S&G 17 (2022), pp. 255-270

S&G JOURNAL
ISSN: 1980-5160

SPARE PARTS DEMAND FORECASTING USING AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Concerning asset maintenance, it is known that forecasting demand for replacement parts is an important condition for inventory management, aiming to reduce costs and avoid product obsolescence. Predictive methods with higher accuracy are fundamental in this context, facing the lack of parts and overstocking. Thus, the present work aims to evaluate the performance of an artificial neural network in predicting the demand for spare parts in the tractor maintenance sector. To this end, the analysis of the average absolute percentage errors of the prediction was used as an evaluation and monitoring method. In order to reach the proposed objective, the study first addressed the main theoretical aspects related to inventory management and demand forecasting methods. Subsequently, the Elman networks were selected, and, regarding the selection of parts for analysis, inventory management tools were used to explore important items for the sector. The proposed methodology showed that the neural networks have a good application for the context in question because, in addition to presenting configurations with acceptable errors, the network often hits the peaks of higher and lower demands, an important analysis for inventory management.

Keywords: Maintenance; Stock Management; Demand Forecasting; Neural Networks.

PROPPI / DOT
DOI: 10.20985/1980-5160.2022.v17n3.1806

S&G Journal
Volume 17, Number 3, 2022, pp. 255-270
DOI: 10.20985/1980-5160.2022.v17n3.1806

INTRODUCTION

Given the current labor market scenario, it is notable that, for companies to survive the competition, it is necessary to have good control over their activities, providing good profits at the lowest possible cost. Thus, planning and monitoring production activities become crucial factors for good performance in the market. Therefore, stock management policies are among the production planning activities (Machado & Santos, 2020; Souza Júnior *et al*., 2022).

The proper management of raw materials and product inventories directly influences the company's performance, given that high costs are involved in this context (Santos & Silva, 2019). One way to manage inventory is based on demand forecasting to obtain and monitor, as efficiently as possible, the need for any essential items for the company's sectors and activities, thus enabling correct investments in production capacity, product acquisition, and inventory maintenance, resulting in the reduction of unnecessary costs (Dias, 2009).

The role of forecasts, including the demand forecast, is to support the organization's strategic planning, whether for monitoring stocks, labor, or sales, among other factors. Demand forecasting allows the managers of these organizations to anticipate the future and plan their actions more conveniently (Tubino, 2017; Santos, 2019).

According to Gonçalves (2013), estimating the future demand for goods and services is an essential condition for the preparation of a work plan that includes the sizing of the capacities involved with the definition of equipment, financial resources, availability of labor, and the number of materials needed for production. For the maintenance sector, the forecast of spare parts demand is an extremely important factor since it helps in planning preventive and corrective maintenance of the assets, reducing the probability of stopping production due to a lack of parts, for example.

Silva (2003) reports that there are several methods of making forecasts, some more intuitive and of a practical nature, known as "qualitative," and others more objective, with a mathematical and statistical base, known as "quantitative." The fact that there is no single, ideal method for forecasting that applies to all situations leaves ample room for technical and scientific research into the applicability and efficiency of each technique.

In both qualitative and quantitative cases, it is possible to extract information from historical data that allows the modeling of a phenomenon's behavior to predict its future behavior. According to Araújo and Gomes (2005), the two main groups of models for forecasting time series are based on statistical methods and Artificial Neural Networks (ANNs). In addition, there are also heuristic techniques.

In this context, it is known that stock management is one of the important items of maintenance management. Thus, it is necessary to follow the consumption of materials in the sector's activities to monitor stock levels (maximum, replacement point, and reserve stock), as indicated by Santos (2019).

Therefore, this situation is valid for any maintenance sector. Regarding the agricultural tractor's maintenance, it would be the same because there are indispensable and more recurrent items in stock for preventive maintenance, besides the importance of the existence of parts that may be needed for corrective maintenance. Thus, for the maintenance to be carried out at the right time, the necessary materials must be available whenever needed.

In grape production, for example, many activities are done with the assistance of tractors, including fertilizing, applying products by spraying, leveling the soil with a plowing harrow, and loading containers onto carts, among other activities. Given this, the tractors exposed to these services usually work for many hours and need frequent maintenance. Given this scenario, it is clear that there is a constant need for material requisition to meet demand.

Thus, considering the importance of using a demand forecasting methodology for spare parts and the advantages that the method can incorporate into stock management, the question to be investigated is as follows: how can we use a demand forecasting model based on neural networks to manage stocks of spare parts in an agricultural tractor maintenance sector?

Therefore, the objective of this research is to elaborate a demand forecast model, using neural networks, to assist in the management of spare parts for a tractor maintenance sector in a grape producing and exporting farm in Vale do São Francisco.

BIBLIOGRAPHIC REVIEW

At the same time that stock is costly and presents a risk of deterioration, obsolescence, and loss, it also provides a certain level of security for the organization, as cited by Fernandes *et al*. (2021). Spare parts stock management for maintenance aims to define a sufficient number of components that should be kept in stock to ensure a quick repair of premature failures and maintain the necessary equipment's availability.

The sizing of the spare parts inventory must ensure that the necessary parts will be available in the right quantity and at the right time. Thus, just as excess parts result in losses, the lack of parts is equally negative, representing production losses by increasing the downtime of assets (Xenos, 2014).

According to Wu and Hsu (2008), equipment availability depends on the spare parts inventory level. For this reason, Molenaers *et al*. (2012) express that the importance of spare items has quite different dimensions from the point of view of maintenance and logistics, and inventory since their proper management must consider the critical aspects inherent to both contexts.

Huiskonen (2001) portrays that research regarding spare parts logistics is more related to stock management, whose main objective is to obtain an adequate level of customer service with minimal investment in stock and administrative costs.

Effective stock management has been the object of study for organizations seeking to reduce their operational costs and investments in current assets. Thus, the management of spare parts inventories is necessary for organizations that use many physical assets in their production processes.

It is significantly different from the management of regular inventories. Spare parts are supplies destined for the eventual replacement of similar items installed in equipment or production units due to loss, wear, and tear malfunction or the prevention of malfunction. They are not part of the organization's core business, but they ensure that the physical assets used in its processes function to maintain the required production capacity (Ferreira *et al*., 2009).

The decisions to define the level of spare parts inventories should consider not only the cost-benefit relationship between performing preventive or corrective maintenance but also the system unavailability costs, the possibility of obsolescence, and the fact that the parts may come from "cannibalism" (the use of spare parts in good condition taken from equipment stopped for lack of other parts). Keeping these stocks on hand can be costly or unnecessary since the spares may never be used, making them obsolete. However, they represent a guarantee that an equipment failure can be circumvented and, thus, the productive capacity can be maintained (Ferreira *et al*., 2009).

