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QUANTITATIVE DEMAND FORECASTING ADJUSTMENT BASED ON QUALITATIVE FACTORS: CASE STUDY AT A FAST FOOD RESTAURANT

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ABSTRACT

This paper proposes a method of forecasting demand that integrates quantitative models with qualitative contextual factors. The proposed method selects the mathematical (quantitative) model that best fits the historical data, based on the determination coefficient R^2 and the mean absolute percentage error (MAPE). Next, the forecasts generated by the selected model are adjusted based on expert opinion on contextual factors (judgemental adjustment), such as events and renovations, for example, not included in the historical data. The proposed method was applied at a fast food restaurant to forecast the demand of meat. The adjusted method yielded an average error of 10% in the worst scenario when compared to the real demand of the period, whereas the quantitative model, with no judgemental adjustment, led to an average error of 38%.

Keywords: Forecast of Demand; Time Series; Quantitative Models; Qualitative Adjustment; Fast Food.

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1. INTRODUCTION

Faced with a scenario with frequent changes and a demand for a level of service increasingly personalized by the consumer, companies in the tertiary sector have been looking for competitive differentials to excel in their segments. For Machado et al. (2006), offering high quality services is an essential factor in the company's performance. Within this context, Cranage (2003) reinforces that management strategies in the hospitality industry should become differentiated due to the high competition of this market. The restaurant sector, included in this type of industry, suffers from deep changes in customer requirements, necessitating alternatives to compete.

Liu *et al.* (2001) argue that there are three essential skills required of a manager that impact the profitability of a restaurant: predicting staffing needs, forecasting inventory levels, and predicting orders to schedule food preparation in a timely manner. In addition, predicting the meals to be sold provides valuable information to reduce costs, use resources more efficiently, and improve the ability to compete in a constantly changing environment (Cranage, 2003). According to Ansel *et* Dyer (1999), forecasting demand at a restaurant is the first step in solving critical planning problems, such as table availability, workforce, and quantity of raw material storage.

Choi (1999) concludes that fast food restaurant managers need to predict demand for their services and also effectively control their inventory so that waste is reduced. In a fast food restaurant, there is a crucial point that confronts the waste of inputs with customer service. Since a number of processes are done without planning in the kitchen of a restaurant, it is critical to rely on accurate demand forecasting, which prevents start-up after customer request and at the same time reduces the violation of "shelf time" of the products. Excess production by anticipation generates waste, while lack of production generates customer dissatisfaction (slow service). Both incur revenue loss and do not contribute to a good corporate image.

Despite the extreme importance of forecasting demand in the context of a fast food restaurant, it is possible to notice a wide use of informal qualitative methods, based only on the manager's experience. For Pellegrini (2000), qualitative methods are vulnerable to trends that can compromise prediction because they are based on the opinion of experts with different preferences. On the other hand, quantitative forecasts are reliable as long as events occurring during the generation of the historical database remain unchanged (Sanders *et* Ritzman, 2004). Mathews et Diamantopoulos (1986) argue that adjustments based on the opinion of specialists in quantitative forecasts increase the accuracy of the results. However, this adjustment, according to Goodwin *et al.* (2007), should be done with the addition of knowledge that is not included in the quantitative method. In fast-food restaurants, there are a number of new factors that affect demand and cannot be included in the quantitative forecast because of the lack of historical data, such as promotions, advertisements, corporation-franchise relations, among others. These factors should be measured by expert judgment and then included in the quantitative method (subjective adjustment).

The purpose of this article is to propose a model of demand forecast supported in the qualitative adjustment of the forecasts generated by the quantitative method and to test it in the process of buying a fast food restaurant. First, the quantitative model of demand forecasting is best chosen to fit the historical data based on adjustment metrics, such as the determination coefficient R^2 and the mean absolute percentage error (MAPE). Next, qualitative factors that could influence demand are identified. Finally, the forecast of quantitative demand is adjusted based on the influence of the factors, and the results of the forecast are compared with the real demand. In this way, the work seeks to help increase the reliability of the forecast of demand of the restaurant and the process of purchase of inputs.

This article is organized as follows: after this introduction, a theoretical reference is presented in section 2, where contents are reviewed on methods of demand forecasting and subjective adjustment. Section 3 deals with the methodological procedures used in the work. Section 4 presents the results of a case study in a fast food restaurant, where the proposed demand forecast method was applied. Finally, in section 5, the final considerations about the present study are presented and opportunities for future work are discussed.

2. DEMAND FORECAST FOUNDATION

Demand forecasting is an essential activity for planning, strategy or any other means that needs to make future decisions (Makridakis, 1988). In the business context, such forecast is of great importance in several sectors, such as sales, financial, logistics and production (Moon *et al.*, 1998). In this last sector, demand forecasting is usually the first step in planning its operation because, based on it, capacity, labor, inventory and production plans are developed (Elsayed *et* Boucher, 1985; Tubino, 2000).

