Available online at www.sciencedirect.com
ScienceDirect
IFAC PapersOnLine 52-13 (2019) 844–850

Towards a Predictive Approach for Omni-channel Retailing Supply Chains

Marina Meireles Pereira*, Enzo Morosini Frazzon*

* Graduate Program in Production Engineering, Industrial and Systems Engineering Department, Technology Center, Federal University of Santa Catarina, Florianópolis, Santa Catarina, Brasil (Tel: +55 48 3721-7076; e-mail: eng.marinameireles@gmail.com, marina.m.p@posgrad.ufsc.br, enzo.frazzon@ufsc.br).

Abstract: The adoption of omni-channel strategy has changed the relation between retailers and customers and brought more complexity to the retailing supply chains. To address the increasing complexity, it is necessary to adopt innovative approaches based on information technologies and intelligent decision methods. The challenges to retailers are improving the accuracy of offline and online channels demand forecasting, better managing offline and online customer's needs, thus reducing the uncertainties of the omni-channel retailing supply chain. In this context, this research paper aims to propose a predictive approach for omni-channel retailing supply chain combining clustering with artificial neural network to handle demand uncertainty.

Keywords: Supply Chain Management; Retail supply chain; Omni-channel; Machine Learning; Clustering; Artificial Neural Network.

1. INTRODUCTION

Retailers are dynamic in nature and in the last two decades have faced some disruptive transformations such as changing scenarios, availability of new technologies and with the online channel, specifically states of mobile channels, have made their strategies evolve (Verhoef, Kannan and Inman, 2015; Kumar, Anand and Song, 2017). According to Galipoglu et al., (2018) retailers are rapidly evolving from single channel to multichannel, then to cross-channel and now to omni-channel.

Saghiri et al. (2017) states that the omni-channel retailer aims to coordinate processes and technologies across all channels to provide a more integrated, consistent and reliable service to customers.

The adoption of omni-channel enables retailers to have a better understanding of the consumer behavior of each channel by applying technologies that allow the analysis of customers' buying behavior of both virtual and physical channels, sustain Chen, Cheung and Tan, (2018). Li et al. (2018) also highlight that omni-channel empower retailers in retaining customers by reducing uncertainty, providing attractive offers, and engendering switching costs. In addition, Mirsch, Lehrer and Jung (2016) argue that the key factors for companies adapting the omni-channel strategy, as a contemporary multi-channel approach, are technological development, infrastructure, and the changing on customer needs.

In this sense, Pantano, Priporas and Dennis (2018) point out that the "intelligent" use of technologies can be extended to the retail processes to make them intelligent, and these intelligent technologies can affect the methods of collecting data of the consumers, the information management and the transfer of knowledge between companies, by creating a partnership between customers and retailers. The Retail 4.0 or Smart Retailing represents retailers that provide consumer interactions with innovative technologies and with online and offline channels without distinction to enhance the consumer shopping experience according to Vazquez, Dennis and Zhang (2017) and Lee (2017). Being the smart retailer benefits the best visibility of the products, and sharing information and cooperation smart among all actors in the supply chain according to Pantano, Priporas and Dennis (2018).

However, Byrne and Heavey (2006) argue that factors such as promotion, price reduction and advertising by retailers can lead to uncertainties in demand, and uncertainties, distortions and fluctuations are major challenges for collaborative supply chain forecasting and replenishment planning (Carbonneau, Laframboise and Vahidov, 2008).

Wong et al. (2012) and Okada, Namatame and Sato (2016) argue that because of the complexity, uncertainty, and other factors involved, most of the actual supply chains are known to have many supply-demand incompatibility problems, which causes excess or lack of stock, as well as delivery delays, with consequent damages to the level of service offered. In this way Pereira et al. (2018) suggest the application of the machine learning with the simulation-based optimization in order to reduce uncertainties and supply-demand incompatibility. Thereof, the identification of the future demand for a given product is the basis for optimizing the supply chain and replacement systems sustain Sarhani and El Afia (2015). Learning to identify demand reduces the costs of the entire supply chain according to Yan-qiu and Hao (2016) and enables the optimization of operations through the development of strategies for acquisition and reduction of storage costs by optimizing the inventory (Sarhani and El Afia, 2015).

