Master’s Thesis

Double Master’s degree in Industrial Engineering and Organization Engineering

Data analysis of the stock management of a manufacturing company

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Abstract

One of the tasks of stock management is determine the safety stock of a product. The aim of the safety stock is to avoid out-of-stock situations when demand increases unexpectedly. In most of manufacturing companies, the safety stock of a material is established by supply planners and they usually do not have a clear method to do it, they simply decide it from previous experience.

Thus, the objective of this project is to perform a neural network capable of substituting this task developed by a human brain. To do so, an international manufacturing company provided real data to test the results.

The research is divided into two parts. In the first trial a linear regression model is fitted to find the significant variables of the data given, and then a neural network is implemented with only the relevant inputs. Secondly, several supply planners are interviewed in order to adopt the variables they use to decide the safety stock as inputs of the neural network, in addition, the dataset is separated into three groups of products according to their similarity, and one neural network is implemented for each group of products.

The results obtained in both parts are not good enough, that is, the neural networks built cannot replace the job done by a supply planner.

However, it is found that the more similar the products of the dataset are, the easier it is for the neural network to predict their safety stock. In fact, the best neural network performed can accurately determine the safety stock of some materials, even though the total error is too high to consider capable of substituting the decision making of a human brain.

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1. Glossary

- **Make to strategy:** the replenishment of the materials can be done according two methods, the make to stock (MTS) strategy or the make to order (MTO) strategy. The MTS strategy consists in restocking the material periodically and, on the other hand, in the MTO strategy the material is restocked whenever an order is sent. Logically, the kind of strategy selected for the material can alter the safety stock as they are two totally different strategies.

- **Minimum Order Quantity (MOQ):** the MOQ is the minimum quantity that has to be ordered in order to replenish the material. Normally, this quantity is determined by the production department, since it could be that producing less than a certain quantity is not profitable.

- **Order lines:** this variable refers to the total amount of orders requested during the period of study. In theory, the more orders a material has, the more important it is and, therefore, the more safety stock it should have in order to fail as few orders as possible.

- **NON-OTIF order lines:** the term "OTIF" refers to On Time In Full, which means that an order was delivered on the day that was requested or before and with the quantity that was requested. Then, a NON-OTIF order line is an order that was not delivered correctly because it arrived later than expected or less quantity than expected was handed in. In conclusion, a NON-OTIF order line is a failed order.

- **Product Activity (PA):** the product activity is a KPI that the company has to measure the percentage of orders delivered correctly. The larger the PA of a material is, the less orders failed of that material. The formula of the product activity is as follows:

$$PA\ (\%) = 1 - \frac{NON - OTIF\ order\ lines}{Total\ order\ lines}$$

- **Total Replenishment Lead Time (TRLT):** it is the total amount of time that passes from the day that the order is confirmed to the day that the order is delivered, in other word, is the time required to replenish a material. Thereby, the Total Replenishment Lead Time is the sum of the time needed to produce the material plus the time needed to transport the material to the warehouse.

- **Standard Price (€/unit):** the standard price is the price of a single unit of a material. The price of some materials are expressed with other currencies, but all prices have been converted to euros.

- **Frequency of demand**: it is the average quantity days that pass between two orders of the same material during the period of study.
- **Daily demand (actual sales):** it is the actual average units ordered each day during the period of study.
- **Daily demand (forecast):** it is the average units per day that were forecasted during the period study. Logically, this field is not the actual demand, it is just a prediction. In theory, the more accurate the forecast, the easier it would be to satisfy the demand and, therefore, the less safety stock there would be.
- **Formula value:** the company of the study has an own formula to help decide the safety stock. This may serve as a guideline for the supply planner in determining the safety stock of the material. The expression of the formula cannot be disclosed due to the company's privacy policy.
- **Epochs:** one epoch is one pass through all dataset. Therefore, the more epochs, the more trained will be the neural network.
- **Batch size:** it is the number samples considered by the model within an epoch before weights are updated.
- **Layers:** layers are where the calculations of the neural network are done, this means that the more layers, the more trained will be the neural network.
- **Neurons:** these are the connections that each layer has. So the more neurons the neural network has, the more calculations it is able to do and the more it is trained.
- **MSE (Mean Squared Error):** it measures the average of the squares of the errors. This parameter is used to evaluate the error of the neural network in the training data. Thereby, the less MSE, the better the neural network can predict the training data. Its formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(p_i - y_i)^2$$

Where n is the total number of predictions, p_i is the predicted value and y_i is the real value.

- **Average prediction error**: it measures the average of the absolute value of the relative error made in predicting the cross-validation data. The neural network will try to predict the value of the safety stock of materials that have not been used in its training, and this parameter will calculate the average of the relative error made in the predictions. The absolute value is added to the formula so that negative relative errors do not mislead the results. So its formula is as follows:

$$Average\ prediction\ error = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{p_i - y_i}{y_i}\right| \cdot 100$$

2. Introduction

The determination of the safety stock of a product is a task that requires spending a considerable amount of time for supply planners. And if the supply planner has to decide the safety of several materials, the time needed turns out to be a lot.

Moreover, supply planners usually do not have a clear methodology to establish the safety stock of a product, their decision making is based on the accumulated experience and knowledge acquired during years of job development.

Thus, if the safety stock decision could be replaced by a machine, it would lessen the workload on supply planners. Even further, it could substitute this part of the job and the company would save money.

2.1. Project objectives

The main objective of the project is to develop a neural network capable of determining the safety stock of a product without human intervention. The person responsible of the material would only introduce data as input to the neural network and it would return the optimum value of the safety stock of that material.

The accomplishment of the project would also be useful for the company of the study, since it would reduce the workload of its employees. In this regard, another objective of the project is to bring value to the company by analyzing whether it is possible to incorporate this technology,

2.2. Scope of the project

First of all, the study company does not allow its disclosure due to its privacy policy. Thus, none of the characteristics of the company nor its name or the name of the products studied can be disclosed.

In this regard, the investigation is limited to the data provided by the company of the study, which has given enough data to carry out the research but obviously it is composed of only products of the company.

Although the code of the neural network is developed in this project, it is not started from scratch. Instead, some libraries are used as a basis for programming. This project is not focused on the code of the neural network, rather on the outcome that it provides.

3. State of the art

In this section all the concepts required to understand the research are explained together with their current situation. This section exposes the theory behind the techniques and methodologies of analysis applied during the investigation.

3.1. Supply chain

The supply chain of a product is all the activities required to plan the consumption of a product, from the planification of the production to the transportation of the goods to the consumer.

Thus, the supply chain is a key factor in the success of a manufacturing company. It is completely useless to produce an excellent product if its delivery is inadequate or the production is done at the wrong time.

In this regard, there are basically two main types of strategies for the supply of a material: the Make to Stock strategy (MTS) and the Make to Order strategy (MTO).

The aim of the Make to Stock strategy is to be able to supply a continuous demand, therefore, the stock is replenished periodically in order avoid a situation of out of stock. Typically, the products planned with a Make to Stock strategy have a safety stock because the demand cannot be forecasted with 100% accuracy, there will always be errors in the forecast.

On the other hand, the Make to Order approach starts the production of the material only when the order is confirmed by the customer. Normally, these kinds of materials do not have safety stock because the orders are simply manufactured when they are demanded.

The investigation of the project is focused on the safety stock so the vast majority of the product studied are planned with a Make to Stock strategy. However, the company also has a safety stock in some Make to Order products to avoid possible problems and always fulfill the demand of a few particular customers

3.2. Safety Stock

The safety stock is an extra stock stored in order to avoid out-of-stock situations. Since it is very difficult to forecast the demand, it is stored a quantity extra in the warehouse to meet the extra demand that was not predicted. The safety stock can also be used for example when there is a failure in the production or the goods have been damaged in the transportation.

Obviously, the more safety stock a product has, the less likely it is to run out of stock. However, the safety stock has an extra cost for the company. So an equilibrium must be found between the risk of not satisfying the demand and the cost of the stock.

In most cases, the safety stock is determined by the responsible of the product whose decision making is based on their own knowledge and their previous experience with that particular product. Even so, there are multiple theories related to computing the safety stock, next the most relevant ones are explained.[1]

The simplest formula to calculate the safety stock of a product it only takes into account the daily demand and the lead time; the formula is as follows:

$$SS = \frac{max.}{daily\ demand} \cdot \frac{max.}{lead\ time} - \frac{avg.}{daily\ demand} \cdot \frac{avg.}{lead\ time}$$

This expression is very limited because it does not consider the fluctuation but on the bright side the calculation is very straightforward.

Another more complicated model to calculate the safety stock is using the Heizer & Render's formula [2], which is:

$$SS = Z \cdot \sigma_{dLT}$$

Where Z is the value of a standard normal distribution at the service level desired and σ_{dLT} is the standard deviation of the demand during the lead time.

An extension of the previous model is the Greasley's formula [3], whose calculation for the safety stock is the product of the same Z factor, the daily demand average, and the standard deviation of the lead time.

$$SS = Z \cdot D_{avg} \cdot \sigma_{LT}$$

The last model exposed in this section it is more difficult than the previous ones. Although it is more accurate, it adds complexity to the model and it requires more data. Its formula is as follows: [4]

$$SS = Z \cdot \sqrt{\mu_L \cdot \sigma_D^2 + \mu_D^2 \cdot \sigma_L^2}$$

Where Z is the value of a standard normal distribution at the service level desired deviation of the lead time, μ_L and μ_D are the mean of the lead time and of the demand respectively, and

σ_L and σ_D are the standard deviation of the lead time and of the demand respectively.

3.3. Linear regression

Linear regression is a method applied in statistics to fit data in a model. The aim of the linear regression is to find the numerical relation between the response and one or more explanatory variables.

When the model has only one independent variable, it is called simple linear regression. On the other hand, if the model has two or more variables, it is called multiple linear regression. The linear regression performed in this study takes several variables so a multiple linear regression is used.

Thus, given the value of the inputs, the output is computed with the following formula: [5]

$$y_i = \beta_o + \beta_1 \cdot X_{1i} + \beta_2 \cdot X_{2i} + \cdots + \beta_p \cdot X_{pi} + e_i$$

Where y_i is the outcome, β_p is the coefficient of the variable *p*, X_{pi} is the value of the variable *p* at input *i*, and e_i is the model error.

The multiple linear regression has mainly two uses: firstly, one can determine whether there effectively a relation between a variable and the outcome and how strong that relation is, and secondly, one can use the training model to try to predict the outcome of new data.

In this investigation, the multiple linear regression is used to find out what inputs of the dataset affect the outcome. To do so, a hypothesis test with confidence intervals is performed for each variable using Minitab. If the student's tu value returned is larger than 2, it means that the variable is significant to describe the model, otherwise the variable is not relevant and it may be removed from the linear regression model. [6]

In this case, to carry out the multiple linear regression it is used a least squares approach, [7] which minimizes the squares of the residuals (difference between the predicted value and the actual value).

It must be taken into account that this methodology makes the following four assumptions [8] and therefore they must be beforehand validated in order to implement the linear regression correctly.

- Independence of observations: there is no relationship between two different observations.
- Constant variance: the variance of the errors do not change significantly from one

value to another. In general, the standardized errors should be between 2 and -2.

- Normality: the dataset may be described using a normal distribution.
- Linearity: the response values is a linear combination of the independent variables.

3.4. Neural Network

A neural network is a set of algorithms that use computational models to process data in order to determine the value of an outcome as if it was a real person. The aim of a neural network is to simulate the thinking process of a human brain, thus the output can be reached by artificial intelligence instead of a human.

Also, a neural network well implemented is very useful for humans since the person only needs to introduce the inputs to the neural network and it will return the outcome much faster than if calculations had to be done by hand.

Logically, a neural network requires to be trained with large dataset to be able to effectively determine the outcome. In general, the more examples the algorithm is trained with, the more accurate will be the outcome. [9]

In neural networks there are three main components: the input layer, the output layer, and the layers in-between (also called hidden layers) where the majority of the calculations are made. The input and the output layers are mandatory, but there are neural networks that describe very simple models that do not require intermediate layers because the computation of the outcome is straightforward.