There are two main approaches to demand forecasting: qualitative methods and quantitative methods. The qualitative approach is based on the opinions, judgments and past performance of experts (Slack *et al.*, 2009). The quantitative approach takes historical data into account and performs a projection through some mathematical model (Corrêa *et* Corrêa, 2005).

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In the restaurant sector, qualitative methods predominate. However, there are several studies that have used quantitative demand forecasts in this branch of activity. Reynolds *et al.* (2013) applied a (causal) regression model in restaurants of different segments, such as fast food, à la carte, non-commercial restaurants (establishments such as hospitals and factories) and outsourced restaurants (contractors from establishments such as the former) obtaining reliable forecasts. Cranage (2003) conducted sales forecasts through a wide range of methods (among them, exponential smoothing, moving average and decomposition) in a restaurant and compared with actual demands of the forecast period, having succeeded with some of the techniques. Cranage *et* Andrew (1992) concluded in a survey of a midtown restaurant that time-series models (such as exponential smoothing and the Box-Jenkins method) behaved better than causal models in sales prediction.

2.1 Quantitative methods

Quantitative methods are characterized by using well defined processes for data analysis, allowing the method to be replicated by other experts and they have the same predictions (Armstrong, 1983). In this method category, historical data are the basis for the forecast (Elsayed *et* Boucher, 1985).

Quantitative methods are divided into causal methods and time-series methods (Slack *et al.*, 2009). Causal methods predict demand based on a cause and effect relationship between variables. On the other hand, time-series methods use only historical demand data to predict the future, assuming that the demand trend in the past will remain unchanged (Davis *et al.*, 2003). The most widely used time series methods in the literature are moving average and exponential smoothing.

Exponential smoothing techniques are the most used in all other demand forecasting techniques (Davis *et al.*, 2003). This is due to the fact that these methods are simple, easy to adjust and provide good accuracy (Pellegrini, 2000). The following are the more traditional methods of exponential smoothing (Ritzman *et* Krajewski, 2004; Elsayed *et* Boucher, 1985).

(i) **Simple exponential smoothing:** when there is no trend or seasonality in demand. It is simple and requires only three data: the forecast of the last period, the demand for the current period and an approximation parameter with a value between 0 and 1.

(ii) **Holt double exponential smoothing:** used when there is a trend, that is, a systematic increase or decrease in the mean of the series over time. In this case, there is a need to soften not only the average of each period, but also the trend.

(iii) **Seasonal Exponential Softening of Holt-Winters:** method used in the presence of a seasonal aspect, that is, changes regularly repetitive in the demand up or down.

2.2 Qualitative methods and subjective adjustment

Qualitative methods are techniques based on subjective data (Tubino, 2000). In general, they are used when there is a shortage of suitable historical data, as in scenarios where there is introduction of new products or change in technology, which requires a forecast based on the judgment and experiences of the manager (Ritzman *et* Krajewski, 2004).

Among the main qualitative prediction methods, the Delphi method (Slack *et al.*, 2009) stands out. Other frequently used qualitative methods can be found in the literature, such as sales force and market research.

According to Song *et al.* (2007), quantitative methods can produce more precise results than qualitative methods, since they employ objective criteria less susceptible to subjective errors. On the other hand, the authors argue that on occasions when there are contextual factors that cannot be included in the statistical model, the qualitative model obtains a better performance in the forecast.

Wright *et al.*, (1996) affirm that the robustness generated by the combination of strategies has encouraged the integration of forecasts, allowing aggregating the contextual knowledge to the statistical methods. Ritzman *et* Krajewski (2004) argue that the combination of forecasts may outperform the best single prediction method. Sanders (1992) supplements this view by stating that the accuracy of statistical models is generally augmented with a subjective fit.

In this way, Webby *et* O'Connor (1996) propose four methods of integration of predictions: (*i*) model construction, (*ii*) combination of forecasts, (*iii*) subjective decomposition and (*iv*) subjective adjustment. The latter, with a focus on the work, will be deepened.

According to Webby et O'Connor (1996), the subjective adjustment consists of making a prediction by means of a quantitative method and adjusting it based on contextual factors. Lawrence et al. (2006) exemplify the adjustment to a sales forecast, where historical data (generators of quantitative forecasting) are the sales history and the contextual factors are promotions, production data and macroeconomic factors. Figure 1 illustrates the subjective adjustment.