This fact was confirmed by Gao et al. (2017) by analysing the impact of the wave effect caused by interruptions in the demand, production, and distribution process in the retail supply chain, and to point out that price discounts in the online retail market generally amplify the bullwhip effect in the supply chain of online retail.

Therefore, to minimize the uncertainty factors in the smart retail scenario, Gao et al. (2017) argue that choosing the best forecasting technique to minimize the bullwhip effect in the online retail supply chain is of great importance and should be

10.1016/j.ifacol.2019.11.235

a priority for future research in this area, and in a complementary way Lee (2017) and Pantano, Priporas and Dennis (2018) point out that retailers are encouraged to invest in the analysis of consumer big data as a way to improve forecasting.

In order to minimize uncertainties of the demands, this research paper aims to propose a predictive model for omni-channel retailing supply chain combining clustering, to understand consumers' consumption pattern through the product sales pattern, with artificial neural network, to improve the accuracy of product forecasting. For that purpose, a brief literature review embracing demand of omni-channel retail and supply chain and demand on smart scenarios. Finally, the predictive model is presented and applied in a Brazilian retailer.

2. LITERATURE REVIEW

2.1 Demand on Omni-Channel Retail Supply Chain Management

In order to minimize uncertainty about demand and better understand the consumer behavior in the omni-channel retailing supply chain scenario, researchers diversified into the choice of methods used to collect and analyze data. To carry out this analysis, the searched keywords were supply chain and logistic with the variations of omni-channel on Scopus, ISI Web of Science, Emerald and EBSCO host, and selected conference / proceedings papers, journals and articles related to Industrial/Manufacturing/Production Engineering such as engineering, business, computer science, decision science and mathematics. The articles were analyzed in relation to the objective, if they were applied, area of application, qualitative or quantitative analysis, data collection method, data analysis method and which software used.

The most adopted method was Partial least squares (PLS). Yurova et al. (2017) developed and evaluated a model to test the hypothesis concerning the adaptive selling behavior for omni-channel consumer (OCC) and Murfield et al. (2017) applied a survey to investigate the impact of logistics service quality on consumer satisfaction and loyalty in an omni-channel retail environment, among other papers.

The second most adopted method was the confirmatory factor analysis (CFA) method. One of its applications was in the work of Vazquez, Dennis and Zhang (2017) which applied CFA to examine the effects of an emerging smart retailer-consumer communications technology and consumer behavior and Li et al. (2018) to identify which mechanisms driving customers' reactions to CCI in omni-channel retailing.

Wang et al. (2018) in order to develop a behavioral study on consumers' adoption of self-collection service via Automated Parcel Station (APS) adopted the exploratory factor analysis (EFA), to analyze the factors that impact on the variance of the data, the Structural Equation Modelling (SEM) to test the measurement of the model and to the test the hypotheses the application of CFA.

The clustering algorithm was applied by Xue and Lin (2017) to explores the behavior characteristics and the customer segmentation based on consumption data stream mining. Balakrishnan et al. (2018) applied clustering for studying buying behaviour of customers and improve product recommendations and Wang (2018) combined the method clustering with Particle swarm optimization (PSO) to help retailers find and utilize complementary tariff products for mobile numbers as the basis for future sales and procurement.

Another method adopted is the Statistical Analysis. Gao and Yang (2016) adopted the statistical analysis to identify which factors influence consumer's buying decision and Chatterjee and Kumar (2017) examines differences in consumer willingness to pay for online purchases of functional and expressive products that differ in the length of product life.

Willems, Brengman and Van de Sanden (2017) present a study on the effectiveness of in-store marketing communication appeals via digital signage and for that adopted construal level theory (CLT). Blom, Lange and Hess Jr (2017) used the multivariate analysis of variance (MANOVA) to test hypotheses that using digital customer data in goal- congruent promotions may lead to positive customer reactions. And Frasquet and Miquel (2017) applied Principal component analysis (PCA) to investigate the effects of multichannel integration on customer loyalty.

That way, it can be verified that the choice of methods is divided into mathematical, statistical and data mining models and in the great majority these methods seek to evaluate the dependence and correlation relationship between the variables or hypotheses analyzed and even to create such hypotheses, with the consumer response, and from this understanding the consumers' consumption pattern/behavior. Already clustering method has sought from its analyzes to segment customers to identify the individual characteristics of each cluster and thus better understand the profile of consumption of their customers. The only exception was the marketing area that adopted the constructive level theory (CLT) that sought to analyze and align the content of in-store marketing information to direct consumers.