Moreover, the layers of a neural network are composed of neurons. The neurons are responsible of weighing the inputs of the previous layer and perform the calculations to determine an outcome that will be sent to the next layer. [10]

The more layers and neurons a neural network has, the more trained it is and therefore the better it explains the training data. However, too much training can lead to overfitting the model, which would cause poor results in new data.

Neural networks train the algorithm using a process called back-propagation. Basically, it consists in going back and check every neuron to see whether the outcome would improve if a change on a weight was made, so the algorithm is constantly reevaluating the weighs of the neural network.

3.5. Cross-validation

The cross-validation is a method to assess whether a model is adequately built or not. In particular, in the neural networks field the cross-validation is used to validate the accuracy of the results.

Thus, the cross-validation consists in introducing new data to the neural network and then evaluating the precision of the outcome returned by the algorithm. So if the neural network returns a value equal or very similar to the outcome of the data, it means that neural network is properly trained.

Obviously, this new data cannot be used in the training phase of the neural network. Normally, a portion of the data is not used to develop the neural network, instead it is reserved for the cross-validation phase.

The cross-validation methodology aims to avoid overfitting the model. One could apply a lot of hidden layers and neurons to the algorithm so that it can perfectly predict the outcome of all the training data, however, the algorithm would yield very poor results for new data since the model is overfitted. [11]

3.6. Literature review

In this section other related investigations are mentioned. Also, the relation and differences between previous researches and this one are explained.

Nancy Deraz, Yi Wang, Jonathan Moizer and Iniega Neaga conducted a study on how to apply a neural network to the stock management, [12] the examination focuses on the optimum quantity to order rather than on the safety stock. Also, it uses as inputs for the neural networks variables that may be implemented in this research as well, such as the sales of the product, the demand forecasted or the purchase price.

Moreover, Fuqiang Zhang, Pingyu Jiang, Jingjing Li, Jizhuan Hui and Bin Zhu investigated the optimization of the service level of a warehouse using different methods. [13] One of the methodologies was a back propagation neural network, which was used to estimate the safety stock of some materials. The research concluded that the safety stock may be predicted by a neural network, although the prediction error increases substantially when there are fluctuations in the demand. The difference between their study and the conducted here is the selection of the inputs of the neural network, they simply choose the inputs that seem to fit instead of performing a previous examination.

Piyush Singhal, Gopal Agarwal and M. L. Mittal analyzed the impact of using a neural network in different risk scenarios of supply chain management. [14] It was concluded that this type of technology may be positive to predict future trends using past data. The article is based on the data provided by a small company, yet the investigation carried out here may be useful for big companies.

In addition, Weiping Zhong and Lili Zhang tried to forecast the safety stock of different materials combining a support vector machine model (SVM) and a radial basis function (RBF) neural network model. The results obtained had a high accuracy, the relative error of the predictions was below 2%, [15] which proves that the safety stock can be determined by artificial intelligence, even though the methodology implemented was quite complex.

Another approach in the study of the safety stock is the forecast of the demand, since the safety stock can easily be calculated once the forecasted demand is known. Cao Qingkui and Ruan Junhu investigated how to accurately forecast the demand of a hospital, and thus the stock level, using a back propagation neural network. [16] Previously, various techniques are applied to process the data, such as data cleaning, data integration and data transformation.

Hao Zhang and Jia-Hui Mu showed that the inventory of a tradition pharmacy could be managed by artificial intelligence. In particular, they implemented a back propagation neural network together with a multivariate regression analysis. [17] The difference between this study and the investigation conducted here is that in this case the multivariate regression analysis is only performed to check whether there is multicollinearity in the dataset, whereas here the multivariate regression is used to determine the significant parameters of the dataset.

Finally, L. Zhang, D. Wang and L. Chang deduced that a back propagation neural network is an effect method to estimate the safety stock. [18] Although in their research many variables are used as inputs for the neural network, no technique was applied to clean data and make the interpretation of the results easier.

Thus, the study conducted in this project is in some way a continuation of the investigations mentioned above, the aim of the research is to predict the safety stock using a neural network. However, two methodologies are applied to decide the inputs of the neural network: in the first place, the significant variables are determined by performing a linear regression analysis, and in the second place, the variables are selected by asking various experts on the field.

4. Current stock management system

Before diving into the optimization of the stock management of the company, an analysis of the current stock management system of the company has been carried out. This way, we will know the strengths and the weaknesses of the company and therefore the aspects that should be improved in order to perform better.

The data that the company has provided consist of a total of 2624 materials, which had a total amount of 222354 orders during the period of March 2021 and August 2021. Note that they are not actually 2624 different materials, some of them are repeated but are considered as different because the plants in which the stock management was done were different.

As seen in Figure 1, the vast majority of the materials had less than 50 orders during the period, in particular, 1786 out of 2624 materials had 49 or less orders. Therefore, the majority of the portfolio of the company consist of a large quantity of materials with few orders, only 29 materials had 1000 or more orders during the span of the study.

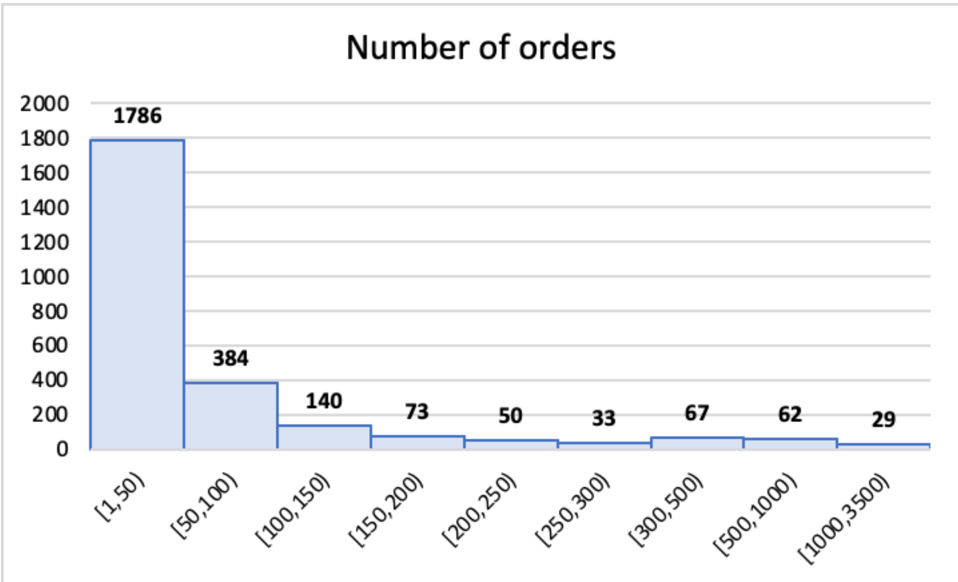

Figure 1: Number of orders of materials

This does not mean that the materials with few orders are the most important. Despite there are few materials with a large number of orders, they are the most relevant because they accumulate more orders than any other group.

As seen in Figure 2, the group of materials with more than 1000 orders represent 20% of the total orders of the period. Also, the group between 500 and 1000 orders is 20% of the total as well. On the other hand, the group with less than 50 orders correspond to the 15% of the total orders. Thereby, these three groups are the most important for the company because they represent the 55% of the total orders.

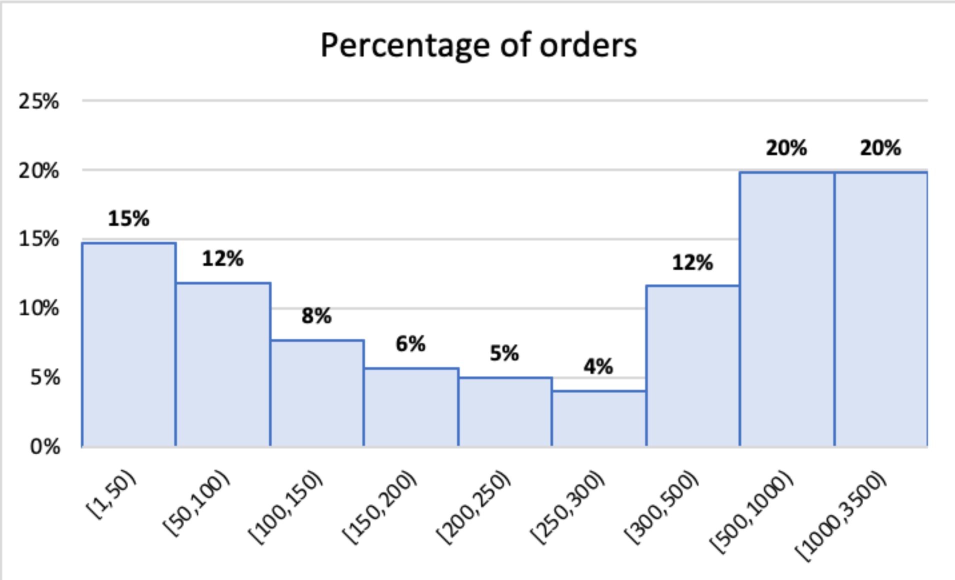

Figure 2: Percentage of orders of materials

Another aspect of the stock management is the strategy used to satisfy the demand. As seen in Table 1, the vast majority of the materials (99%) are managed with a Make to Stock (MTS) strategy, whereas only 19 materials have a Make to Order (MTO) strategy.

Stock Strategy	Number of materials
MTS	2605
MTO	19
Total	**2624**

Table 1: Number of materials according to stock strategy

The current system used to manage the safety stock of the company is an ABC model, which consists of classifying the materials in several groups according three criteria. These criteria is as follows:

- **Number of orders:** the first criterion used to divide the materials is the number of orders requested during the period. Obviously, the most important materials are the ones with more orders.

- **Number of failed orders compared to the total number of orders:** it is calculated the percentage of orders not satisfied on time with respect to the total amount of orders of the material. The most critical materials have a larger percentage.

- **Number of failed orders compared to the total number of failed orders**: it is calculated the percentage of orders not satisfied on time of a material with respect to the total amount of failed orders of the company. The most relevant materials have a larger percentage.

Furthermore, there are three classes in each criterion. The “A” materials are the 80% most important materials of each criterion, the “B” materials are from the 80% to the 97% most significant materials of each criterion, and finally, the “C” materials are the 3% less important of each criterion.

For example, a material whose number of orders are larger than the 80% of the materials would be classified as “A” in the criterion number of orders. However, if the percentage of number of failed orders with respect to its number of orders is fewer than the 3% of the materials, would be classified in class “C” of the second criterion. Lastly, if the percentage of failed orders of this material with respect to the total amount of failed orders is between the 80% and the 97% of the materials, it would be classified in class “B” of the third criterion. Therefore, combining the three classes of this material, it would be classified as a ACB material.

Then, every material is classified according a combination of three letters (A, B or C), such as, AAA, ACC, BCA, CAB, ACB, CBB, etc. And each letter represents the importance of the material according to its criterion, being the AAA the most significant materials.