Tools for Inventory Management: ABC Curve and XYZ Classification

One of the examples of tools to manage stock management in an organization is the ABC curve methodology. Also known as the 80/20 curve, engineer Vilfredo Pareto created it in the mid-twentieth century. The ABC analysis entails verifying and characterizing which items require more attention based on their importance to the company (Dias, 2009).

As a result, they will be prioritized for presenting higher demand values, which refer to the demand quantity times the item's unit cost. According to Tubino (2017), the ABC curve is an important tool for the manager because it allows for identifying those items that warrant adequate attention and treatment regarding their management. The ABC curve is obtained by ordering the items according to their relative importance.

The XYZ classification can be used as a complement to the ABC curve. This curve uses the criticality or indispensability degree of a material in the performance of a given activity as a classification criterion. According to Viana (2012), based on the responses obtained, it is possible to classify the items considering the following characteristics: class X: materials of low criticality, given that their absence does not interrupt any activity and presents much less risk to the organization's safety; they can easily be replaced by equivalent materials and are easily available on the market; class Y: materials of intermediate criticality, i.e., their absence causes losses to certain activities, but can be replaced by equivalents with relative ease; and class Z: items of maximum criticality. The absence of these items can paralyze one or more areas of operation if they cannot be replaced or if there are no similar items on the market (Viana, 2012).

Demand forecasting methods: Artificial Neural Networks

The most prominent forecasting methodologies are the Arithmetic Moving Average, Average with Exponential Smoothing, Models with Trends and Seasonality, ARIMA Models (Box-Jenkins), Linear Regression, Econometric Models, and, more recently, Artificial Neural Networks.

Pasquotto (2010) describes Neural Networks as computational structures that mimic parts of the biological nervous system. The principle is to reproduce the brain's information processing with an artificial model of neurons, which are functionally linked through connections, thus forming Neural Nets.

In the human brain, the neuron is the basic unit that receives the stimuli transmitted by other neurons; communication is accomplished through impulses. When a given neuron receives the impulses that arrive through its dendrites, it processes them and, according to a given action threshold, produces a neurotransmitter substance that flows through the axon to other neurons (Pasquotto, 2010).

Similarly to the human brain, ANNs have their most basic processing unit in the artificial neuron. **Figure 1** displays the neuron's basic structure, as stated by Haykin (2009). The output y is given by the function of the sum of the inputs, , $x1$, $x2$, ..., xm, weighted by their respective weights, $wk1$, $wk2$, ..., wkm, to provide a mathematical model of its synapse state

S&G Journal
Volume 17, Number 3, 2022, pp. 255-270
DOI: 10.20985/1980-5160.2022.v17n3.1806

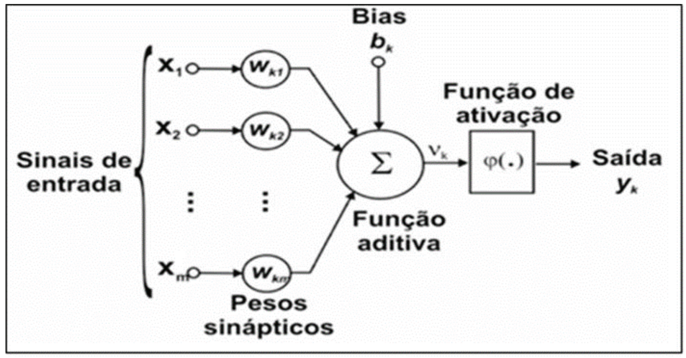

Figure 1. Basic Structure of an Artificial Neuron

Legend: Bias; Activation Function; Output; Additive function; Synaptic weights; Input signals
Source: Haykin (2009)z

(excitation or inhibition). The weight $wk1$ applied to the fixed input $bk = 1$ is called bias and is intended to control the level of the output v of the linear combiner (Freitas, 2008).

Where:

- m is the number of input signals received by the neuron;
- xm is the mth input signal of the neuron;
- wkm is the weight associated with the mth input signal in neuron k;
- bk is the threshold of the kth neuron, often called bias;
- vk is a weighted combination of the input signals and the bias in the kth neuron;
- yk is the output neuron;
- $\psi(.)$ is the activation function of the kth neuron.

The inputs xm of the neuron can be output from other neurons, external inputs, a bias, or any combination of these elements. They are weighted by the wkm weights, inspired by the synaptic connection strength. It is worth noting that the architecture of ANNs varies according to their purpose. Moreover, how neurons are distributed in a network is also related to the learning algorithm.

Furthermore, single-layer nets are nets with neurons arranged in parallel in a single layer. Multilayer nets, on the other hand, have one or more layers positioned between the input nodes and the layer that generates the outputs (Souza *et al*., 2018).

According to Vaz (2014), the transfer function, or activation function, controls the amplitude of the neuron's output and is based on neuron reactions to input values and the neuron's level of activity (activation state). This assumption is based on the biological model in which each neuron is always weakly active. Essentially, neurons are activated when the network input exceeds the maximum gradient of the activation function value, known as the assigned threshold (Florêncio, 2016).

According to Vaz (2014), training is fundamental to implementing artificial neural networks. This process should be designed so that the network learns a task successfully. However, it should be noted that a precise definition of training is difficult to achieve because there is no simple method for doing so. The learning process consists of adjusting the weights under some learning rules.

Artificial Neural Networks (ANNs) knowledge is obtained by weighting that the connection weights between neurons of different layers exchange among themselves. Regarding ANN training, different training algorithms that differ in how the weights are adjusted can be divided into two paradigms: supervised and unsupervised learning (Freeman & Skapura, 1992).

Haykin (2009) indicates that the most widely used training algorithm is backpropagation, also known as "backpropagation." It uses the gradient descent technique to adjust the synaptic weights so that the error produced by the net reaches a pre-set threshold, and it can be used with supervised or unsupervised learning.

Redes de Elman

Elman nets are named after their creator, University of California professor Jeffrey Elman. They are known as "simple recurrent networks" and are an improvement over feedforward networks due to the inclusion of feedback between the immediate and adjacent layers, giving the network a memory of previous immediate events and affecting the updates of the weights in each of the network layers (Elman, 1991).

According to Elman (1991), in addition to input, intermediate, and output units in the networks in question, there are also context units, as in partially recurrent networks in general. The input and output units interact with the external environment, while the intermediate and context units do not.

The input units are buffer units that pass the signals through without modifying them. Output units are linear units that sum the signals they receive. Intermediate units can have linear or non-linear activation functions, and context units are used only to store the previous activations of intermediate units and can be considered a one-step time delay (Elman, 1991).

Figure 2 shows a recurrent Elman network with a hidden layer. The architecture is denoted by Elman (dE+ q, q,1), highlighting the dimensions of the input vector (dE), the dimension of the context vector (q), the number of hidden neurons (q) and the number of output neurons, which is only one in this case.

According to Schatz (2014), the Elman network works as follows: at instant t (initial), the signal is propagated through the network, and the context units initialized with the hidden layer output with the value zero will not influence the network output, i.e., in the first iteration, the network will behave as a feedforward network.