It is noticed that main goal is to understand how the technologies and actions, be they marketing, product recommendation, service quality and consumer relations, are impacting on the consumer's way of doing the shopping or how changing a consumer's purchasing profile across more than one channel is changing their ways of managing and operationalizing activities within companies.

Thus, it is noteworthy that there is still no study that shows how these customer profile / behavior analyses can be translated and inserted into the study of demand forecasting of the omni-channel retailing supply chain in order to obtain a forecast of demand with greater accuracy and lower error percentage, in order to reduce the uncertainties regarding the demand for the entire supply chain.

2.2 Demand on Industrie 4.0 and Retail 4.0

Wu et al. (2016) states that the smart supply chain enables data collection and real-time communication of all stages of the supply chain, intelligent decision making, and an efficient and appropriate process to better serve customers. Nevertheless Liao et al. (2017) sustains that some research guidelines are not officially listed as priority areas, some research efforts can be found in relation to Data Science, such as real-time data analysis, data integration, and Big Data Analytics. Thus, in order to identify the best method for smart retailers were analyzed all retailers, whether or not omni-channel, but who already do the application of large data analysis techniques.

When analyzing the demand forecast in the Big Data scenario, Islek and Oguducu (2015), Sarhani and El Afia (2015) and Shen and Chan (2017) have identified that the use of advanced machine learning techniques to initially train the large amount of data, to later predict demand, provides more accurate information in the supply chain. However, build individual forecasts for a large number of unique customer demands is impractical states Murray et al. (2015), being necessary the application of grouping customers into logical segments, like partitional clustering, that represent the total customer population states. Loureiro et al. (2018) also suggest that determine the selection of the variables and parameters first will lead to a better performing model than using only historical data, and then, evaluate the performance of the best model.

Loureiro, Miguéis and Lucas (2018) applied data mining techniques to predicting future product sales for new individual stock keeping units (SKUs) in a fashion retail industry. The authors first applied a greedy feature selection method and then utilized the deep neural network. To test the model the authors compared the result with other data mining techniques such as: Decision trees, Random forest, Support vector regression and Artificial neural networks. In conclusion, they sustain that none of the considered techniques exhibits higher performance in all the metrics explored and therefore no single technique can be considered as the best and the choice of the best technique should represent a balance between the performance of the models, their interpretability and their comprehensibility.

Villegas and Pedregal (2018) applied the method hierarchical time series forecasting based on SS modelling for a Spanish grocery retailer. The dataset analyzed contains daily observations on the sold units of 97 products covering the period 2013: Q1–2014:Q2 and concluded that proposed approach provides significantly better results than existing approaches which analyzes and forecasts each product independently

In the retail 4.0 scenario two articles were found. Bag, Kumar and Chan (2017) develop an approach to build the prediction model using the brands' social perception score and reviews' polarity computed from social network mining and sentiment analysis from an e-commerce. The attributes of each product were analyzed, and a multiple linear regression and a Non-linear regressions analysis (neural network) were developed. Researchers identified that reviews maximize the influence of attribute choice and can increase the product demand and that the choice of the forecast method depends on the data and the variables to be analyzed in the model. However, we can observe that the purpose of this paper is to identify consumers' online purchasing behavior and to propose a prediction model for the products sold by the online channel and not by omni-channel.

Lee (2017) applied a predictive analytic model for customer behavior and proposed an optimization model for determining the allocation of products to different DCs. The prediction analysis was carried out in two stages that consisted of the analysis of the network level, with the application of the association rule mining to discover the relationship between purchased items from customers, and then the application of the cluster level, which the demand point (stores) were divided into different clusters. And afterward the optimization problems were developed. Although the study did not address the forecast as a way to improve demand forecasting performance, but rather to form demand clusters to optimize the distribution process.

What it can observe is that as well as in the omni-channel study, the works developed for the smart scenarios are seeking to evaluate the factors that are impacting the demand. Thus, it is observed that demand is being generated for each of the products in an individualized way, but that external inputs are used to improve forecast accuracy, such as the historical series of other products, the individual characteristics of each product and even reviews on the internet. Therefore, the authors are adopting methods that first analyze which variables present a correlation with each of the products and then apply some methods to forecast the demand.