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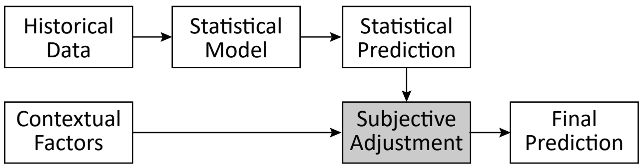

Figure 1. Subjective adjustment
Source: Webby *et* O'Connor, 1996

The application of subjective adjustment is vast. Fildes *et al.* (2009) analyzed the subjective adjustment of specialists in four different companies (pharmaceutical, food, household and retail) and, after generating statistical forecasts based on variations of exponential smoothing using software, concluded that, in three of them, the intervention of the specialists in this result increased the precision of the forecast. Song *et al.* (2013) predicted arrivals of tourists to Hong Kong through a causal model, for, then, to make an adjustment based on the opinion of students specialized in tourism, which improved the final forecast. Forrest *et al.* (2010) used their own experience with contextual factors to adjust the statistical forecast of the number of medals that the participating countries of the 2008 Beijing Olympics would achieve.

Sanders *et* Ritzman (2004) cite as advantages of subjective adjustment the high sense of ownership and the ability to quickly incorporate contextual information. Webby *et* O'Connor (1996) also find similar advantages and emphasize that subjective adjustment has the best cost benefit among the methods. However, Goodwin *et* Wright (2010) emphasize the disadvantage of being susceptible to trends.

Davydenko *et* Fildes (2013) postulate that subjective adjustment should occur when there is a need to consider some factors excluded from the quantitative prediction. For Armstrong *et* Collopy (1998) the opinion of experts is important to make this adjustment, since the quantitative model is not able to include these factors. Reimers *et* Harvey (2011) reinforce the importance of opinion, stating that people tend to improve their predictions when contextual factors are part of their environment.

Reaffirming this latter position, Önkal *et al.* (2003) conducted a study on the exchange rate forecast and concluded that operators who work daily with this operation in their companies obtained, in the majority, better forecasts than university students of bussiness. In a survey of the 2005 national elections in Germany, Andersson *et al.* (2006) showed that policy experts obtained more accurate predictions than German voters and foreigners. According to Sanders *et* Ritzman (2004), simply integrating arbitrary subjective factors with a quantitative method, without taking into account the domain of knowledge, may impair the accuracy of the results.

However, Lawrence *et al.* (2006) believe that human judgment brings benefits to prediction, but it can also lead to bias. Armstrong (2006) exemplifies: managers may overestimate sales forecasting because they believe this would motivate employees or that salespeople could estimate a lower forecast because it is easier to achieve. According to Eroglu *et* Croxton (2010), factors such as personality and motivation of the predictor are great sources of bias. In addition, for Sanders *et* Manrodt (2003), people have limited capacity to consider and process large amounts of information.

Werner et Ribeiro (2006) cite five types of bias: (*i*) inconsistency: inability to apply the same decision criterion on similar occasions; (*ii*) anchoring: tendency of specialists to be influenced by initial information (anchors); (*iii*) conservatism: predictors start from the assumption that the variable under study will follow the same pattern of behavior as it did in the past; (*iv*) optimism: the decision maker's thinking that motivates him to make the forecast more favorable than if it would be based on facts; (*v*) illusory correlation: to believe that two variables are related when in fact they are not. For authors, biased forecasts may lead to loss of orders, inadequate service delivery, and poor utilization of organizational resources.

According to Armstrong (2006), studies indicate that unstructured subjective adjustments often undermine forecasting, since they may generate bias. For Bunn *et* Salo (1993), there is a need to balance subjective informal adjustment with a more structured, that is, more "defensive" process. Thus, studies have developed methods of structuring subjective adjustment.

Wolfe *et* Flores (1990) performed an adjustment in a profit forecast through the Analytical Hierarchical Process (AHP), greatly increasing the accuracy of the results. Flores *et al.* (1992), in turn, compared the adjustment made by the AHP to the adjustment of the Centroid method, concluding that the AHP is more accurate in the results, but little significant because of the complexity and the difficulty of applying the method in relation to the other. Duru *et al.* (2012) performed a subjective adjustment in the waterway transport sector, using a Delphi method adapted to reduce bias. According to Werner *et* Ribeiro (2006), other methods of subjective adjustment can be found in the literature, such as decomposition of time series, graphic methods and Theil's method.

3. METHODOLOGICAL PROCEDURES

According to Silva *et* Menezes (2005), this research is of an applied nature, since it aims to generate knowledge for practical application aimed at solving specific problems. The approach is quantitative, since it uses statistical methods and allows translating opinions into numbers. From the

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point of view of its objectives, the research is exploratory, in order to provide greater familiarity with the problem. As for the technical procedures, it is an action research, since the researcher and the participants are involved in order to solve a collective problem.

The method for adjusting the proposed quantitative demand forecast is divided into five stages: (*i*) historical demand data collection; (*ii*) quantitative modeling; (*iii*) survey of contextual factors; (*iv*) subjective adjustment; and (*v*) validation of the method. Such steps are detailed in the sequence.