Furthermore, in the first iteration, the hidden neurons will activate the context layer's neurons, which will store the output of this iteration and be used in the next cycle. The backpropagation algorithm is then applied to correct the synaptic weights, except for the recurrent synapses, which are fixed at 1. At the time (t + 1), the process is repeated. The difference is that from now on, the hidden neurons will be activated by the input units and the context units that have the output value of the hidden neurons at the time (t), as cited by Schatz (2014).

RESEARCH METHODS AND TECHNIQUES

In order to organize the study steps, an ordered sequence of activities was defined, as shown in **Figure 3**.

In addition, **Table 1** shows certain phases and the tools used.

The object of study was first limited in terms of the parts to be analyzed. The study concentrated on tractor parts because they are in high demand in the industry and play a significant role in production because the implements are made from these assets.

Furthermore, it is worth mentioning that the ABC Curve was utilized considering, in the accumulated percentage, product turnover (cost x demand). For the XYZ classification, two methods were utilized: the first was numerical, considering the average monthly requests and the deviation of this average, and the second considered qualitative criteria. From this, the data was crossed and compared, and then the time series of demand for each item was analyzed to obtain the parts' final selection for the study.

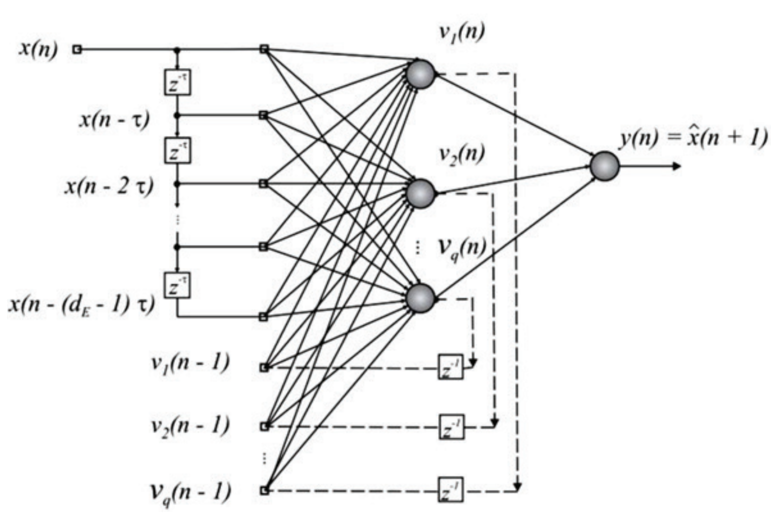

Figure 2. Elman network with a hidden layer
Source: Adapted from Elman (1991)

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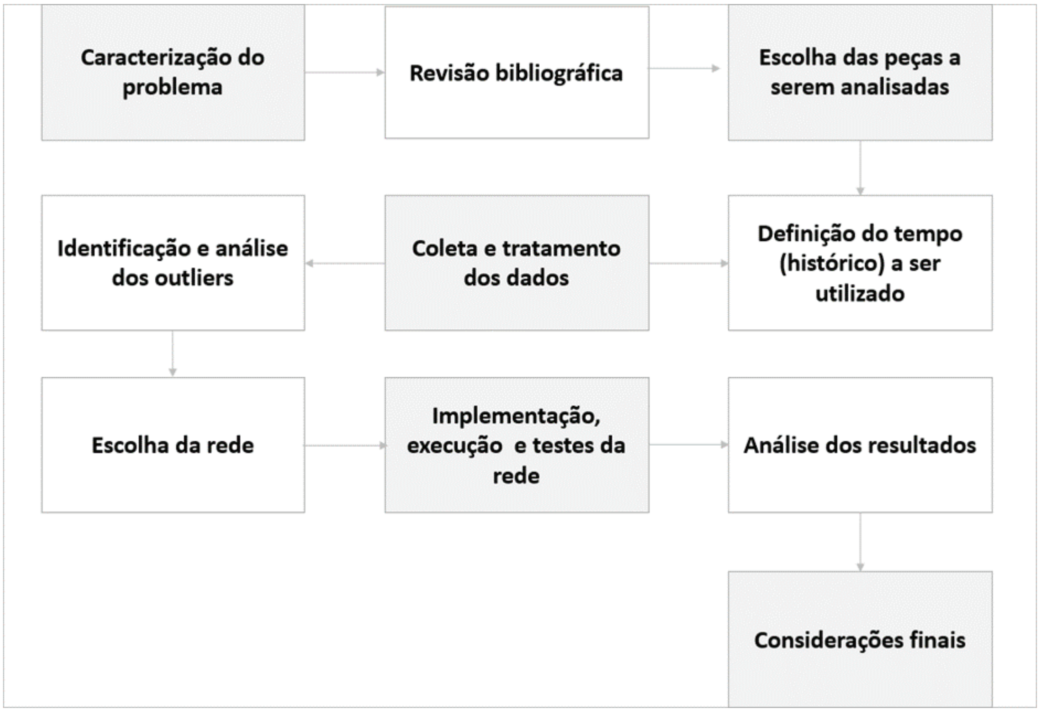

Figure 3. Research steps
Source: The authors (2022)

Data collection took place through the enterprise management system used by the company studied, ERP (Enterprise Resource Planning), from TOTVS, where all parts requisitions made by the maintenance sector are stored in reports.

Concerning data treatment, the Minitab™ software was used. In this software, control charts of individual observations and moving amplitudes analyzed the outliers and smoothed them. Lastly, the network algorithm was implemented in the Matlab™ software, in which the Elman network was chosen.

Neural Network Selection

The choice of neural network was based on the study by Florêncio (2016), who compared the performance of the Elman and TDNN (Time Delay Neural Network) networks to review the demand for automotive vehicle spare parts. In general, the Elman network performed better in this research and because of this and because this study is analogous to the present work, we chose to use this network.

This same author portrays that the nntool in Matlab™ proved to be of little interactivity, and, therefore, in his study, he preferred programming through commands, which, despite seeming more complicated, provide a more detailed configuration, allowing changes in some parameters that are not possible in the toolbox.

In this context, the algorithm used in this work was based on the considerations and functions used by Florêncio (2016). The network developed by him aimed to be as autonomous as possible: from a linear input matrix, the partial autocorrelation between the values is sought to define the number of neurons of the input. With this value, the algorithm remaps the matrices used as training data, training targets, validation, validation targets, and demand forecast targets.

Regarding the algorithm used, the network parameters were defined: the size of the prediction interval was 12 months, a maximum of 1500 iterations, a maximum number of times that the validation error can be increased equal to 30, and the learning rate ranging from 0.025 to 0.125 (0.025, 0.05... 0.125). In addition, as considered by Florêncio (2016), it was decided to keep the number of neurons in the input layer at no less than four since, as presented by Mine (2010), in tests, it was shown to have low efficiency when having a reduced number of neurons in the input layer.