Performing the combinations of all the materials, the following graph is obtained:

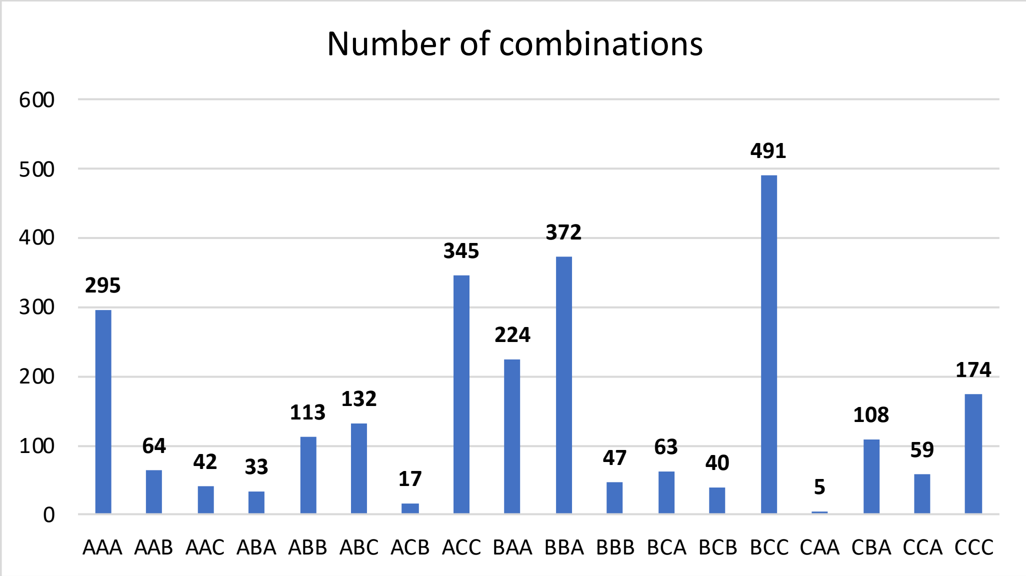

Figure 3: Number of materials of each ABC combination

Note that some combinations do not appear because some materials were eliminated from the dataset provided by the company, since there were obsolete products or no longer sold anymore which obviously makes no sense to study.

As seen in Figure 3, there are 295 materials with a combination of AAA, which are the most critical ones and therefore the materials whose safety stock has to be carefully thought-out. Moreover, there are a total of 1872 materials (71%) with at least an A in its combination. The most repeated combination is BCC, with 491 cases. And the less relevant materials, the CCC combination, are a total of 174.

This classification is very useful for the supply planners to see the importance of each material compared to the total of materials of the company. This way, the supply planner can decide to put a larger or lower safety stock according to relevance of the material, since it is has a major impact failing an order of an AAA material than missing and order of a CCC material.

However, the final decision of the safety stock must take it a person, which is a lot of work because the company has a huge portfolio. The objective of this project is to design a neural network capable of making this decision with a high accuracy. Logically, this would considerably help the company because it would replace the work done by its employees.

Finally, an analysis of the main reasons for failing orders has been carried out. The objective of this analysis is to investigate the risks associate to stock management and the reasons for the safety stock, as if no order had been failed it would mean that there is no need to have a safety stock.

The top reasons of not satisfying an order are as follows:

Cause	Materials	Percentage
Demand Changes / Forecast	936	36%
Stock Available	644	25%
Scheduling Agreement	294	11%
Supplier Delay	197	8%
Raw, pack, SFG delay	123	5%
Logistics issues / Delays	64	2%
Capacity	45	2%
Other	321	12%
Total	2624	100%

Table 2: Reasons for failing orders

These are the main reason for orders failed of each material. That is, if the main reason for failing orders of a materials is "Demand Changes / Forecast", it will be included in this group regardless of having other failed orders because any other cause.

As seen in Table 2 and Figure 4, the main cause of the failed orders is the changes in demand (36%), that is, the forecast predicts a certain amount of demand but there has actually a larger demand during the period. Therefore, not even with the safety stock the company was not able to satisfy the demand of the product.

The other top two causes are "Stock Available", which means that the demand was well predicted but it simply was not satisfied because of a bad planification, and "Scheduling Agreement", which are orders rescheduled, correspond to 25% and 11% respectively.

Several causes have been grouped as "other" because there were minor reasons compared to the rest of causes, even though all these minor causes as a group represent 12% of the total.

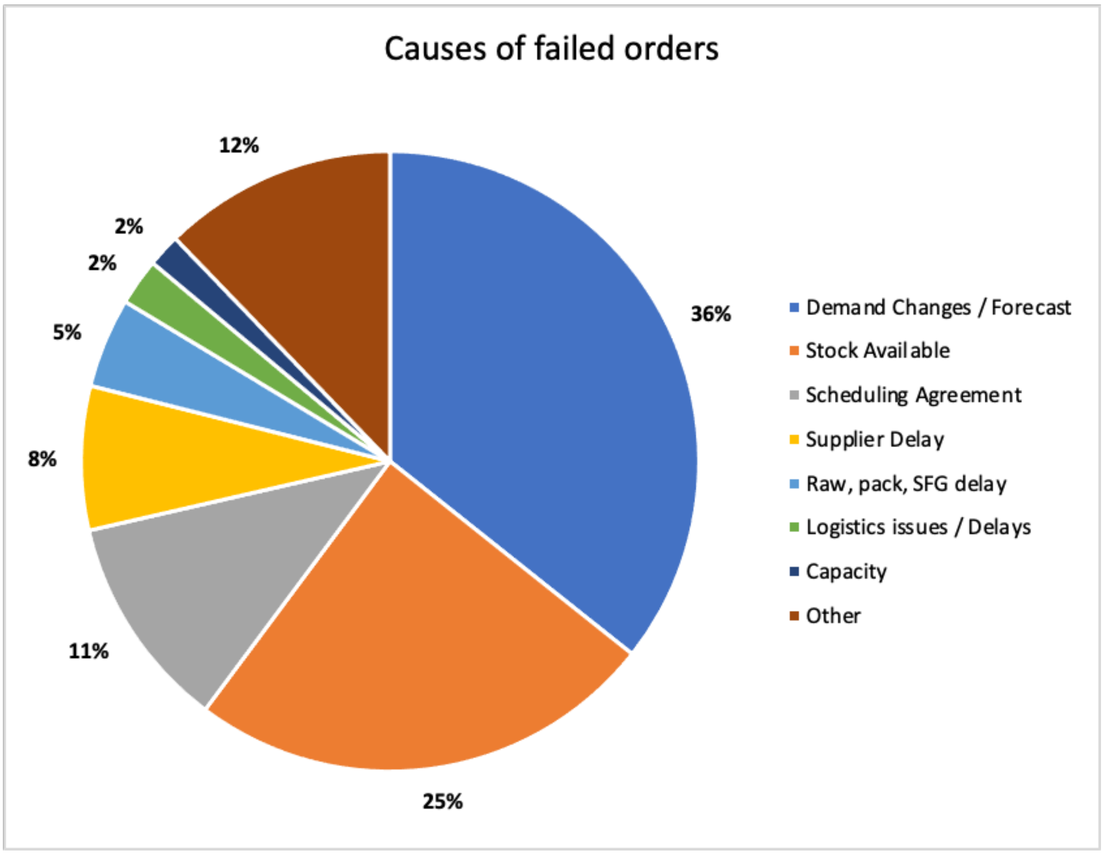

Figure 4: Graph of top reasons for failed orders

5. First trial: neural network based on a linear regression model

In this section, a neural network is performed to predict the safety stock of different types of products. The neural network built should be able to effectively determine the safety stock of any material in the dataset.

Before that, a multiple linear regression analysis is carried out in order to find the variables of the data that are actually relevant for the model. Those variables will be included in the neural network as inputs, but the remaining variables will be discarded.

By building the neural network, all its parameters (epochs, batch size, layers and neurons) will be scrutinized to achieve their best combination, that is, the combination that best fits the model.

Finally, to check the results obtained with neural network implemented, 20% of the data will not be used to train the algorithm. Instead, it will be used to test the predictions of the neural network in data that has not been used in the training phase.

5.1. Significant parameters for the safety stock

In this section, the most relevant parameters for the safety stock are selected. To do so, a linear regression study with Minitab has been carried out in order to know the significant parameters for predicting the safety stock. By doing the linear regression with the safety stock variable as a response, it is possible to find out the parameters that have an influence on the safety stock decision and the variables that do not affect the safety stock.

Thus, the objective of the linear regression is to determine the parameters that will be used to compute the safety stock later with the neural network. These parameters will obviously be only the significant variables according to the linear regression, the non-significant variables will be discarded and they will not be used to design the neural network.

5.1.1. Variables of the linear regression model

Before performing the linear regression, all the variables that help the supply planer to decide the safety stock of a material will be explained. So, all the variables that are taken into account are as follows:

- **Make to strategy:** the replenishment of the materials can be done according two methods, the make to stock (MTS) strategy or the make to order (MTO) strategy. The MTS strategy consists of restocking the material periodically and, on the other hand, in the MTO strategy the material is restocked whenever an order is sent. Logically, the kind of strategy selected for the material can alter the safety stock as they are two totally different strategies.

- **Minimum Order Quantity (MOQ):** the MOQ is the minimum quantity that has to be ordered in order to replenish the material. Normally, this quantity is determined by the production department, since it could be that producing less than a certain quantity is not profitable.

- **Order lines:** this variable refers to the total amount of orders requested during the period of study. In theory, the more orders a material has, the more important it is and, therefore, the more safety stock it should have in order to fail as few orders as possible.

- **NON-OTIF order lines:** the term “OTIF” refers to On Time In Full, which means that an order was delivered on the day that was requested or before and with the quantity that was requested. Then, a NON-OTIF order line is an order that was not delivered correctly because it arrived later than expected or less quantity than expected was handed in. In conclusion, a NON-OTIF order line is a failed order.

- **Product Activity (PA):** the product activity is a KPI that the company has to measure the percentage of orders delivered correctly. The larger the PA of a material is, the less orders failed of that material. The formula of the product activity is as follows:

$$PA\ (\%) = 1 - \frac{NON - OTIF\ order\ lines}{Total\ order\ lines}$$

- **Total Replenishment Lead Time (TRLT):** it is the total amount of time that passes from the day that the order is confirmed to the day that the order is delivered, in other word, is the time required to replenish a material. Thereby, the Total Replenishment Lead Time is the sum of the time needed to produce the material plus the time needed to transport the material to the warehouse.

- **Standard Price (€/unit):** the standard price is the price of a single unit of a material. The price of some materials are expressed with other currencies, but all prices have been converted to euros.

- **Frequency of demand**: it is the average quantity days that pass between two orders of the same material during the period of study.

- **Daily demand (actual sales):** it is the actual average units ordered each day during the period of study.

- **Daily demand (forecast):** it is the average units per day that were forecasted during the period study. Logically, this field is not the actual demand, it is just a prediction. In theory, the more accurate the forecast, the easier it would be to satisfy the demand and, therefore, the less safety stock there would be.

All the variables that interfere in the decision making of the safety stock are numerical variables except for the make to stock strategy, which is a categorical variable whose values can be MTS o MTO.

To include the categorical variable in the linear regression model, a binary variable has been added. If the value of the binary variable is 1, it means that the material has an MTS strategy. But if the value of the binary is 0, the material has an MTO strategy.

Moreover, to perform the linear regression model and include the categorical variable correctly, it cannot only be added the binary variable, but it also must be added the product of each numerical variable by the binary variable. These invented variables must be included in the study to take into account the interaction between the continuous and the categorical variables.

Thus, all the variables included in the linear regression analysis are all the variables explained above and the product of each continuous variable by the binary variable.

5.1.2. Multiple Linear Regression

In this section a multiple linear regression model study is performed to find out the relevant parameters of this dataset. This will be useful to only take into account the significant variables in the neural network analysis and discard the variables that explain very little of the model.

By doing the regression model, an outlier has been identified in the data when observing the graphs of the residuals and its normal probability plot.