3.1. Collection of historical demand data

The first step is to verify whether there are sufficient data for the application of the method. Initially, the availability of historical data on the demand for the product to be analyzed, as well as their quality, is evaluated; following, the existence of specialists with the conditions to make the subjective adjustment.

3.2. Quantitative modeling

In the next step, a purely quantitative demand forecast is performed. It is necessary to define the quantitative demand forecasting method that best fits the historical demand data. For this, the data collected are divided into two groups: training and testing. The first uses 80% of the data (for the construction of the model) and the second, the remaining 20% (more recent data, for the validation of the modeling), as indicated in Figure 2.

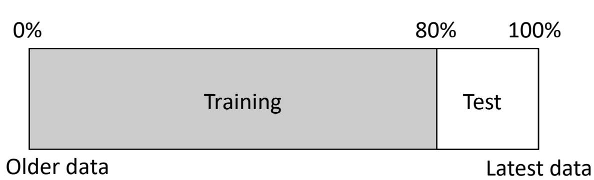

Figure 2. Data group: training and testing

N forecast models are elected and are candidates to be tested; then, using only training group data, the training data is intended to predict the levels of demand for the observations of the test group. For example, if 30 data were collected, method predictions are based on the first 24 data (training group, 80% of the data), predicting six periods ahead (test group, 20% of the data). Thus, each model generates a determination coefficient R^2, which represents the degree of adjustment of that model to the historical data. High values of R^2 are desired, since they denote a good adherence of the model to the data.

In the sequence, the predictions made by each mathematical model with the data of the test group are compared. This step aims to evaluate the predictive capacity of each model built against existing data. According to Makridakis *et al.* (1998), accuracy represents the degree of ability with which the methods predict already existent data. In the propositions of this article, MAPE is used, which calculates the average of the absolute differences between the actual value and the predicted value. Reduced MAPE values are desired, since they indicate good predictive capacity of the model generated. Finally, we calculate the indices *I* of each method, given by equation 1. The model that has the highest *I* value will be chosen.

$$I_n = \frac{R^2{}_n}{MAPE_n} \qquad (1)$$

Finally, a prediction $F_t F_t$ is performed for the desired period t with the selected model, using as a basis for extrapolation both the training data and the test data

3.3. Survey of contextual factors

The purpose of this step is to find out whether there are contextual (qualitative) factors that allow the accomplishment of the adjustment in the statistical forecast. These factors are environmental events that influence demand, such as sales promotions, introduction of a brand new product, store reform, and more aggressive marketing. The experts are interviewed individually, pointing out possible factors that may influence the demand of the variable under study. Following this, a meeting is held with the selected experts and the factors are defined. If there is no context factor capable of changing the demand, the quantitative forecasting performed in the previous step is sufficient, and subjective adjustment is not necessary.

3.4. Subjective adjustment

This phase adjusts the predictions generated by the quantitative model, made in the quantitative modeling stage, based on the contextual factors raised by the specialists in the stage of the survey of contextual factors, according to Webby et O'Connor's definition of subjective adjustment (1996). Firstly, the contribution of each specialist is weighted: the objective is to quantify the importance of the opinion of more experienced specialists. However, there must be a minimum weight, which represents equal division among all over 50% of the general opinion. For example, if there are three experts, the minimum weight of each is 50% divided by 3, that is, 16.67%. The remaining 50% of the general opinion is used to weigh the importance of individual specialists.

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Such a proposition is operationalized in the following way: the specialists evaluate each other, commenting whether they consider the colleague more, equal or less experienced than himself. A table is prepared, listing the specialists in the rows; in the columns -1 is placed when the expert considers himself less experienced than the other, 0 when he considers himself with equal experience level and 1 when he regards himself as more experienced. Subsequently, the individual sum of the specialist's score is made and the percentage of the overall sum of the points is calculated. If the individual sum is less than zero when the overall sum of the points is taken, it should be considered zero. This value refers to the remaining 50% of the general opinion for the weighting. Thus, this value is multiplied by 50% and the minimum weight is added to it, resulting in the weight w of the expert opinion. Table 1 exemplifies such a proposition.