To do so, the activation function tansig (hyperbolic tangent), the training algorithm trainlm (Levenberg Marquardt for backpropagation), the learning adaptation function learngdm (a learning method that uses the gradient to adjust the neuron weights at each time), and the performance function MSE were used. The monthly observations in this paper are divided into three parts: training, validation, and prediction.

Phase	Tool(s) used
Choice of pieces to be analyzed	ABC Curve and XYZ Classification
Data collection and treatment	Collection by RM TOTVS system and
Outlier identification and analysis	treatment in Minitab software
Network implementation, execution, and testing	By means of MatlabTM software

Chart 1. Research phase and tools used

Source: The authors (2022)

Training the net consisted of presenting it with neuron weights to be adjusted according to the time series behavior. The stopping criteria seek the lowest mean squared error (MSE) for training, but as mentioned earlier, when the MSE does not decrease or reaches 1500 iterations after 30 training runs, the net ends training.

DATA PRESENTATION AND ANALYSIS

To choose the parts, as previously mentioned, the ABC Curve and XYZ Classification were used. It was decided to select the parts classified as "AZ" and "BZ" since the second method complements the first. Initially, the ABC Curve was used, considering in the accumulated percentage the parts turnover: "A" was considered as the accumulated percentage lower than 50%, "B" lower than 80%, and "C" equal to or higher than 80%, obtaining the results of **Table 1** for the parts classified as "A" and "B."

Furthermore, for the XYZ classification, the ratio between the average deviation of the quantities of the 2018 requisitions and their average was considered. The values "X" lower than 50%, "Y" between 50 and 100%, and "Z" equal to or greater than 100% were taken into account. **Table 2** shows this method's list of items classified as "Z."

From this, the data was cross-referenced and the pieces classified as "AZ" and "BZ" are evident in **Table 3**.

Furthermore, the XYZ Classification was also used, now considering qualitative criteria to compare the convergence of the data selected in the previous method based on important observations for stock management:

X - The lack of material does not interrupt the activity, as it has equivalents in the market;

Y - The absence of material causes losses, but market equivalents can replace it;

Z - The lack of material paralyzes the activity; furthermore, it cannot be replaced by similar ones.

The ABC Curve data was again crossed with the new XYZ criteria, obtaining the parts in **Table 5**.

In this context, it is noted that the number of items remained the same, but there was no convergence of them. Besides, in the second combination, no item was classified as "AZ." Taking into account the results of both methodologies, the demand graph of the items included in the two methods was analyzed to obtain a final choice of the parts for the study, considering the data to be used in the Neural Network. **Figures 4** (a), (b), (c), and (d) show the demand for the pieces from the first crossing of data.

In this context, it is noted that, for some of the items, there is a constant request for parts, except for a significant period referring to the filter element, a situation justified because only in 2014 did tractors in need of this item begin to be used. In addition, the demand for the battery was low during the total time interval analyzed. Thus, although the latter was one of the items selected in the first methodology comparing the demand data of the parts, it is noted that the battery would not be a good choice for analysis in the network. In previous years, another code was probably used for requesting tractor batteries, making it unfeasible to collect the requests for this item. Furthermore, dealing now with the second selection made, we have the graphs in **Figures 5** (a), (b), (c), and (d), referring to the demands of the indicated parts.

Based on this, the same analysis showed that the two retainers are also not interesting for the study of demand in the network, compared to the data of the other parts. Thus, the final selection of the items to be studied was made, as shown in **Table 6**.

It is important to emphasize that, due to the variation in demand for the selected items, it is difficult to use a single form of predicting demand, whether through traditional qualitative or quantitative methods or Artificial Neural Networks. As already mentioned, for data treatment, Minitab™ software was used to identify outliers employing control charts of individual observations and moving amplitudes and, subsequently, their smoothing.

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Table 1. Items classified as "A" and "B" on the ABC curve

Code	Item	ABC Classification
15.01.3049	Fuel Filter 12990755800 - R	A
15.02.0484	Battery 12 V 60 A	A
15.01.3092	Front axle retainer YB40T - 15232	A
15.01.0778	Retainer YB40T - 15213	B
15.01.3050	Air filter TNE8812670	B
15.01.1111	Steering Terminal YB40 - 12070	B
15.01.3572	Filtering element BTD4012590	B
15.01.0558	Bulb H5 12 V	B
15.01.1638	Belt A - 38	B
15.01.3159	Work lamp	B

Source: The authors (2022)

Table 2. Items classified as "Z" according to XYZ criteria

Code	Item	Classification
15.01.0956	H3 lamp - 12V Philips	Z
15.01.1682	Blade fuse 30 A	Z
15.01.3050	Air filter TNE8812670	Z
15.01.3159	Work lamp	Z
15.01.3291	Slide YA44-20320	Z
15.01.3572	Filtering element BTD4012590	Z
15.01.3573	Safety Element BTD40T12570	Z
15.01.3671	Bushing 25x31x25 YB-4521340	Z
15.01.4900	Retainer YB40T - 15233	Z
15.02.0484	Battery 12 V60 A	Z

Source: The authors (2022)

Table 3. Classificação inicial das peças

Code	Item	Classification
15.01.3050	Air Filter TNE9912670	BZ
15.01.3159	Work lamp	BZ
15.01.3572	Filtering Element BTD404012590	BZ
15.02.0484	Battery 12 V 60 A	AZ

Source: The authors (2022)

Table 4. Items classified as "Z" according to qualitative XYZ criteria

Code	Item	Classification
15.01.0111	Bearing 6004	Z
15.01.0778	Retainer YB40T-15213	Z
15.01.1112	Steering Terminal YB40-12060	Z
15.01.1500	Needle bearing ROH 2520	Z
15.01.3092	Front axle retainer YB40T 15232	Z
15.01.3291	Slide YA44-20320	Z
15.01.3671	Bushing 25x31x25 YB-4521340	Z

Source: The authors (2022)

Table 5. Classification according to the ABC Curve and qualitative XYZ criteria

Code	Item	Classification
15.01.0778	Retainer YB40T - 15213	BZ
15.01.1112	Steering Terminal YB40 - 12060	BZ
15.01.1638	Belt A-38	BZ
15.01.3092	Front axle retainer YB40T - 15232	BZ

Source: The authors (2022)

Table 6. Final choice of parts according to ABC Curve and XYZ classification

Code	Item	Classification
15.01.3050	Air filter TNE8812670	BZ
15.01.3159	Work light	BZ
15.01.3572	Filtering element BTD404012590	BZ
15.01.1112	Steering Terminal YB40–12060	BZ
15.01.1638	Belt A-38	BZ

Source: The authors (2022)

Artificial Neural Network Application

Figure 6 shows the Elman net with several neurons in the input layer, the hidden layer, the training algorithm, and the performance measure as the root mean square error.