We can still highlight from the articles studied that to perform demand forecast two of the three articles that carried out the study focused on demand forecasting applied the neural networks and their variations. According to Amirkolaii et al, (2017) the best and frequently used method for uncertain demand forecasts, in the literature, is neural network and its variants, because of their inherent ability to perform better on unpredictable and uncertain demand patterns.

In line with what was found in the literature, as this article aims to identify and better understand the profile of consumption of their customers by historical sales data, this article will adopt the clustering method, that was applied for that purpose in the omni-channel retailing supply chain scenario, and to provide a more accurate forecast the article adopted the neural network as it is the most applied method in the "4.0" scenario.

3. METHODOLOGY

3.1 General Description

In order to minimize uncertainty about demand and better understand the consumer behavior in the omni-channel retailing supply chain scenario this article followed the methodology presented in Fig. 1 and is described in the following paragraphs.

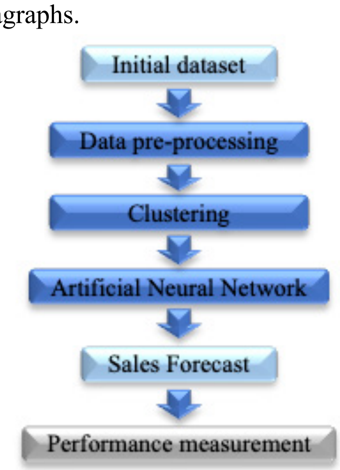

Fig. 1. Methodology adopted

3.2 Initial dataset and Data Pre-Processing

The data was collected from a Brazilian retailer that is migrating its multi-channel operation to omni-channel. The "room" category was chosen because it is the category that most impacts on the company's billing and is composed of 684 products. To forecast future sales based on customers' consumption needs the historical data on the daily sales of the period of January/2016 to October/2018 were collected. Currently the company adopts as a forecast method the moving average (MA) of a period of 6 months.

In order to be able to analyze the correlation of the sale of the products by channels, the products were classified into 4 categories: products that were sold exclusively in the online channel (EOn), exclusiveness in the offline channel (EOff), the products that were sold in both channels but that the sale was effected by the off-line channel (OffOn) and the products that were sold in both channels but that the sale was made through the online channel (OnOff). Thus, separating the 684 products on the 4 categories gave a total of 1,108 historical sales series, being the category EOn with 50 SKUs, EOff with 82, OffOn with 530 SKU's and OnOff with 446 products.

After the data were collected and classified, they were pre-processed to remove the outliers and thus did not negatively impact the analysis. Outliers in the data were identified through statistical methods. And for the analysis Matlab2018 software was initially used to identify and remove the outliers, and later the Excel software to develop demand forecasting through the application of the moving average method as it is performed at the company.

3.3 Clustering

The clustering method divide related objects into groups to examine similarities of objects within their corresponding groups and is used to describe a group's characteristics and to simplify comprehension of a whole data set and for that many clustering algorithms have been developed, such as K-means and hierarchical according to Park and Kim (2018).

This paper adopted the K-means method to analyze the historical data sales and group the products based on their product sale pattern. The K-means clustering algorithm aim to find the representative cluster centers in each cluster calculating the square and the minimum of the distance between each data point, and the corresponding cluster center is obtained through repeated iterative operations in an effort to find the most representative cluster center according to Wang (2018). In order to determine the optimal number of clusters, Kantardzic (2011) states that optimum value of the criterion function must be achieved by reducing the total squared error, or until the cluster membership stabilizes.

In this article we used the Matlab clusters evaluation function based on the silhouette, that is, we chose the cluster quantity by the similarity that point is to points in its own cluster, when compared to points in other clusters. Subsequently the products were evaluated by k-means for the amount of cluster defined in the previous step.

3.4 Artificial Neural Network and Sales Forecast

Artificial neural networks (ANN) are computational networks that simulate the network of nerve cells (neurons) of a central human nervous system, being cell-by-cell (neuron by neuron) Graupe (2013). Haykin (1998) states that the human brain is a highly powerful, complex, non-linear and parallel computer (information processing system), and because of the neurons it is able to process and organize an immense amount of information in a very short time.