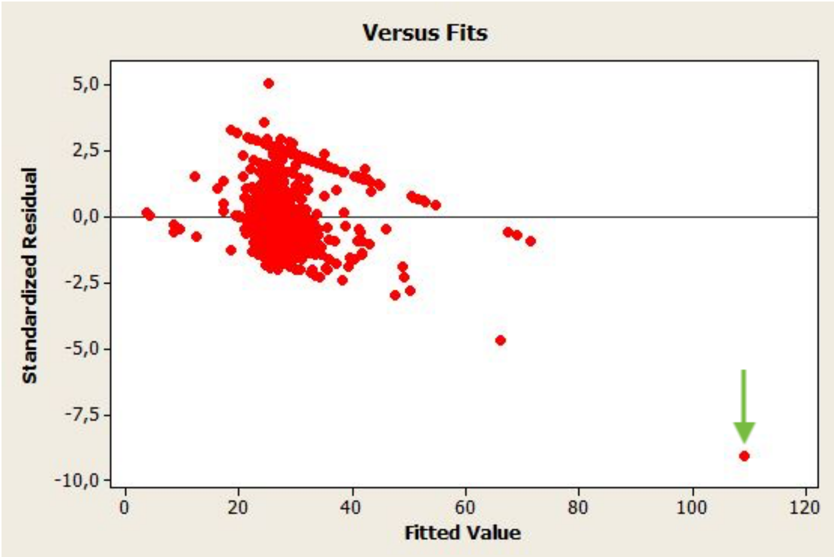

Figure 5: Standardized residual plot of the model of safety stock

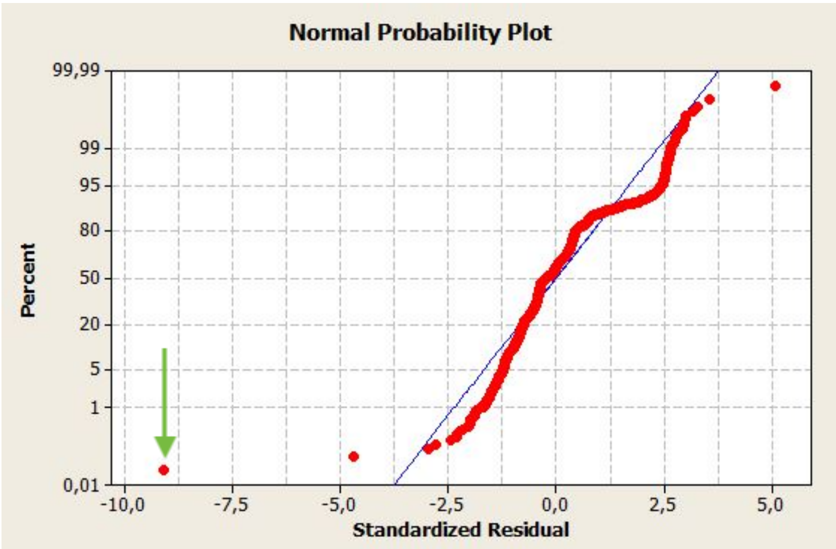

Figure 6: Probability distribution plot of the model of safety stock

As the two figures above exhibit, there is an outlier since the value of its standardized residual is exceedingly low and it is also isolated from the other values in the normal probability plot. So this material has been removed to perform the linear regression model, as it would negatively interfere in distinguishing the relevant variables from the non-relevant.

Once the outlier is discarded, a multiple linear regression analysis is performed. The value of the student's t of each variable is used to decide whether a variable is significant or not. If the value of the student's t of a variable is lower than 2, that variable is taken out from the regression model since it means that the variable does not help in describing the data by a linear regression, otherwise, if the value of the student's t is larger than 2 the variable is not removed.

Thus, the result of the linear regression model is as follows:

```
The regression equation is
Sfst [days] = 11,0 + 0,907 OL2 + 4,62 PA TOTAL - 0,508 Freq of Demand
              + 0,0310 Demand daily avrg (Sales)
              - 0,00694 Demand daily avrg (FC) + 18,4 MT (CV) - 0,907 MT*OL
```

Predictor	Coef	SE Coef	T	P
Constant	11,011	4,804	2,29	0,022
OL	0,9065	0,4182	2,17	0,030
PA	4,617	1,346	3,43	0,001
Freq of Demand	-0,50837	0,07001	-7,26	0,000
Demand daily avrg (Sales)	0,030965	0,004535	6,83	0,000
Demand daily avrg (FC)	-0,006942	0,003443	-2,02	0,044
MT (CV)	18,352	4,741	3,87	0,000
MT*OL	-0,9066	0,4182	-2,17	0,030

Figure 7: Multiple linear regression model of the safety stock

All the variables with a student's t value lower than 2 have been discarded, remaining only the variable whose value were larger than 2.

When removing a variable, it must to be taken into account that if a variable had a student's t value lower than 2 but its interaction term with the binary variable was larger than 2, that variable cannot been removed. However, this is not the case since the interaction term of the binary variable and the order lines (MT*OL) and the order lines variable have values larger than 2.

Therefore, the significant parameters to the safety stock are the total amount of Order lines, the Product Activity KPI, the Frequency of the demand, the Daily demand (actual sales), the Daily demand forecasted, the binary variable corresponding to the Make to strategy, and the interaction between the Make to strategy and the Order lines.

5.2. Neural network to predict the safety stock

In this section a neural network is performed in order to predict the safety stock of the materials. First, the characteristics of the neural network are explained, and then the results obtained are discussed.

In the first place, all the variables of the dataset are standardized since their values differ markedly. The standardization of the variables is fundamental to implement the neural network as they tend to yield better. [19]

The Adam algorithm is used to perform the neural network combined with the Mean Squared Error as a loss function, which will be explained later. In addition, not all dataset is used to carry out the neural network, instead, only the 80% of the data is used to train the neural network and the remaining 20% is used to do cross-validation, in other words, the 20% of the data is used to analyze whether the neural network is capable of correctly predict values that have not intervened in its training.

Stock Strategy	Number of materials	Percentage
Training data	2098	80%
Cross-validation data	525	20%
Total	**2623**	**100%**

Table 3: Number of materials to train the neural network and to evaluate it

5.2.1. Results of the Neural Network

The training of the neural network depends on the value of its parameters, which are:

- **Epochs:** one epoch is one pass through all dataset. Therefore, the more epochs, the more trained will be the neural network.
- **Batch size:** it is the number samples considered by the model within an epoch before weights are updated.
- **Layers:** layers are where the neural network do calculations, this means that the more layers, the more trained will be the neural network.
- **Neurons:** these are the connections that each layer has. So the more neurons the neural network has, the more calculations it is able to do and the more it is trained.

Depending on the value of these four parameters, the neural network will return better or worse results. In order to analyze the output of the neural network, three parameters are calculated:

- **MSE (Mean Squared Error):** it measures the average of the squares of the errors. This parameter is used to evaluate the error of the neural network in the training data. Thereby, the less MSE, the better the neural network can predict the training data. Its formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(p_i - y_i)^2$$

Where n is the total number of predictions, p_i is the predicted value and y_i is the real value.

- **Average prediction error**: it measures the average of the absolute value of the relative error made in predicting the cross-validation data. The neural network will try to predict the value of the safety stock of materials that have not been used in its training, and this parameter will calculate the average of the relative error made in the predictions. The absolute value is added to the formula so that negative relative errors do not mislead the results. So its formula is as follows:

$$Average\ prediction\ error = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{p_i - y_i}{y_i}\right| \cdot 100$$

- **Time:** it is the time required to train the neural network and do all the predictions. Obviously, a heavily trained neural network will take longer to yield, but more time means more resources deployed.

Next, several neural networks are performed in order to analyze the effect of each parameter (epochs, batch size, layers and neurons). And finally, it will be determined the best neural networks for this model.

5.2.1.1. Number of epochs and batch size

To determine how affect the number of epochs of the neural network and its batch size, several neural networks are carried out changing these two parameters. Below are the epochs and the batch size of each neural network with their results. In this case all neural networks have one single hidden layer and seven neurons (one for each input).

Epochs	Batch size	MSE	Average prediction error	Time
50	10	168,93	56,39 %	9,28 s
100	50	173,29	56,72 %	4,81 s
1.000	20	165,81	56,27 %	1 min 27,79 s
1.000	200	166,69	55,89 %	10,33 s
10.000	200	165,58	55,37 %	1 min 40,42 s
10.000	2.000	165,95	55,51 %	28,08 s
100.000	5.000	128,18	48,55 %	3 min 2,43 s
500.000	10.000	127,36	47,14 %	14 min 12,17 s
10.000.000	800.000	126,94	48,14 %	4 h 33 min 58,90 s

Table 4: Trials to analyze the effect of the number of epochs and the batch size

As seen in the table above, the batch size does not practically affect to the results, since different neural networks with same characteristics but unlike batch size have similar MSE and average prediction error. For example, the neural networks trained with a batch size of 200 nearly had the same MSE and average prediction error despite having different number of epochs.

However, the smaller batch size, the longer the neural network takes to yield. This is completely logical, because it means that weights are updated more frequently and therefore more calculations are required.

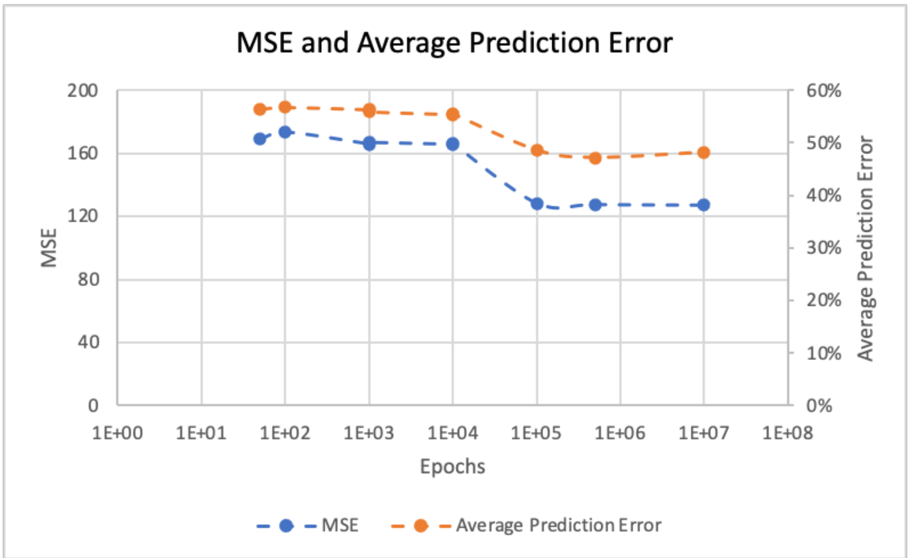

Figure 8: MSE and Average Prediction Error made depending on the number of epochs of the neural network

As seen in the graph above, both MSE and average prediction error drop when the 10.000 epochs are surpassed. On spite of that, by incrementing substantially the number of epochs the errors remain practically equal but the neural networks require much more time to yield. Therefore, it seems that the ideal number of epochs is around 100.000, but increasing a lot this characteristic only implies more time without any gain.

5.2.1.2. Number of layers

After investigating the effect of the epochs and the batch size, in this section the optimal number of hidden layers is examined. To do so, several neural networks are performed with different number of layers, as seen in the following table.