In this context, the number of input neurons used in the study was defined similarly to how Mine (2010) addressed it, based on partial autocorrelation of data, which is a measure of correlation used to identify the existence of a relationship between current values of a variable and its previous values, accumulating the effects of all intervals (or lags) in interval constants. Thus, the graphs with the study series' autocorrelation functions are explained below. **Figure 7** shows that the best input quantity option for the air filter is five neurons.

For the working beacon, according to **Figure 8**, one has three options for the amount of input from neurons 1, 11, or 18. Option 11 was chosen due to the choice of not using an amount smaller than 4, as indicated by Florencio (2016), and for having a higher correlation than that of 18.

In the case of the filtering element, according to **Figure 9**, the best option is the one with seven input neurons.

For the direction terminal, the best option is 5 input neurons (**Figure 10**).

Finally, as of **Figure 11**, it was preferred to use four input neurons for the belt. A higher quantity, such as 20, for example, was not chosen because, according to Mileski Junior

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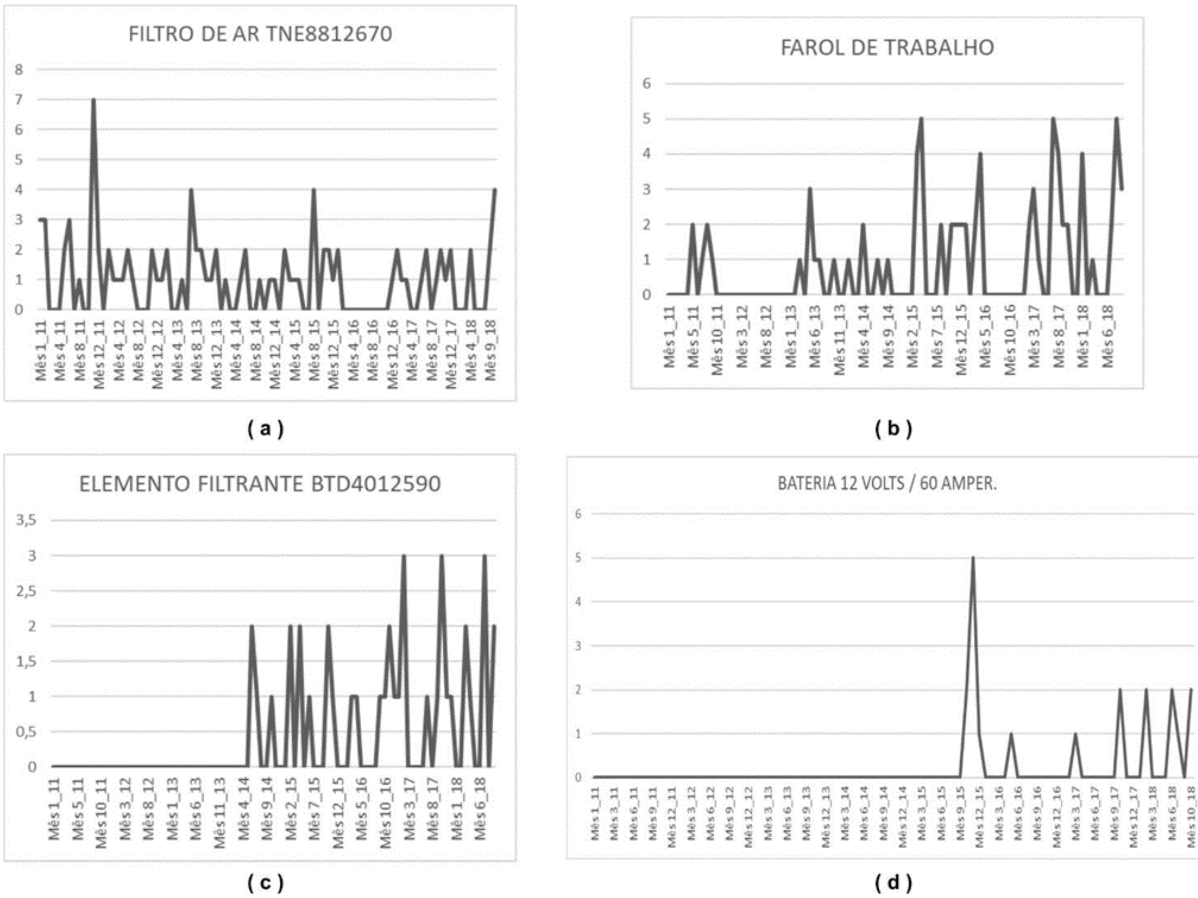

Figure 4. Demand of the parts of the first selection

Legend: AIR FILTER TNE8812670; WORK LIGHT; FILTERING ELEMENT BTD4012590; BATTERY 12 VOLTS / 60 AMPER

Source: The authors (2022)

(2010), the greater the number of inputs used, the greater the complexity of the problem to be solved as well as the number of possible solutions for analysis by the neural methodology.

It is important to mention that one factor that determines the quality and speed of net training is the number of neurons in the hidden layer. The network cannot model more complex data when using only a few neurons in the hidden layer. Conversely, if too many neurons are used, training will become long, and the net may suffer from overfitting problems, resulting in the loss of the predictive ability of the net.

Noisy or redundant data can cause the network to fail to converge on a generic solution. It is also worth mentioning that the number of layers also influences the results. Studies (Gomes, 2005; Mine, 2010; Pasquotto, 2010; Lima, 2014) show that for most problems, one hidden layer is sufficient.

As a result, tests were conducted with only one hidden layer, with the number of neurons varying between five and thirty (5, 10... 30) and the learning rate varying between 0.025 and 0.125 (0.025, 0.05... 0.125). It was noted that, despite the 1500-iteration limitation, the mean square error values tend to approach zero very quickly in training.

The objective interpretation of the results has led to the evaluation of the MAPE, which indicates the average error size expressed as a percentage of the observed value. From this, it was noted that the configuration for the smallest MAPE was different for each case due to the diversification of demand characteristics, thus reinforcing the difficulty in evaluating different series using the same method.

Thus, regarding the best results for the error, the part that obtained the lowest MAPE in the tests was the work lamp (5.91%), and the one with the highest error was the filtrating element (20.52%), a result considered satisfactory since what is being considered in the study is only the autocorrelation of the data without external variables, hindering a greater assertiveness.