Table 1. Example of method of weighing of expert opinion

	Espec. 1	Espec. 2	Espec. 3	Sum	Percentage	Weight (w)
Espec. 1	0	1	1	2	66,67%	50%
Espec. 2	0	0	1	1	33,33%	33,33%
Espec. 3	-1	1	0	0	0%	16,67%
Total	-1	2	2	3	100%	100%

The next step is to collect the opinions of the experts on demand variation. This should be done with individual interviews. The expert must provide two guesses about the change in demand in each factor (on a percentage scale): optimistic and pessimistic. For example, the promotion factor, in expert opinion 1, will increase demand by 5% at worst, and 8% at best. Then, the mean of both scenarios is calculated and this value is multiplied by the weight *w* of the expert opinion. This operation is repeated for all specialists, and after that, the results of each one are added, obtaining the adjustment coefficient *a* of the factor in question. This process is performed for the other factors and, finally, the sum of all the adjustment coefficients *a* is obtained, obtaining the final adjustment coefficient $a'a'$. Thus, the demand forecast P for the period t is defined by equation 2

$$P_t = F_t(1 + a') \qquad (2)$$

where P is the adjusted forecast, F is the quantitative forecast and $a'a'$ is the final adjustment coefficient

3.5. Method Validation

The last step is to evaluate the performance of the method. For this, the forecasts made with the subjective adjustment are compared with the real demand of the period and with the forecasts obtained only with the quantitative method. With this, it is possible to evaluate the importance of including experts' experience in adjusting the demand forecast.

4. RESULTS

This work was applied in a franchise of one of the largest fast food chains in the world, located in Porto Alegre. The group that controls the store has three other franchises of the same network in the state of Rio Grande do Sul.

The network, focusing on the sale of sandwiches, works with different types of meats. However, burger is the product sold on a larger scale: this type of meat represents about 80% of the total amount of meat consumed in the franchise; there are four distinct types of hamburger meat used in sandwiches, and the same type can make different sandwiches.

The process of order placement, as it is called in the company, is the purchase of inputs for the restaurant. This process occurs four times a week; for him there is a person responsible for indicating the quantities to be purchased in fast food network software. The cost of inputs is the largest expense of the store, accounting for approximately 25% of the value of monthly invoicing, justifying the need to forecast the demand for sales as accurately as possible. As the company had no formal demand forecasting process, the objective of this work was to apply the proposed demand forecast method to some product of the restaurant.

By means of an interview with the person responsible for the order placement process, it was decided to apply the proposed method to two types of hamburger meat (A and B). The results, in line with the sections proposed in the method, are presented in the sequence.

4.1. Collection of demand and identification historical data of specialists for subjective adjustment

In this stage, daily data were collected on hamburger meat consumption types A and B from the fast food network database. The period collected comprises 75 days (between 07/01/2013 and 09/13/2013). It is worth remembering that the consumption data includes, besides the sale to the customer, meal for employees and waste.

Following that, three employees were identified for the supply of qualitative information: the current responsible for the application placement process (Specialist 1) and two other employees who have already worked in this area (Specialist 2 and Specialist 3). The criteria taken into account in the decision were the employee's experience in the sector

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and the operation of the restaurant, degree of education and familiarity with demand forecast. Selected experts have the following credentials:

(i) *Specialist 1:* just over six months in office. He was hired to do this once he is graduating in Production Engineering;

(ii) *Specialist 2:* spent a year in office and left the company about six months ago. He holds a degree in Production Engineering; and

(iii) *Specialist 3: served for four years; has 14 years in the company and contact with the operations of the fast food chain. He works as a restaurant kitchen manager. He has completed high school.*

4.2. Quantitative modeling

Initially, graphs were generated with the daily demand profiles of the meat, allowing the identification of 10 data considered as spurious (associated to atypical events and with little or no possibility of repetition in the analysis period), which could compromise the forecast. Such data were replaced by the average demand for that day of the week in past periods (for example, replacement of data from an atypical Friday by the average of the previous four weeks). At the end of this process, a new demand graph was generated for each type of meat, with the existence of the seasonal component in types A and B.

Due to the seasonal component, the following forecast models were tested: additive and multiplicative exponential smoothing of Holt-Winters (HWA and HWM, respectively) and the moving mean (MM). The latter method, according to Ritzman *et* Krajewski (2004), calculates the average demand for the last n periods, which, in turn, will be adopted as forecast for the next period. In the present study, two and three previous periods (MM2 and MM3, respectively) will be used. Although not considered a recommended model for profiles with seasonality, the MM will be tested because of its wide use in the practical context of demand forecasting

Following the method of this work, which uses 80% of the data for training and 20% for test, the 60 oldest data for the first phase were used, in which the determination coefficient *R^2* will be calculated. The HWA and HWM models were modeled by NCSS 6.0 software, and MM2 and MM3 software by spreadsheet. MM models used the same days of the week in the previous weeks. For example, the demand for a Thursday more closely resembles that of the previous Thursday than the previous day (Wednesday). Thus, it was necessary to collect data from three weeks before July 1st, 2013. For the test phase, where the remaining 15 data were used, the MAPE of each model was calculated with the aid of a spreadsheet. Finally, it was possible to determine the indices *I* for models tested, according to Table 2; the model responsible for the largest *I* is recommended for the realization of the forecast