Layers	Epochs	Batch size	MSE	Average prediction error	Time
2	1.000	200	166,05	55,53 %	12,21 s
2	10.000	2.000	164,85	57,26 %	29,26 s
2	100.000	20.000	98,64	59,02 %	3 min 5,79 s
2	500.000	40.000	103,55	50,39 %	14 min 45,05 s
2	1.000.000	80.000	104,93	49,13 %	32 min 27,27 s
2	5.000.000	100.000	97,41	51,62 %	2 h 33 min 27,05 s
4	1.000	200	165,56	56,00 %	13,72 s
4	10.000	2.000	165,35	54,88 %	33, 48 s
4	100.000	20.000	90,37	54,21 %	3 min 22,92 s
4	500.000	40.000	97,43	56,50 %	16 min 12,49 s
4	1.000.000	80.000	85,86	68,25 %	35 min 39,36 s
6	1.000	200	165,21	55,41 %	14,62 s
6	10.000	2.000	165,40	55,75 %	35,80 s
6	100.000	20.000	85,70	54,17 %	4 min 0,69 s
6	500.000	40.000	192,52	54,96 %	19 min 35,79 s
6	1.000.000	80.000	100,99	54,26 %	39 min 22,74 s
8	1.000	200	165,92	56,23 %	15,28 s
8	10.000	2.000	164,45	57,25%	37,88 s
8	100.000	20.000	192,52	54,96 %	4 min 0,67 s
8	500.000	40.000	88,00	82,97 %	21 min 25,78 s
8	1.000.000	80.000	87,80	54,95 %	42 min 44,49 s
10	1.000	200	123,80	52,75 %	15,86 s
10	10.000	2.000	165,05	55,78 %	40,21 s
10	100.000	20.000	192,53	54,96 %	4 min 20,60 s
10	500.000	40.000	192,53	54,96 %	22 min 40,42 s
10	1.000.000	80.000	104,19	52,39 %	47 min 13,65 s

Table 5: Trials to analyze the effect of the number of layers of the neural network

The results obtained are summarized in the following graphs:

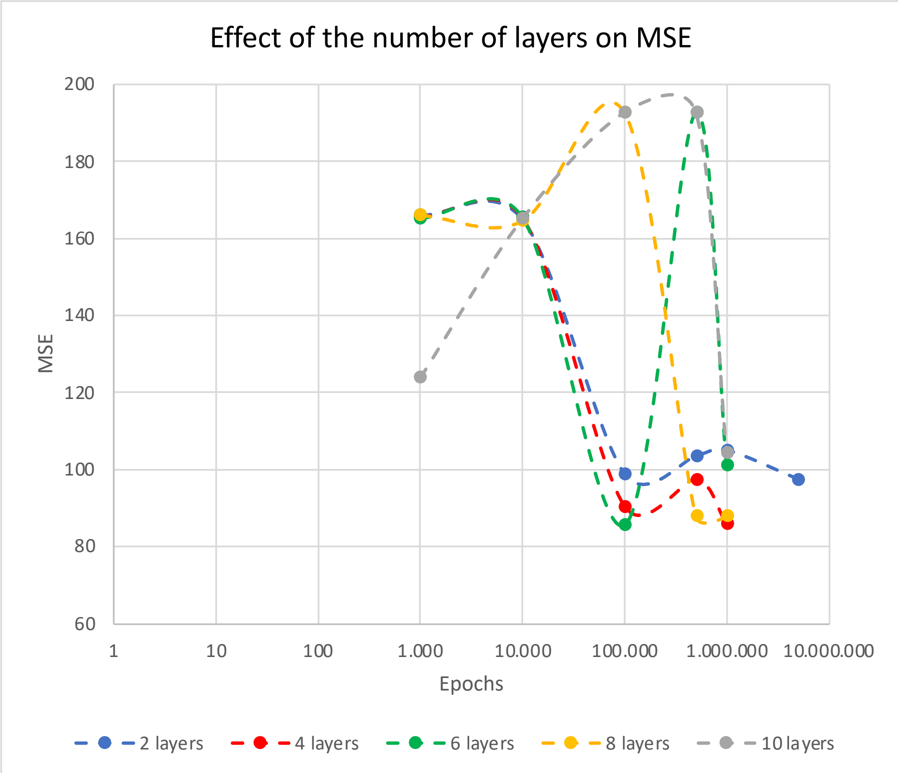

Figure 9: Relation between number of layers and MSE

As seen in Figure 9 above, in general the MSE decreases substantially when reaching the 100.000 epochs independently of the number of layers, likewise to the analysis of the number of epochs (chapter 5.2.1.1.).

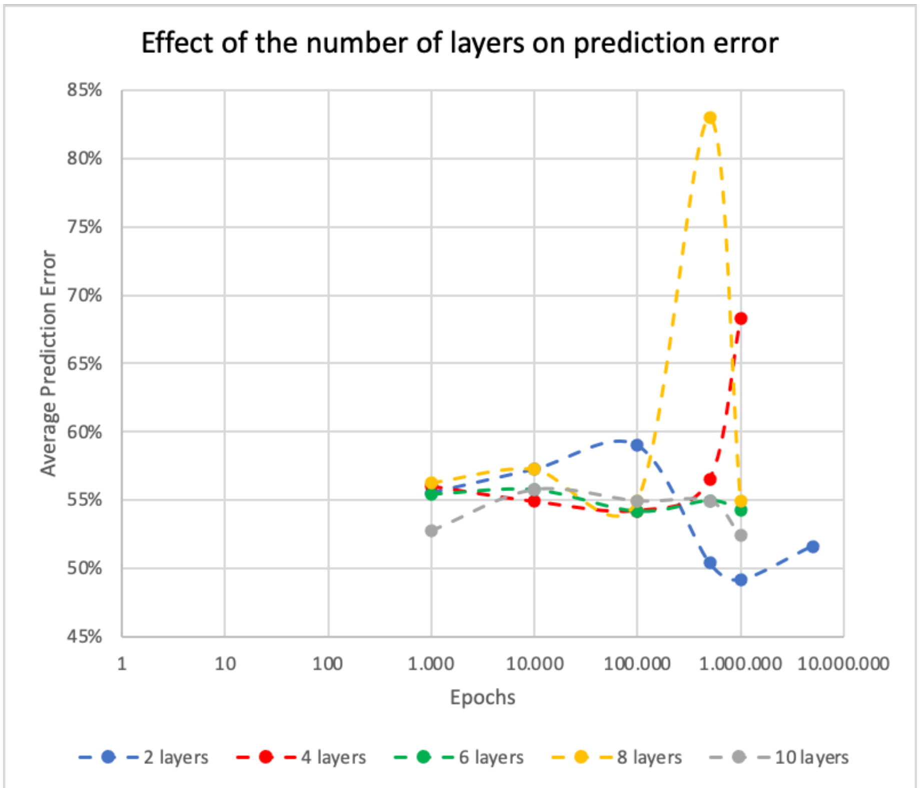

Figure 10: Relation between number of layers and prediction error

However, the effect on the average prediction error does not relate in the same way. In fact, the more layers the neural network has, the larger the error is. And the minimum error is obtained with 2 layers (49,13%).

In addition, to reach such “low” error it is necessary to heavily train the neural network, 500.000 epochs or more are needed to get the lowest prediction error possible. But this value of error is reached implementing one single layer with much less epochs (see Figure 8), for example the neural network performed with 1 layer, 100.000 epochs and a batch size of 5.000 got an error of 48,55% with approximately 3 minutes. In comparison, the time needed to achieve a similar error with two layers is 32 minutes.

Therefore, it is much better to implement a neural network with just one layer, since it requires less training and less time to obtain a relative error below 50%.

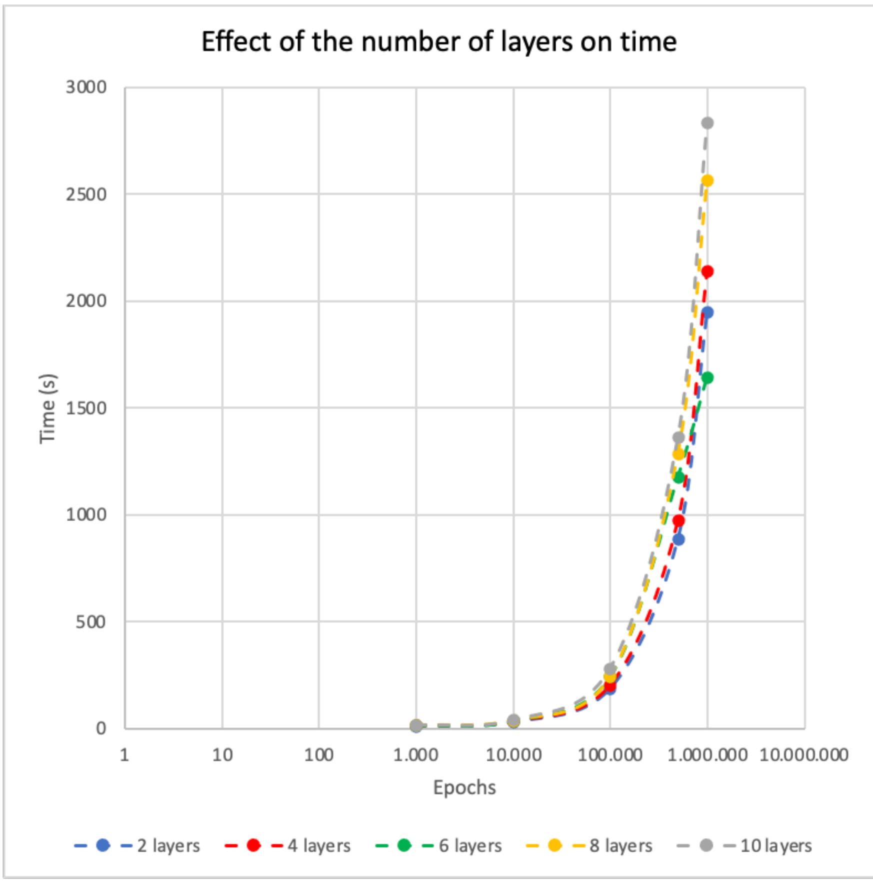

Figure 11: Relation between number of layers, epochs and time

As seen in Figure 11, the time required to develop the neural network and its number of hidden layers are clearly related. The more layers, the longer the neural network takes to yield. This is normal because the algorithm needs more time to do all the calculations.

The time is also related to the number of epochs in a similar way, the more epochs has the neural network, the longer takes the algorithm to finish. Again, this is logical because it means that the algorithm passes through all dataset more times.

5.2.1.3. Number of neurons

The last parameter to analyze of the neural network is the number of neurons. Below is the table with the neural networks carried out in order to determine the effect of this parameter. All of the neural networks of this table have been performed with only 1 hidden layer due to the conclusions drawn from the previous section.

Neurons	Epochs	Batch size	MSE	Average prediction error	Time
7	1.000	200	166,69	55,89 %	10,33 s
14	1.000	200	166,08	55,41 %	12,48 s
50	1.000	200	165,52	55,44 %	11,48 s
100	1.000	200	127,65	48,37 %	13,62 s
200	1.000	200	118,35	46,12 %	12,83 s
500	1.000	200	111,84	45,76 %	15,17 s
1.000	1.000	200	106,06	45,98 %	16,93 s
2.000	1.000	200	101,45	47,67 %	20,96 s
7	10.000	2.000	165,95	55,51 %	28,08 s
14	10.000	2.000	165,83	55,70 %	29,18 s
50	10.000	2.000	123,38	46,95 %	31,15 s
100	10.000	2.000	118,24	46,46 %	34,93 s
200	10.000	2.000	111,05	46,25 %	39,22 s
1.000	10.000	2.000	100,53	47,55 %	1 min 25,69 s
2.000	10.000	2.000	96,18	47,42 %	2 min 21,71 s
7	100.000	20.000	125,17	47,29 %	2 min 58,17 s
14	100.000	20.000	117,08	48,71 %	3 min 31,48 s
50	100.000	20.000	97,65	58,01 %	3 min 17,08 s
100	100.000	20.000	81,17	59,02 %	4 min 4,36 s
200	100.000	20.000	66,53	71,20 %	4 min 48,99 s
1.000	100.000	20.000	48,07	91,77 %	13 min 8,01 s
2.000	100.000	20.000	41,98	83,08 %	22min 58,48 s

Table 6: Trials to analyze the effect of the number of neurons of the neural network

From the data above the following two graphics are made.