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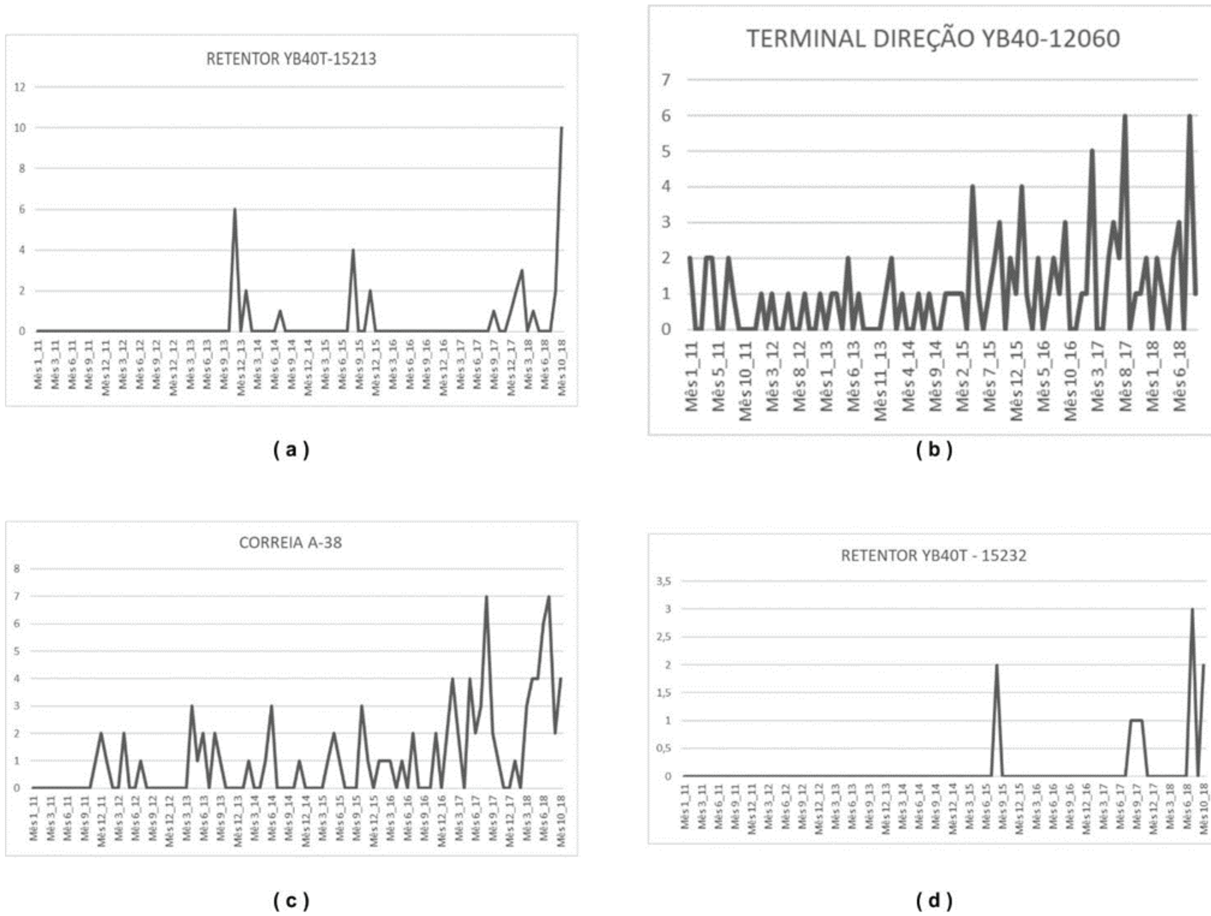

Figure 5. Demand for second selection parts

Legend: RETAINER YB40T-15213; STEERING TERMINAL YB40-12060; BELT A-38; RETAINER YB40T-15232
Source: The authors (2022)

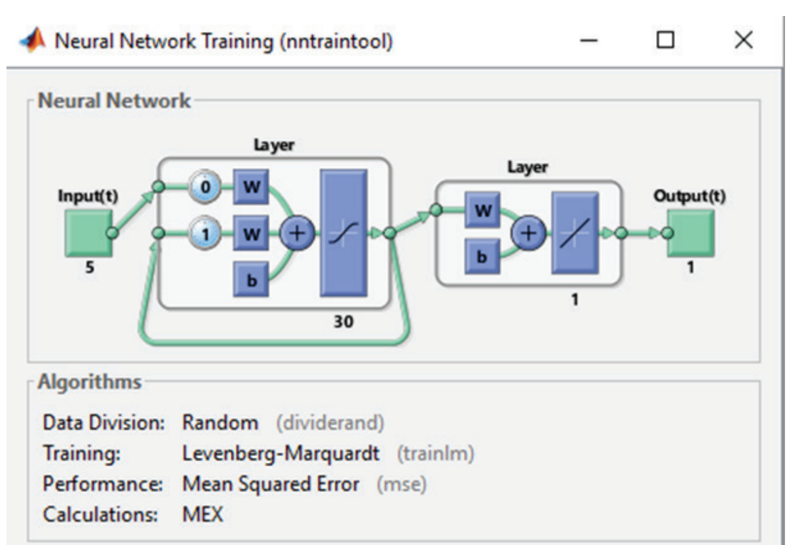

Figure 6. Elman Network
Source: Matlab™ R2015a

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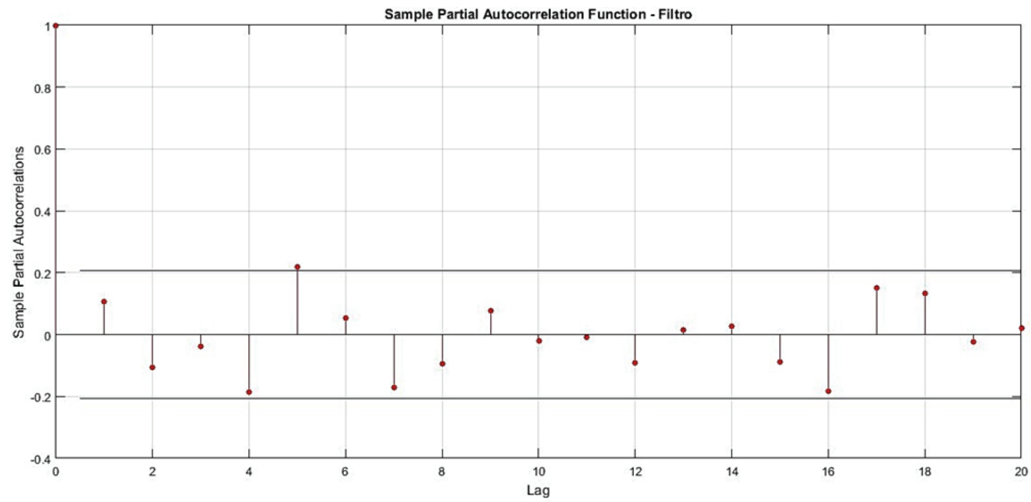

Figure 7. Partial Autocorrelation of the Air Filter
Source: The authors (2022)