Table 2. Performance of demand prediction models for type A and type B hamburger

	Type A Hamburger		
Forecast model	**R^2**	**MAPE**	**I (R^2/MAPE)**
HWA	0,83	0,103	8,06
HWM	0,82	0,105	7,80
MM2	0,73	0,101	7,21
MM3	0,68	0,119	5,69
	Type B Hamburger		
Forecast model	**R^2**	**MAPE**	**I (R^2/MAPE)**
HWA	0,66	0,104	6,34
HWM	0,66	0,127	5,21
MM2	0,55	0,104	5,29
MM3	0,54	0,086	6,31

According to the data in Table 2, the HWA model presented better performance in terms of data adherence and predictive capacity, and was then used to forecast the following 14 days (09/14/2013 to 09/27/2013). Figures 3 and 4 illustrate the graphs with the historical data and the adjustment of the HWA; the predicted values for the 14 days are in the appendices (A3 and A4).

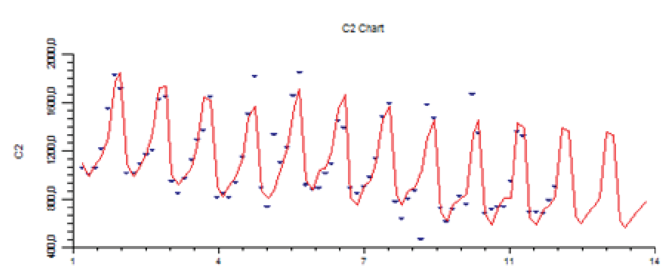

Figure 3. Demand forecast chart for type A hamburgers generated by NCSS 6.0

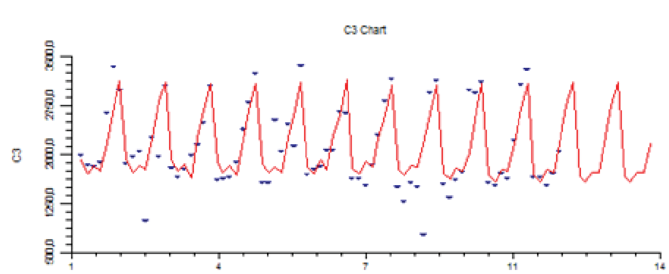

Figure 4. Demand forecast chart for type B hamburgers generated by NCSS 6.0

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4.3. Survey of contextual factors

After completing the mathematical modeling of demand, the qualitative part of the work was started. To this end, the three specialists were assembled to raise the context factors that could influence the sale of hamburgers. The identification of such factors aims to list attributes not present in the historical data modeled and that can change the forecast suggested by the quantitative method. Four factors were listed:

- *Promotional factor:* on 09/14/2013, the promotion of a sandwich that uses two type B meats would be started. This promotion would replace a sandwich produced with a type A hamburger. In this way, experts believe in a variation for both.

- *Reform factor:* the restaurant under analysis went into renovation of its accommodation in early June 2013. According to experts, sales fell from that date until September. However, now the work is in the final stages and there is less inconvenience to the consumer, leading to the belief that there will be a return to normal consumption.

- *October factor:* For those interviewed, October is a time of high sales due to Children's Day. With the proximity of the date, demand may increase in this month transition.

- *Climate factor:* The climate interferes directly in the movement of the restaurant, according to experts. Sunny and warm weekends draw families to enjoy the infrastructure the store holds for children, while rainy days scare shoppers, for example.

4.4. Subjective adjustment

Each specialist then evaluated his colleague in terms of experience; it was aimed to consider their opinion about the influence of the factors on the forecast demand. Given that three experts were consulted, the minimum weight of their opinion is 16.67% (one-third of 50% of the general opinion). Table 3 shows the evaluation, the weight of the remaining 50% of the general opinion and the final weight of each interviewee.

Table 3. Expert assessment and final weight of opinion.

	Espec. 1	Espec. 2	Espec. 3	Sum	Percentage	Weight (w)
Espec. 1	0	-1	0	-1 (0)	0	16,67%
Espec. 2	1	0	1	2	50%	41,67%
Espec. 3	1	1	0	2	50%	41,67%
Total	-1	2	2	4	100%	100%

Separately, each specialist quantified the influence of each factor on demand over the next two weeks (with an optimistic and pessimistic guess), measured on a percentage scale. The averages of such results are presented in Table 4, and the individual values in the appendices (A1 and A2).

Table 4. Average between the experts' expectations (optimistic and pessimistic) for each factor.