According to Loureiro, Miguéis and Lucas (2018) the neurons are organized in layers where each neuron receives a set of inputs and outputs a nonlinear weighted sum of its inputs to the neurons in the next layer to which it is connected and the most popular neural network algorithm is the backpropagation.

And to Bag, Kumar and Chan (2017) the neural network function is described by (1), where X is the input value, W is the weight, f the activate function and H the output.

$$H_1 = f\left(\sum_{i=1}^{10} W_{1i} X_i\right) \tag{1}$$

In order to forecast the demand using the artificial neural network, the time series analysis was adopted due to the fact that the data to be analyzed were historical product sales data. Thus, the data were separated into data for training, validation and testing. Finally, the network architecture was determined in relation to the number of hidden neurons, the input delay, which represent how many periods the input take to show its effect on the output, and the feedback delay representing how many periods the output take to show its effect on itself.

3.5 Performance measurement

The forecasting performance of the methods applied were evaluated by the R^2 coefficient of determination to observe the adjustment of the forecast equation and the Mean Squared Error (MSE) to analyze the accuracy measure. To analyze the methods according to R^2 the best method will be the one that achieve the highest value close to 1, and with MSE are those that present the lowest values of MSE. Thus, we compared the performance of the forecast method currently adopted by the company, which is the MA, with the performance of the two aritificial neural networks, the NAR being without external input and the NARX with external inputs provided by the clustering.

4. RESULTS

In this section the results obtained are presented and discussed.

4.1 K-means Clustering algorithm

To determine the optimum number of clusters, the data were initially tested and evaluated by varying the number of clusters from K = 1 to K = 100 and for each one the silhouette value was calculated until the largest value of the silhouette value with the smallest amount of cluster was found. From this it was possible to determine that the optimal number of clusters for the analyzed data are 47 by reaching the maximum value of the silhouette value, which is 1, as shown in Fig. 2.

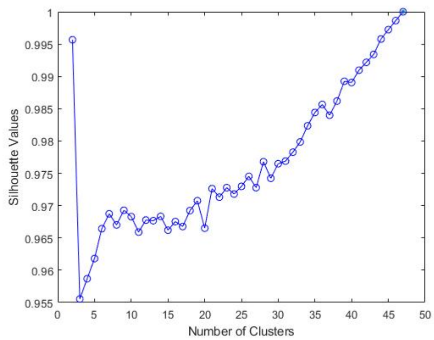

Fig. 2. Optimal number of clusters.

This way the k-means algorithm was applied for the 47 clusters avoiding the local minimum when applied the algorithm replications with different initializations. And we can conclude that the products were well divided in the 47 clusters when evaluating the quality of the clusters by the graph of the silhouette plot as shown in Fig. 3, as all clusters present the silhouette value as 1.

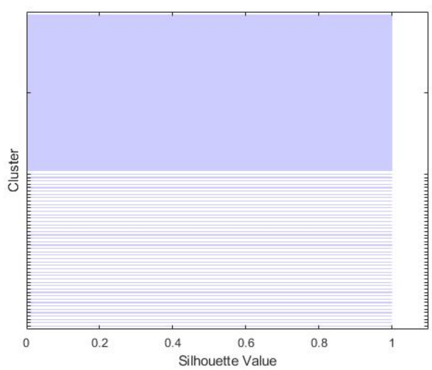

Fig. 3. Silhouette Plot chart with the distribution of families in clusters.

We can observe from the formation of the cluster that cluster 1 was the largest cluster and in it were all the products EOn and EOff, and also products OffOn and OnOff. When analyzing the other clusters, they were formed by only 1 product, that is, their consumption pattern does not resemble any other product, and those products belong to either OffOn or OnOff. And although these products belong to both channels, the products did not show similar sales behavior between the channels, so they cannot be analyzed in a similar way.

4.2 Artificial Neural Network

In order to develop the artificial neural network, the ntstool toolbox from Matlab2018 was adopted. And to evaluate if the products within the same cluster positively influence the prediction of the others were selected 4 products that were in cluster 1 to compare the performance of the neural network with and without external inputs. Initially the neural network is applied to the time series without using external inputs the historical series of the product, the nonlinear autoregressive (NAR), and later it is applied the neural network using external inputs, the nonlinear autoregressive with external input (NARX), which in this case are the historical series of the other products, in order to compare the performance of the two.