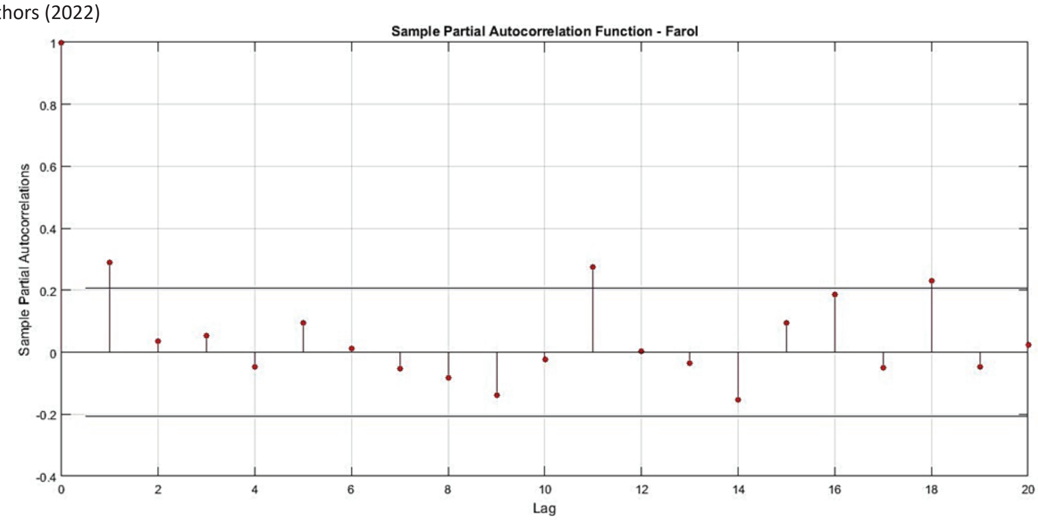

Figure 8. Partial Autocorrelation of the Work Light
Source: The authors (2022)

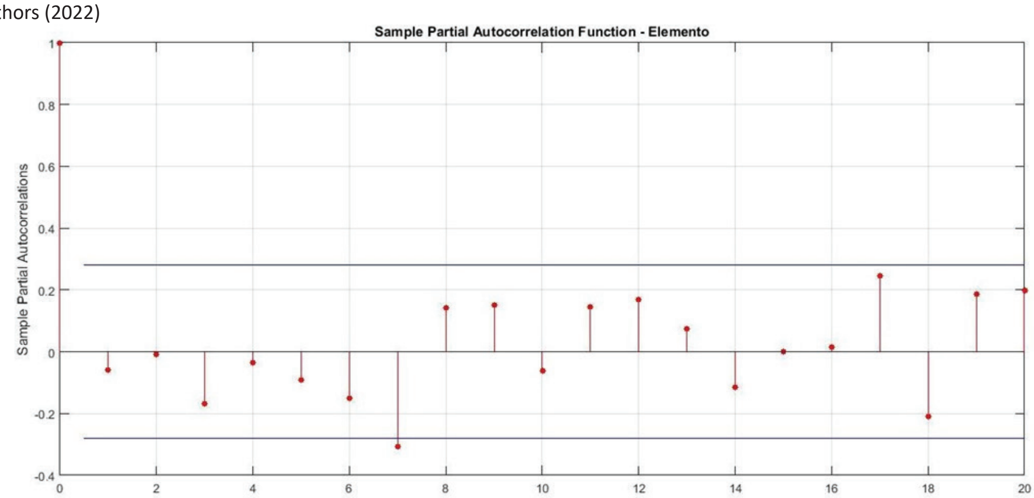

Figure 9. Partial autocorrelation of the filtering element
Source: The authors (2022)

Furthermore, it was also found that, according to the variability of neurons in the hidden layer, the largest quantity is not always necessarily the best. In addition, based on the errors obtained, it can be seen that, in some cases, overfitting occurred since very small errors were found in the training stage but with poor generalization in the prediction, presenting significant errors in the latter phase.

Therefore, a graphical analysis was made between the predicted demand curve and the real values of the last 12 months of the demands studied. In several cases, the net could predict peak demand times, as shown in the graphs in **Figures 12**, **13**, and **14**. Since the peaks are well defined, optimization of the result could be possible with some adjustment in the network, besides changes in the evaluated parameters (number of neurons and learning rate). Another attempt is to change the activation function.

In this scenario, it is known that in forecasting, the analysis of peaks is very important since, in the case of demand, it is important to know whether there will be an increase or decrease in behavior. Furthermore, according to Tubino (2017), despite the mathematics and computer resources, it is impossible to predict demand accurately.

FINAL CONSIDERATIONS

The study sought to investigate and apply the Elman network to analyze the efficiency of spare parts forecasting in the tractor and agricultural implement maintenance sector as an alternative methodology source to aid in the study of item demand forecasting.

It was evident that, according to the errors found and the graphical analysis of behavior performed, the method used

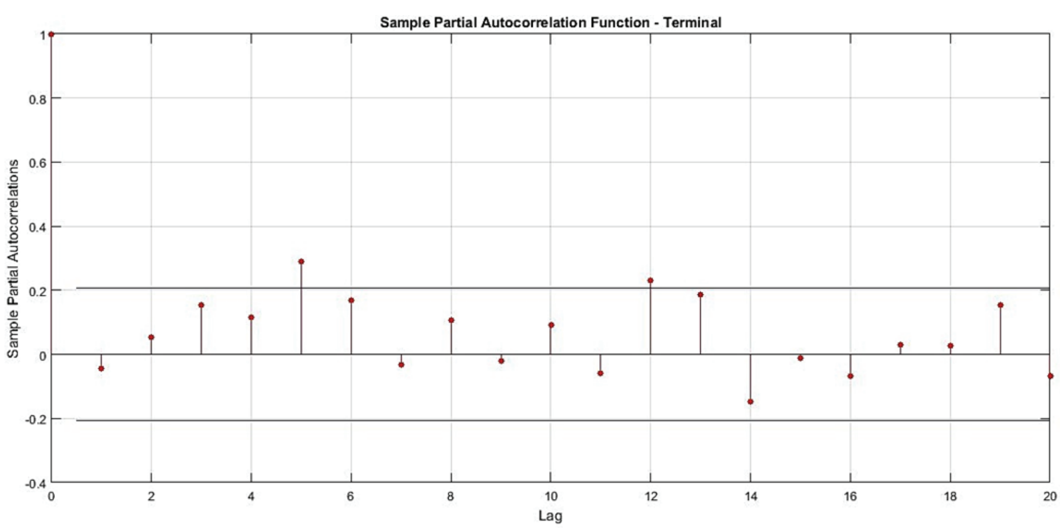

Figure 10. Partial autocorrelation of the direction terminal
Source: The authors (2022)

