception of three products that are within the 20% error level.

5.3 Forecasted Demand

Once that the best methods for forecasting demand were determined for each product, Tables 6, 7 and 8 present the monthly, fortnight and weekly demand forecasts.

5.4 Implementation of the *P* Inventory Control Model

Once the demand is estimated, the inventory model for supply planning is selected. In this case the supply must be made in short periods due to the expiration of the products. Therefore, the planning was performed based on the forecast demand for weekly periods. Because the weekly demand forecast is not highly accurate due to the variability of the demand (uncertain demand), the *P* inventory control model was considered as the most suitable option (see Eq. 12).

Due to the expiration of the food products, it was decided to use a weekly review period with a planning horizon of 52 weeks. The lead time (*LT*) is 2 days which is equivalent to 0.29 weeks. For safety levels, a service level of 98% was established. The results of the implementation of the periodic review inventory model, which consists in the most reliable lot size Q to be ordered at each time the inventory is reviewed, are shown in Table 9.

6. DISCUSSION AND CONCLUSIONS

The present work is aimed to improve the management of the demand for food materials in restaurants to reduce their rate of food waste. For this purpose, having a highly accurate forecast is crucial for an efficient supply planning with limited stockout and surplus risks.

Thus, it is important to analyze the demand patterns of the required food products and select the most appropriate forecasting method for each one of them. In this case study, the forecasts for monthly periods were more precise than the forecasts for weekly periods, which is very useful for long-term planning as they allow observing the behavior of demand throughout the year in order to negotiate prices with suppliers and assign budgets. However, the monthly forecast is not useful for monthly purchases due to the expiration period of perishable products.

To consider the expiration of perishable products, forecasts were made with weekly periods to establish a supply schedule with shorter purchase periods. This to keep products in good condition and avoid food waste. However, the weekly forecasts did not show a highly accurate result, but presented a reasonable result, which allows to observe an approximation of future demand, but does not guarantee the reduction of food waste. Therefore, it was decided to add the implementation of a periodic review inventory model, which works when demand is uncertain or very variable.

Applying the periodic review inventory model allowed the ordering of Q kilograms of each food product on a weekly basis with a service level of 98%. As food waste is caused by poor purchase or supply planning, the periodic review strategy can support the reduction of surplus and stockout risks. Particularly for food waste reduction, the surplus risk is more important. An advantage of this model is that, based on its mathematical formulation (see Eq. 12), the available inventory is considered at the review time. Thus, a smaller Q may be ordered, which can reduce the surplus risk.

While these results are encouraging, there are certain limitations. For example, we implemented standard forecast methods which, based on the weekly/monthly periods, provided different levels of accuracy. In this case, more complex forecast methods such as those based on Artificial Neural Networks (ANNs) must be considered [22]. Future work is focused on extending the quantitative tools portfolio to address these limitations.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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