Specialists' guess	Type A			Type B		
Factor	Esp. 1	Esp. 2	Esp. 3	Esp. 1	Esp. 2	Esp. 3
Promotion	-40%	-38%	-18%	65%	63%	45%
Renovation	8%	10%	6%	8%	10%	12%
October	3%	0%	6%	3%	0%	6%
Climate	0%	-4%	0%	0%	-4%	5%

Each expert's guess was multiplied by the weight w of his guess and then a sum of this result is made for each factor, finding the adjustment coefficients of each factor *j* for each

type of hamburger *i* ($a_{ij}a_{ij}$), where *i* = 1 and *i* = 2 represent, respectively, type A and type B burgers. Table 5 indicates the calculation

The sum of the adjustment coefficients $a_{1j}a_{1j}$ and $a_{2j}a_{2j}$ results in the final adjustment coefficients $a'_1a'_1$ and $a'_2a'_2$, respectively, where the first represents type A burgers and the second represents type B burgers.

$$a'_1 = \sum_{j=1}^{4} a_{1j} = -29{,}6\% + 7{,}7\% + 3\% - 1{,}5\% = \mathbf{-20{,}3\%} = \mathbf{-0{,}203}$$

$$a'_2 = \sum_{j=1}^{4} a_{2j} = 55{,}6\% + 10\% + 3\% + 0{,}6\% = \mathbf{69{,}3\%} = \mathbf{0,693}$$

Thus, the prediction performed by the HWA model should have its forecast changed according to Equation (2), which represents the adjusted prediction of type A hamburgers:

$$P_{t1} = F_{t1}(1 - 0{,}203)$$

and type B,

$$P_{t2} = F_{t2}(1 + 0{,}693).$$

Finally, the comparison between the purely quantitative forecasts (HWA) and those generated by the proposed method against real demand during the analyzed period (14 subsequent days) was made. Figures five and six and Table 6 show the results. The actual values were multiplied by a random coefficient in order to maintain the confidentiality of the data, due to a requirement of the company. The ta-

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bles comparing the individual values are in the appendices (A3 and A4).

From the comparison graphs and the percentage error table, we can see the increase in the accuracy of the consumption forecast for both hamburgers by the proposed method: the average error of the proposed method reaches up to 7% when compared to the real demand verified in the period, whereas the purely quantitative forecast (HWA) generates deviations at the 38% mark. The factors renovation, October and climate offer moderate contribution to the modification; the promotion factor, however, plays a fundamental role in this change, which occurred precisely on 9/14/2013 when the promotion exchange between the sandwich with meat type A and the other with meat type B.

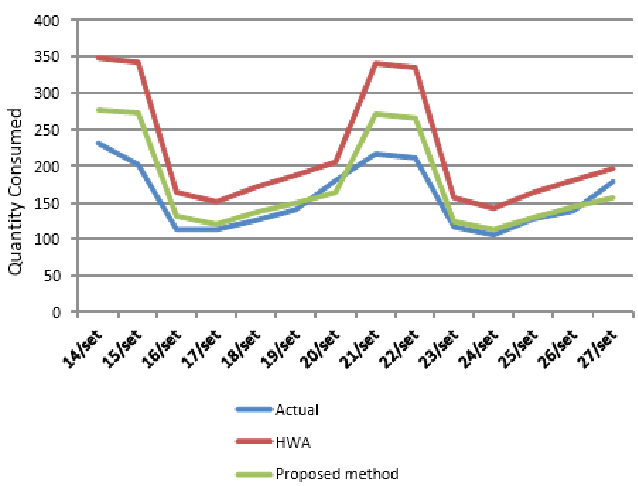

Figure 5. Comparison between the actual demand, the HWA and the proposed method for type A hamburger.
Set=September

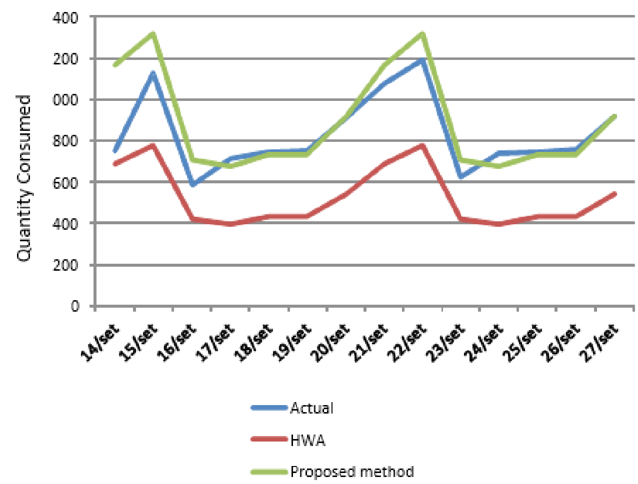

Figure 6. Comparison between actual consumption, HWA and the proposed method for type B hamburger
Set=September

Table 6. Comparison of the mean of the percentage error for the actual consumption between the mathematical model and the proposed method.