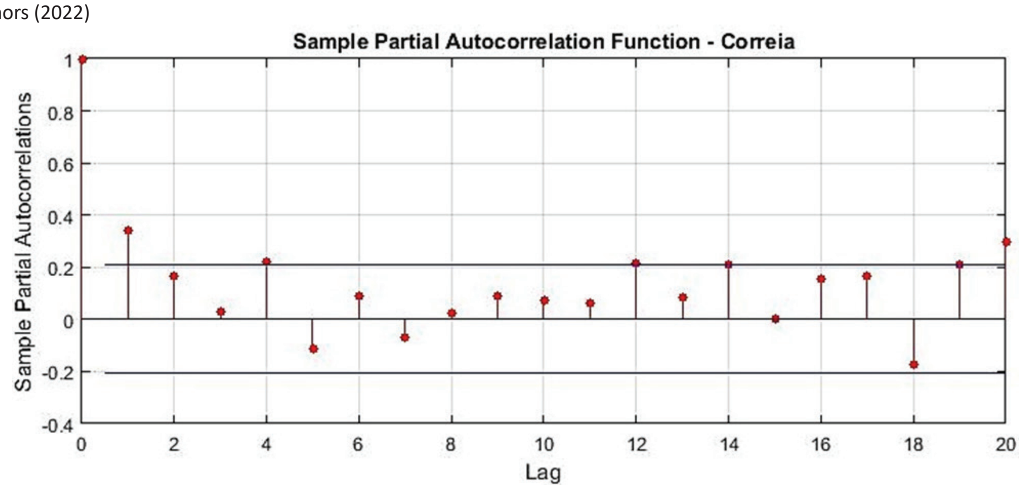

Figure 11. Partial autocorrelation of belt data
Source: The authors (2022)

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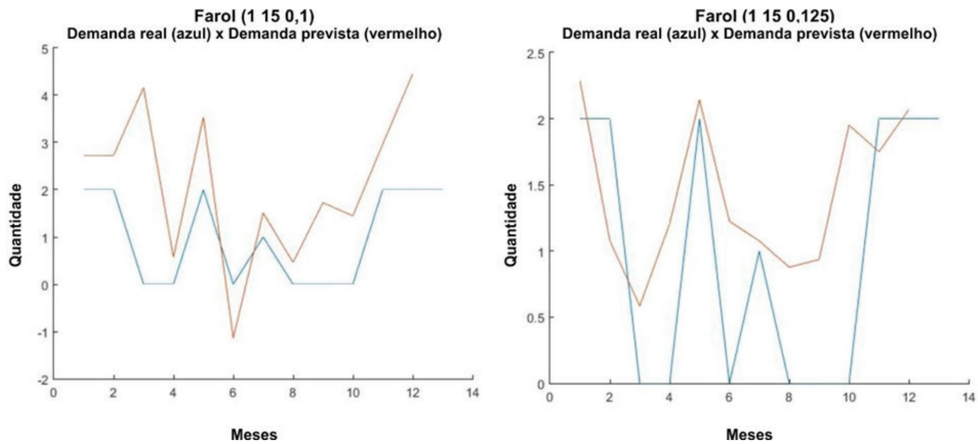

Figure 12. Actual Demand x Expected Demand (Worklight)

Legend: Lighthouse (1 15 0.1); Actual demand (blue) x Expected demand (red); Quantity (Vertical); Months. Actual demand (blue) x Expected demand (red); Quantity (Vertical); Months

Source: The authors (2022)

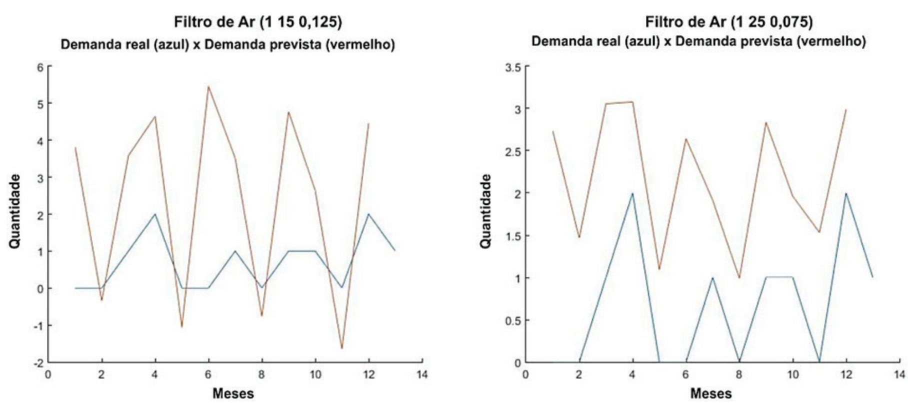

Figure 13. Actual Demand x Expected Demand (Air Filter)

Legend: Air Filter (1 15 0.125); Actual demand (blue) x Expected demand (red); Quantity (Vertical); Months. Air Filter (1 25 0.075); Actual demand (blue) x Expected demand (red); Quantity (Vertical); Months

Source: The authors (2022)

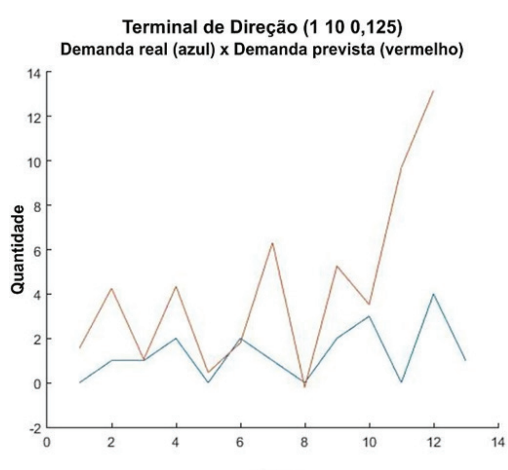

Figure 14. Actual Demand x Expected Demand (Direction Terminal)

Legend: Direction Terminal (1 10 0.125); Actual demand (blue) x Expected demand (red); Quantity (Vertical); Months

Source: The authors (2022)

can assist in decision-making, even if used with other methodologies that can optimize the accuracy of the forecast. The network could show when there was higher and lower demand for specific parts and could help stock management in a company with a high turnover of replacement items for its assets.

Despite the complexity in the parameterization of the network due to the various possibilities of parameter combinations, the neural network studied is viable within a work scope since, due to the results found, it could reach the objective initially proposed. Another relevant factor is that the network predicts the demand 12 months in advance. This information may contribute to the process of defining the company's budget forecast for the following year.

In future work, exogenous variables such as harvest period, tractor number, and maintenance performed should be used as network input to obtain a neural network that provides greater accuracy for the results obtained. Furthermore, it would be interesting to analyze whether it is possible to verify future obsolescence by the network resulting from the decrease in requests to reduce the cost of inventory.

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Received: Aug 1, 2022

Approved: Dec 8, 2022

DOI: 10.20985/1980-5160.2022.v17n3.1806

How to cite: Soares, L.M.C., Silva, A.C.G.C., Silva, J.C., Santos, P.V.S. (2022). Spare parts demand forecasting using an artificial neural network. Revista S&G 17, 3. https://revistasg.emnuvens.com.br/sg/article/view/1806