The products chosen for analysis were the product 1 that is sold in both channels but the sale by the online channel was in cluster 1 and the sale by the offline channel was in cluster 2, product 2 that is also sold in both channels and that both were in cluster 1, product 3 that was sold exclusively in the online channel and product 4 that was sold exclusively in the offline channel.

To analyze the data, these were separated and 70% of the data were used for training, 15% for validation and 15% for the test.

To develop the neural network to forecast each product the number of hidden layers was tested with 1, 5, 10 and 15 layers containing the same number of input and output neurons. In the case of NAR it was a single-layer for the input layer and the standard NARX network is a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The Input and Feedback delay values have been tested from 1 to 12 for representing the 1-year period. And to train the algorithm it was chose the algorithm Levenger-Marquardt.

4.3 Performance measurement

The best architecture for each product results is show through the analysis of the R^2 value, of the Testing and All, and MSE in Tab. 1. From Tab. 1 it can be observed that the result of the forecast of demand by the moving average was considerably lower in relation to the adjustment (R^2), although it presented good results in relation to the accuracy, when compared to the NAR and NARX, thus discarding this solution when compared to the others.

The performance of the forecast of demand using external inputs from clustering was superior for products 1 and 4, being respectively the values 0.95 and 0.94. Thus, showing a high adjustment between the actual values used for testing with the predicted values and the R^2 value of the general solution (All), thus compensating for the slightly higher value in the MSE. And that when analyzing products 2 and 3 we can observe that the best performance was without using the external inputs when analyzing the Testing R^2, being 0,99 and 0,95 respectively. However it is worth mentioning that the NAR did not perform much better than NARX in Testing R^2, and in relation to the R^2 of the general solution (All), NARX presented better results for both product 2 and 3 with respective values of 0.9 and 0.94 and very close results for MSE, so it is recommended to use NARX to predict the demand of the products.

In this way, we can highlight that NARX presented a good performance for all the products, thus corroborating that the application of the clustering, for the identification of consumer consumption pattern through the sales history of the products, together with the neural networks, to conduct demand forecasting, is considered a good method for forecasting demand for omni-channel retailing supply chain products.

5. CONCLUSIONS

With the increase in the number of sales channels, retailers are having to rethink how to forecast the demand for their products to reduce the uncertainties not only of their processes but also of the omni-channel retailing supply chain.

Table 1. Performance of moving average and artificial neural network

					R^2				MSE
Products	Problem	Hidden Neurons	Input Delay	Feedback Delays	Training	Validation	Testing	All	Validation
Product 1	MA	-	-	-	-	-	0,02	-	64
Product 1	NAR	10	6	-	0,87	0,99	0,8	0,85	171
Product 1	NARX	10	1	6	0,99	0,89	0,95	0,94	200
Product 2	MA	-	-	-	-	-	0,14	-	228
Product 2	NAR	10	1	-	0,76	0,9	0,99	0,75	546
Product 2	NARX	10	2	1	1	0,71	0,94	0,9	532
Product 3	MA	-	-	-	-	-	0,29	-	23
Product 3	NAR	10	1	-	0,63	0,76	0,95	0,62	0,26
Product 3	NARX	10	1	1	0,99	0,57	0,92	0,94	0,28
Product 4	MA	-	-	-	-	-	0,04	-	113
Product 4	NAR	10	1	-	0,81	0,87	0,87	0,82	54
Product 4	NARX	1	1	1	0,89	0,85	0,94	0,87	214

For this reason, it is important for retailers to increasingly understand the behavior of their consumers and to insert this analysis into their operations, thus adopting forecasting methods that combine identification of patterns in forecasting methods.

In this way, this paper has proposed a predictive approach for the omni-channel retailing supply chain base on the application of clustering algorithm and artificial neural network in order to reduce uncertainties related to demand.

And through the application of the method in a Brazilian retailer it was possible to analyze its performance and to conclude that for the omni-channel retailers demand forecasting needs to combine the analysis of patterns and with forecasting methods to improve the accuracy of the forecast and thus enable reducing the uncertainties of the omni-channel retailing supply chain.

As future research, we suggest the insertion of more parameters referring to the products in order to improve the segmentation of the products and consequently the forecast of demand and compare this method with others presented in the literature.

ACKNOWLEDGEMENT

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

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