Percent error for actual consumption		
Hamburger type	**HWA**	**Proposed method**
A	38%	10%
B	-37%	7%

5. FINAL CONSIDERATIONS

In this paper a method of forecasting demand using quantitative modeling based on qualitative factors was proposed. To test its effectiveness, the same was applied in a fast food restaurant, comparing the predictions of a purely quantitative model with those of the proposed method; the accuracy of the second results was significantly higher. Thus, it was concluded that the influence of qualitative contextual factors not included in the mathematical model database significantly impacts predictions.

In this study, the experts were essential for a more accurate forecast of demand. Their knowledge on the process of purchasing inputs and the factors that influence meat

Table 5. Weight (*w*) x opinion (% of Table 4) and the adjustment coefficients of each factor.

Adjustment coefficient		**Type A**				**Type B**			
j	**Factor**	**Esp. 1**	**Esp. 2**	**Esp. 3**	a_{1j}	**Esp. 1**	**Esp. 2**	**Esp. 3**	a_{2j}
1	Promotion	-6,7%	-15,6%	-7,3%	-29,6%	10,8%	26,0%	18,8%	55,6%
2	Renovation	1,3%	4,0%	2,5%	7,7%	1,3%	4,0%	4,8%	10,0%
3	October	0,5%	0,0%	2,5%	3,0%	0,5%	0,0%	2,5%	3,0%
4	Climate	0,0%	-1,5%	0,0%	-1,5%	0,0%	-1,5%	2,1%	0,6%

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consumption provided information that did not exist in the modeled databases, justifying the importance of merging mathematical models with subjectivism.

For the selection of specialists, qualifications such as experience, schooling and company time were considered. To make the adjustment based on the opinion of the experts (subjective adjustment) weights were made in their guesses (so that the employee with the best qualification had more relevant opinion). As a result of the adjustment, a maximum error of 10% was obtained against the actual demand, while the isolated mathematical model incurred an error of up to 38%.

Future developments include a more in-depth analysis on the qualitative part of the method, since the purpose of this paper was to validate the importance of including contextual factors. The adoption of formal methods of interviews is suggested to further characterize the problem. Moreover, the approach of this work could be improved with the modification of the forecast horizon, seeking to break the time in hours, separating the peak hours of movement in the restaurant, for example.

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ANNEXES

A1. Pessimistic opinion of experts.

Worst hypothesis	Type A			Type B		
Factor	**Sp. 1**	**Sp. 2**	**Sp. 3**	**Sp. 1**	**Sp. 2**	**Sp. 3**
Promotion	-50%	-45%	-25%	60%	55%	40%
Renovation	5%	7%	5%	5%	7%	8%
October	2%	0	5%	2%	0	5%
Climate	-5%	-12%	-10%	-5%	-12%	-5%

A2. Optimistic opinion of experts.

Best hypothesis	Type A			Type B		
Factor	**Sp. 1**	**Sp. 2**	**Sp. 3**	**Sp. 1**	**Sp. 2**	**Sp. 3**
Promotion	-30%	-30%	-10%	70%	70%	50%
Renovation	10%	12%	7%	10%	12%	15%
October	4%	0	7%	4%	0	7%
Climate	5%	5%	10%	5%	5%	15%

A3. Comparison of predictions between the HWA and the proposed method for the 14 extrapolated days (type A).

Date	Real Consumption	HWA	Divergence of the real	Proposed method	Divergence of the real
14/Sept	232	348	50%	277	20%
15/Sept	202	343	70%	273	35%
16/Sept	113	164	46%	131	16%
17/Sept	114	151	33%	120	6%
18/Sept	126	171	36%	137	9%
19/Sept	141	188	33%	150	6%
20/Sept	181	205	13%	163	-10%
21/Sept	217	340	57%	271	25%
22/Sept	212	335	58%	267	26%
23/Sept	117	156	34%	124	7%
24/Sept	106	143	35%	114	8%
25/Sept	128	163	28%	130	2%
26/Sept	139	180	30%	143	3%
27/Sept	178	197	11%	157	-12%
Mean	157	220	38%	175	10%

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A4. Comparison of predictions between the HWA and the proposed method for the 14 extrapolated days (type B).

Date	Real Consumption	HWA	Divergence of the real	Proposed method	Divergence of the real
14/Sept	755	691	-8%	1169	55%
15/Sept	1130	778	-31%	1316	17%
16/Sept	589	420	-29%	711	21%
17/Sept	712	398	-44%	674	-5%
18/Sept	747	433	-42%	733	-2%
19/Sept	751	435	-42%	736	-2%
20/Sept	912	541	-41%	915	0%
21/Sept	1080	691	-36%	1169	8%
22/Sept	1192	778	-35%	1316	10%
23/Sept	622	420	-33%	711	14%
24/Sept	739	398	-46%	674	-9%
25/Sept	749	433	-42%	733	-2%
26/Sept	760	435	-43%	736	-3%
27/Sept	916	541	-41%	915	0%
Mean	832	528	-37%	893	7%

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