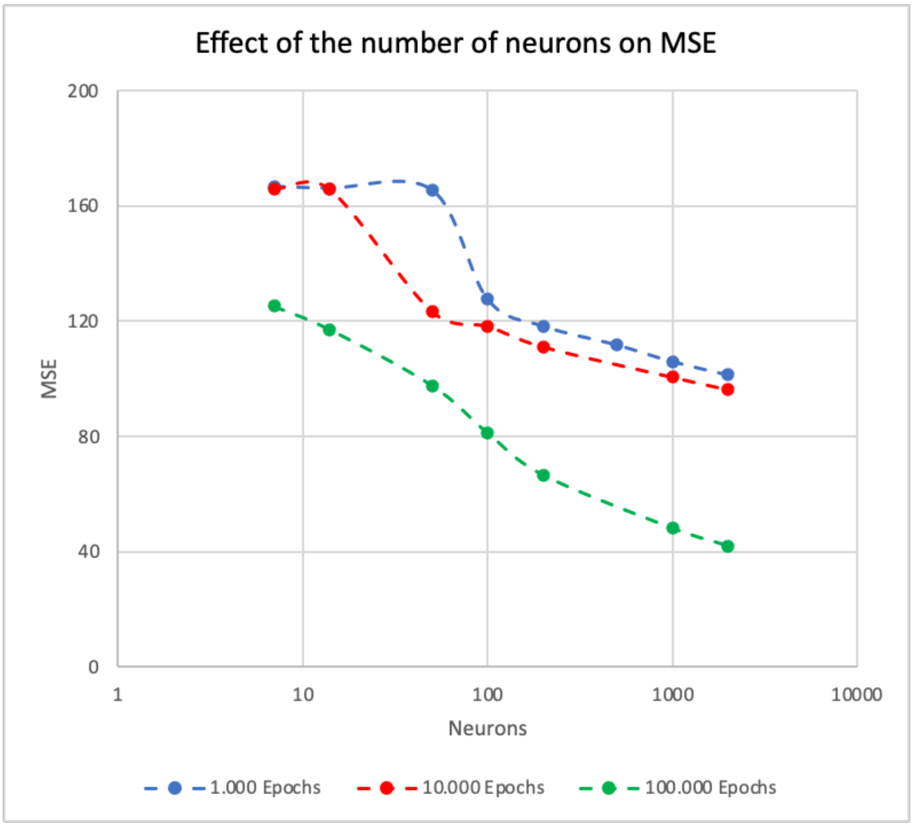

Figure 12: Relation between number of neurons, number of epochs and MSE

As seen in the graph above, the MSE diminishes when the number of neurons increases, which is coherent because the neural network is more trained and therefore it should explain better the model. Furthermore, the MSE also declines when the number of epochs enlarges, which is also logical for the same reason.

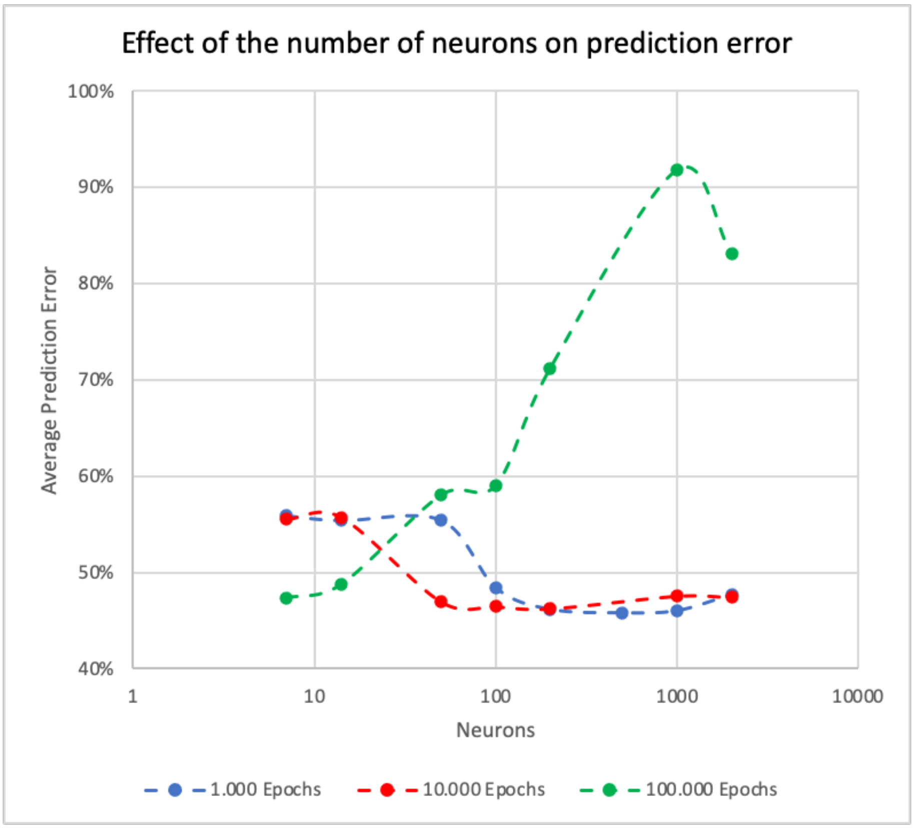

Figure 13: Relation between number of neurons, number of epochs and prediction error

However, the average prediction error drastically increases when the neural network has many epochs and neurons, which in theory makes no sense since the neural network had a longer training time. But this is due to overfitting, the neural network is so trained that fits the training data greatly but its performance in predicting drops extremely. Therefore, it is better not to train so much the neural network to avoid overfitting the model.

The neural networks with 1.000 and 10.000 epochs have a similar average prediction error from 100 neurons. Moreover, from the graph is deduced that the optimal neural network has between 1.000 and 10.000 epochs and between 100 and 500 neurons.

5.2.1.4. Optimum neural network

Based on the results obtained in the previous sections, now the optimum neural network is discussed. The objective now is to find the characteristics of the neural network that minimizes both the MSE and the Average prediction error, which means that the neural network is able to predict adequately the safety stock of the training data and of the cross-validation data.

To do so, several trials have been made combining the four parameters of neural networks: number of epochs, batch size, number of hidden layers and number of neurons.

In the previous sections it has been concluded that the performance of the neural network is better with only one layer. Also, the neural networks with less prediction error have between 1.000 and 10.000 epochs and between 100 and 500 neurons. So the experiments will start from this conclusions in order to get the best result.

The neural networks performed with their results can be seen in the following table:

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
100	1	1.000	200	121,77	46,74 %	13,36 s
100	1	2.500	200	121,65	46,53 %	28,05 s
100	1	5.000	200	119,04	46,39 %	57,37 s
100	1	7.500	200	111,44	48,27 %	1 min 24,31 s
100	1	10.000	200	107,78	47,42 %	1 min 55,27 s
200	1	1.000	200	121,20	47,30 %	14,90 s
200	1	2.500	200	110,73	45,69 %	32,29 s
200	1	5.000	200	102,98	50,38 %	56,91 s
200	1	7.500	200	101,18	48,06 %	1 min 40,54 s
200	1	10.000	200	99,30	47,65 %	1 min 56,62 s
300	1	1.000	200	115,14	45,73 %	13,35 s
300	1	2.500	200	107,86	48,05 %	31,40 s
300	1	5.000	200	101,28	46,74 %	1 min 1,24 s
300	1	7.500	200	96,86	47,04 %	1 min 27,68 s
300	1	10.000	200	94,69	47,06 %	2 min 4,02 s
400	1	1.000	200	113,22	46,19 %	14,74 s
400	1	2.500	200	104,50	47,36 %	33,45 s
400	1	5.000	200	97,81	48,32 %	1 min 0,88 s
400	1	7.500	200	92,08	46,78 %	1 min 33,15 s
400	1	10.000	200	88,26	45,76 %	2 min 8,32 s
500	1	1.000	200	111,38	45,92 %	15,12 s
500	1	2.500	200	103,12	47,81 %	35,83 s
500	1	5.000	200	96,75	48,94 %	1 min 8,78 s
500	1	7.500	200	90,80	48,40 %	1 min 50,64 s
500	1	10.000	200	83,74	48,68 %	2 min 20,17 s

Table 7: Trials of different neural networks to find the best combination of its parameters

From the data in the table above two graphics have been made: the first one to analyze the behavior of the MSE, and the second graph to examine the changes in the average prediction error.

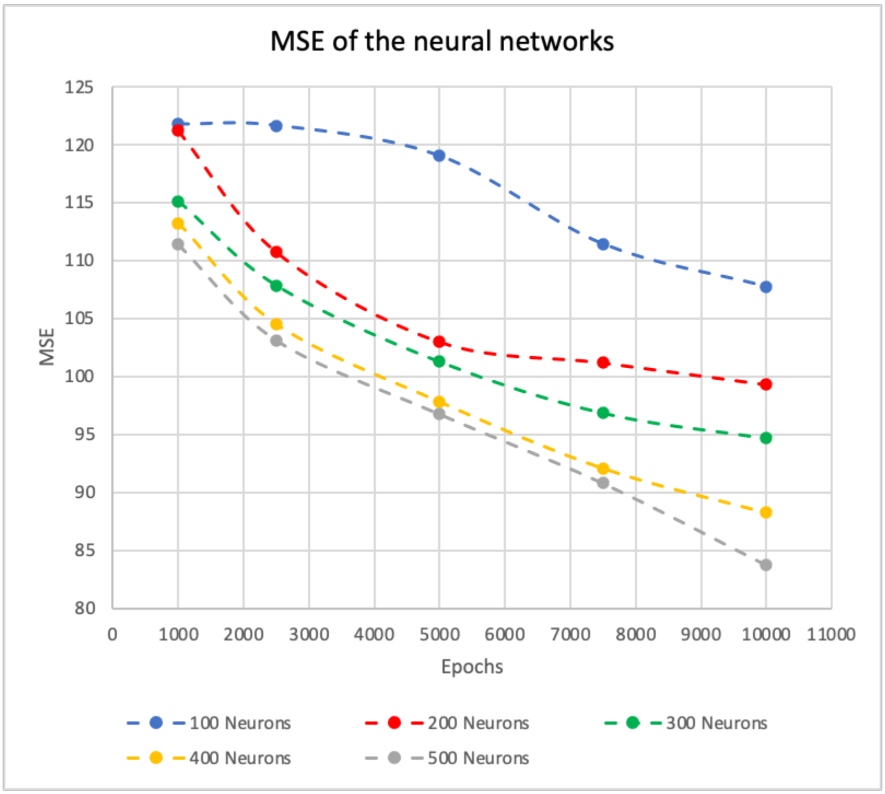

Figure 14: MSE of the neural networks broken down by number of neurons

As seen in Figure 14, the Mean Squared Error decreases as the number of epochs increases. This is completely normal since the training of the neural network has a strong relation with the number of epochs. However, more epochs does not mean a better neural network, because the neural network may be overfitted.

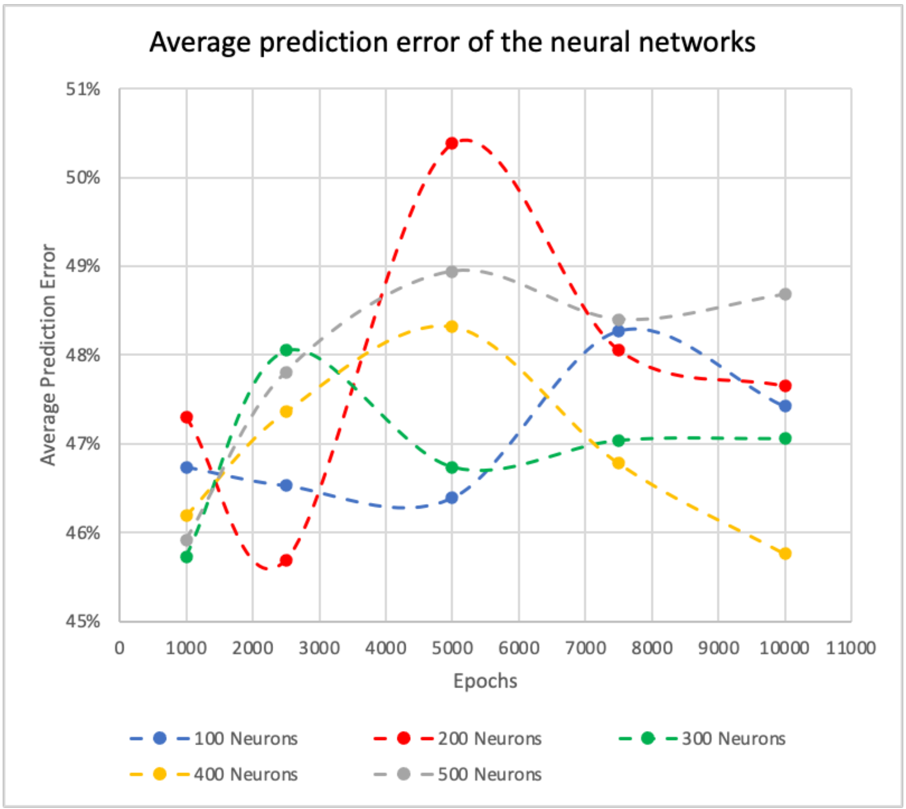

Figure 15: Average prediction error of the neural networks broken down by number of neurons

On the other hand, there is no large difference between all the neural networks regarding the average prediction error (see Figure 15), as all the values are between 45% and 51%, although the smaller the value the better.

The minimum values are 45,69%, which is obtained implementing 200 neurons and 2.500 epochs, and 45,76%, which is achieved with 400 neurons and 10.000 epochs. However, the first neural network has a MSE of 110,73, whereas the second neural network has a MSE of only 88,26 (see Figure 14).

The difference between these two values of average prediction error is almost null, so both of them explain the cross-validation data alike. But the difference between the MSE is considerably, which means that the second neural network explains better the training data.

Therefore, it is concluded that the optimum neural network of the model is the one obtained with 10.000 epochs, batch size of 200, 1 layer and 400 neurons.

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
400	1	10.000	200	88,26	45,76 %	2 min 8,32 s

Table 8: Parameters of the optimum neural network

Obviously, this does not mean that we would obtain exactly the same neural network if we apply these parameters, since two neural networks are never identical. But we would get a neural network very similar.

Moreover, it must be taken into account that not all neural networks have been tested out. For example, a neural network with one layer, the same batch size, 431 neurons and 9.972 may accomplish slightly better results. However, the outcome would be practically equal.

5.3. Conclusions of the first trial

In this section the results of the first trial are discussed and it is analyzed whether this procedure is enough to predict the safety stock of a material without the intervention of a person.

After performing the multiple linear regression model, the parameters shown below were considered as significant for the dataset. Thus, these were the variables used as inputs in all neural networks built in this first part of the investigation.

Neural network inputs
Order lines
Product Activity (PA)
Frequency of demand
Actual demand (sales)
Forecasted demand
Make to strategy
Make to strategy * Order lines

Table 9: Significant variables according to the linear regression model

The Make to strategy*Order lines input is the variable calculated as the product of the binary variable representing the make to strategy and the continuous variable of the order lines. In other words, it is the parameter that represents the interaction term between the make to strategy and the order lines.

As a first conclusion drawn from the neural networks implemented, the number of epochs is fundamental to the performance of the neural network. In general, the more epochs have a neural network, the more training is applied to the algorithm and, therefore, the better the outcome is predicted.

On the other hand, it has been clearly identified the effect of overfitting a model. A neural network can be trained as much as wanted, and the more trained the neural network is, the better it will be able to explain the model. But one does not want that the neural network perfectly predicts every value because it would mean that the model is overfitted, thus, it wouldn't be able to predict new data.

Below are the predictions values of an example of an overfitted neural network:

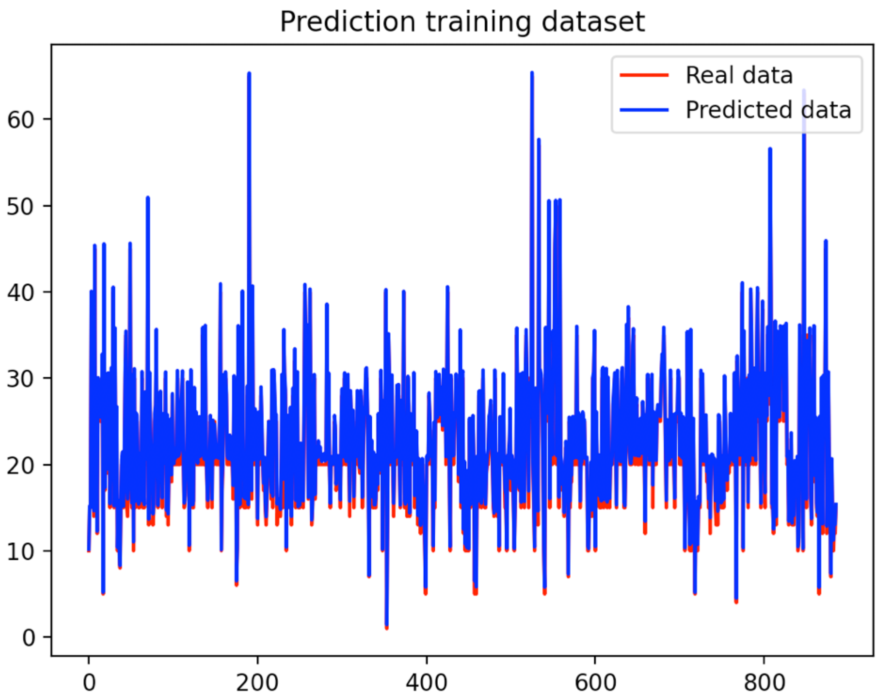

Figure 16: Predicted values of the training data of an overfitted neural network

The neural network represented in the graph above is definitely overfitted because the predicted values coincide with the real values.

Yet, as seen below in Figure 17, the predicted values for the cross-validation data are totally inaccurate, there are even negative values.

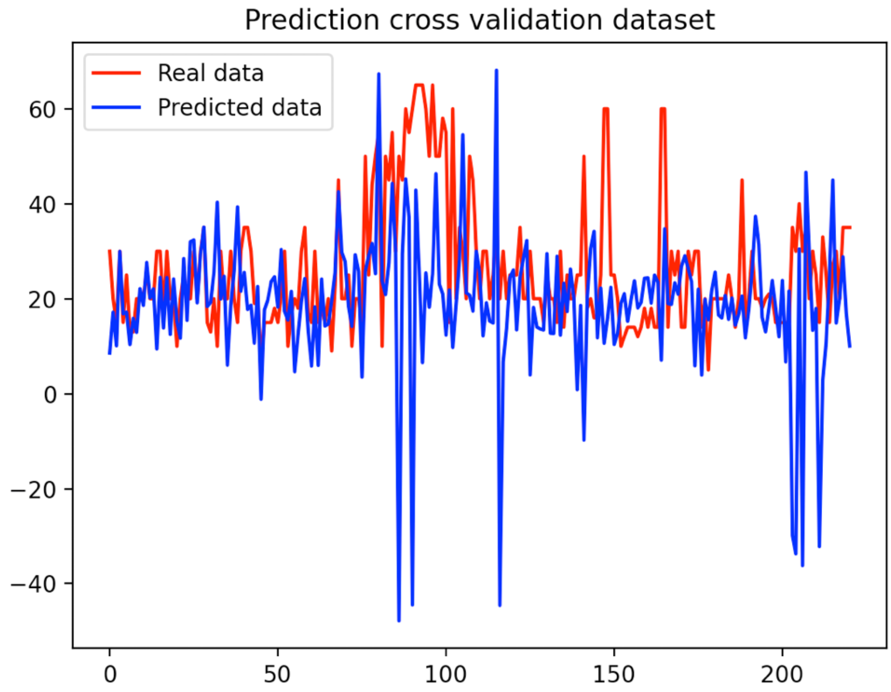

Figure 17: Predicted values of the cross-validation data of an overfitted neural network

This consequence was clearly seen when adding layers to the neural network. Obviously, the error of the training data decreased with each added layer, however, the error of the cross-validation data is significantly lower implementing one single layer.

Another conclusion of the investigation is that the batch size do not affect much the error obtained, only the time it takes for the neural network to yield. Thereby, it is better to input a high batch size so that the algorithm works faster.

The parameter that affects the most to the error of the neural network is its number of neurons. A substantial number of neurons reduces considerably both the training error and the cross-validation error. Again, too many neurons in the neural network cause the algorithm to overfit the model and thus rise the prediction error.

Taking into account the effect of all these parameters, the best neural network accomplished in the research has an average prediction error of 45,76%, obtained with a batch size of 200, 10.000 epochs, 1 layer and 400 neurons.

Finally, the results of this investigation are evidently not good enough, since no neural network with an average prediction error below the 40% has been achieved. And 40% as an average is already extremely high.

The breakdown of the prediction error is seen in the following histogram:

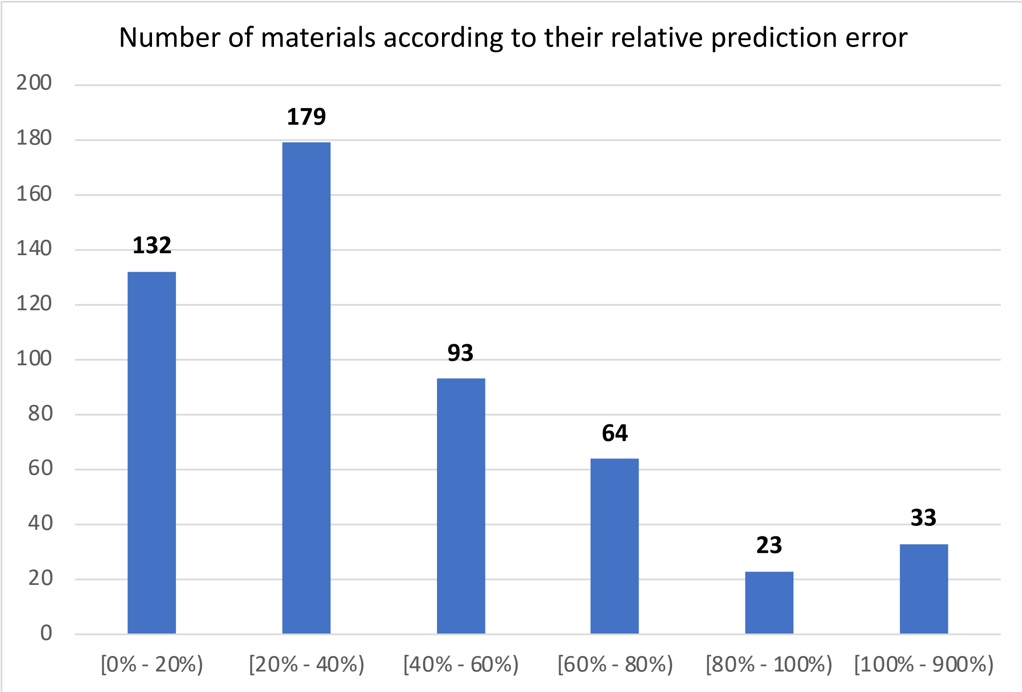

Figure 18: Number of materials according to their relative prediction error (first trial)

Although there are some materials whose safety stock are predicted with complete accuracy, there are too many materials with huge relative error. In fact, the maximum prediction error is 879%, which is totally unacceptable.

6. Second trial: neural network based on professional experience

After the failure of the trial explained in the previous section, which consisted of a neural network whose variables were determined by a linear regression model, in this section is examined another approach of building the neural network.

In particular, several supply planners who decide the value of the safety stock of different materials in their job are asked in order to identify the relevant parameters in choosing the safety stock.

Then, a neural network is performed based on the answers obtained by the experts. The results of the interviews are used to select the input of the neural network.

In addition, to carry out the neural network the materials are grouped according to their characteristics. Thus, a neural network for each type of material is performed.

The objective of this section is to find a better way of training the algorithm so that the neural network improves the prediction error obtained in the previous chapter. In theory, by only selecting the variables that the supply planners actually use and grouping the materials by typology it will be easier for the neural network to be trained and it will explain better the model.

6.1. Interviews to supply planners

In this case, the input of the neural networks will be deduced from the answers received from the surveys. The objective is to introduce to the neural network only variables that are used in real decision making, instead of all the variables of the dataset. For this reason, professionals are interviewed, to find out the variables they actually use.

The possible responses of the supply planners are as follows:

- **Make to strategy:** the replenishment of the materials can be done according two methods, the make to stock (MTS) strategy or the make to order (MTO) strategy. The MTS strategy consists of restocking the material periodically and, on the other hand, in the MTO strategy the material is restocked whenever an order is sent. Logically, the kind of strategy selected for the material can alter the safety stock as they are two totally different strategies.

- **Minimum Order Quantity (MOQ):** the MOQ is the minimum quantity that has to be ordered in order to replenish the material. Normally, this quantity is determined by the production department, since it could be that producing less than a certain quantity is not profitable.

- **Order lines:** this variable refers to the total amount of orders requested during the period of study. In theory, the more orders a material has, the more important it is and, therefore, the more safety stock it should have in order to fail as few orders as possible.

- **NON-OTIF order lines:** the term "OTIF" refers to On Time In Full, which means that an order was delivered on the day that was requested or before and with the quantity that was requested. Then, a NON-OTIF order line is an order that was not delivered correctly because it arrived later than expected or less quantity than expected was handed in. In conclusion, a NON-OTIF order line is a failed order.

- **Product Activity (PA):** the product activity is a KPI that the company has to measure the percentage of orders delivered correctly. The larger the PA of a material is, the less orders failed of that material. The formula of the product activity is as follows:

$$PA\ (\%) = 1 - \frac{NON - OTIF\ order\ lines}{Total\ order\ lines}$$

- **Total Replenishment Lead Time (TRLT):** it is the total amount of time that passes from the day that the order is confirmed to the day that the order is delivered, in other word, is the time required to replenish a material. Thereby, the Total Replenishment Lead Time is the sum of the time needed to produce the material plus the time needed to transport the material to the warehouse.

- **Standard Price (€/unit):** the standard price is the price of a single unit of a material. The price of some materials are expressed with other currencies, but all prices have been converted to euros.

- **Frequency of demand**: it is the average quantity days that pass between two orders of the same material during the period of study.

- **Daily demand (actual sales):** it is the actual average units ordered each day during the period of study.

- **Daily demand (forecast):** it is the average units per day that were forecasted during the period study. Logically, this field is not the actual demand, it is just a prediction. In theory, the more accurate the forecast, the easier it would be to satisfy the demand and, therefore, the less safety stock there would be.

- **Formula value:** the company of the study has an own formula to help decide the safety stock. This may serve as a guideline for the supply planner in determining the safety stock of the material. The expression of the formula cannot be disclosed due to the company's privacy policy.

Thus, a total of 10 supply planners have been interviewed and their responses are shown in the following table. The variables marked are the ones used by the corresponding supply planner in their decision making.

	Make to strategy	Minimum Order Quantity (MOQ)	Order lines	NON-OTIF order lines	Product Activity	Total Replenishment Lead Time	Standard Price	Frequency of demand	Daily demand (sales)	Daily demand (forecast)	Formula value
Supply planner 1									✓		✓
Supply planner 2						✓			✓		
Supply planner 3	✓					✓		✓	✓	✓	
Supply planner 4				✓	✓				✓		✓
Supply planner 5						✓			✓	✓	✓
Supply planner 6						✓		✓	✓		✓
Supply planner 7					✓	✓			✓	✓	
Supply planner 8									✓	✓	✓
Supply planner 9						✓			✓	✓	
Supply planner 10						✓		✓	✓		✓
Total	**1**	**0**	**0**	**1**	**2**	**7**	**0**	**3**	**10**	**5**	**6**

Table 10: Answers of the supply planners

The most repeated responses are the demand of the material (actual sales), the total replenishment lead time, the formula value and the demand forecasted with respectively 10, 7, 6 and 5 times answered.

Therefore, in this second trial the neural network will only have four inputs, almost half of the inputs of the first neural network. Thus, the neural network should be easier to train and the results should be better.

6.2. Grouping the materials

One of the possible explanations for the failure of the first trial may be that the dataset was composed of a lot of materials, each with its characteristics. That is to say, the data was very heterogeneous.

Therefore, in this second trial the materials are grouped into smaller subsets according to their properties. And later a neural network will be made for each group separately.

The idea is that now it will be easier for each neural network to explain the model and consequently predict the safety stock of a material. Since now the algorithm will not have to disaggregate the materials and recognize each type of material to be able to predict its safety stock, this job will already be done.

Due to the privacy policy of the company of the study, neither the attributes of the materials nor the characteristics of each group cannot be disclosed. So from now on the three groups in which the dataset is divided will be called group 1, group 2 and group 3.

The first group consists of 1107 materials, which is 42% of the total, the second group consists of 887 materials, which is 34% of the total, and the third group is made up of 629 materials, which is 24% of the total.

	Number of materials	Percentage
Group 1	1107	42%
Group 2	887	34%
Group 3	629	24%
Total	**2623**	**100%**

Table 11: Number of materials of each group

It should be noted that in this study, if a material is located in two or more warehouses, each material stored in a different plant is considered as a different material, since the safety stock in each location may also be different.

Then, the actual number of different materials in each group is less than the amounts in Table 11, but in this research they will be considered as non-equal materials because they are stored in different warehouses.

6.3. Neural network of each group of materials

In this section it is found the optimum neural network for each group of materials, a total of three groups are studied.

From the conclusions of the first trial, it is drawn that for this dataset the batch size of the neural network has an almost inexistent effect to the results of the neural network, it only negatively alters the time in yielding of the neural network. Therefore, this parameter will not be studied again.

Likewise, the effect of the number of epochs of a neural network is straightforward: the more epochs a neural network has, the smaller the error in the training data, but the longer it takes to the algorithm to yield. Thus, the neural network should have a well-balanced number of epochs, enough to train the data but not too many to avoid overfitting.

Then, as the effect of the batch size and the number of epochs is clear, they will not be studied again. Simply, the knowledge gained in the first trial will be used to carry out the following investigation.

Furthermore, all neural networks performed in this chapter will have as inputs the variables that the supply planners use the most when deciding the safety stock of a material. These inputs are the actual demand of the material (sales), the total replenishment lead time, the value of the formula provided by the company, and the demand forecasted.

6.3.1. Group 1

This group consists of 1107 materials. However, 20% of the data will be used later to do the cross-validation of the model, that is 221 materials. The rest of the materials, 886, is used to train the neural network.

Thus, to analyze the most suitable parameters for the neural network of this subset, the experiments shown in the following table are made. All of the neural network are performed with only 4 neurons, the minimum recommended to meet the four inputs.

Layers	Epochs	Batch size	MSE	Average prediction error	Time
1	100	20	63,47	36,54 %	5,09 s
1	1.000	200	57,62	34,27 %	5,72 s
1	10.000	2.000	57,21	34,41 %	17,62 s
1	100.000	20.000	57,18	34,40 %	2 min 52,04 s
1	500.000	100.000	57,18	34,40 %	13 min 25,00 s
2	100	20	57,49	34,36 %	4,86 s
2	1.000	200	57,36	34,47 %	6,12 s
2	10.000	2.000	54,09	32,70 %	19,29 s
2	100.000	20.000	50,64	33,26 %	2 min 57,44 s
2	500.000	100.000	57,35	34,49 %	13 min 54,76 s
4	100	20	57,34	33,95 %	5,35 s
4	1.000	200	57,28	34,35 %	7,34 s
4	10.000	2.000	57,52	34,48 %	20,15 s
4	100.000	20.000	53,02	32,02 %	2 min 57,14 s
4	500.000	100.000	52,63	32,34 %	14 min 31,21 s
8	100	20	57,34	34,22 %	6,20 s
8	1.000	200	57,42	33,79 %	8,35 s
8	10.000	2.000	57,19	34,33 %	24,86 s
8	100.000	20.000	61,57	36,86 %	3 min 37,75 s
8	500.000	100.000	61,57	36,86 %	17 min 52,35 s

Table 12: Trials to analyze the effect of the number of layers of the neural network (Group 1)

As seen in Figure 19, the minimum values of MSE are obtained between 2 and 4 layers around the 100.000 epochs. Being the smallest MSE of 50,64.

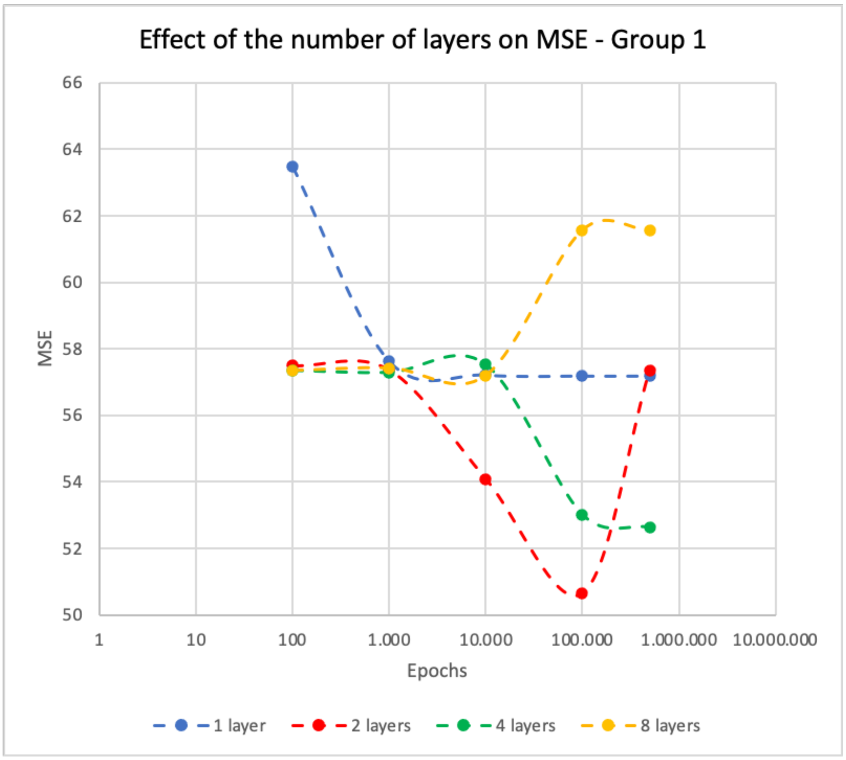

Figure 19: Relation between number of layers and MSE (Group 1)

In addition, the average prediction error is minimized implementing a neural network with the same characteristics. Between 10.000 and 100.000 epochs and using between 2 and 4 layers is when the minimum values are reached as seen in Figure 20.

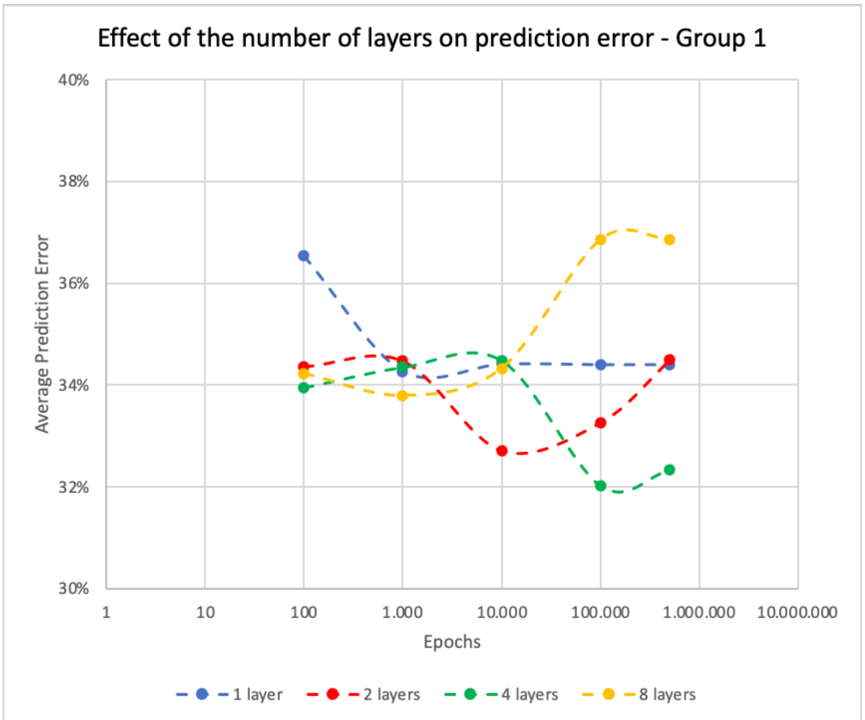

Figure 20: Relation between number of layers and Average Prediction Error (Group 1)

Therefore, in the absence of checking the effect of the number of neurons, the best neural networks are achieved with 2-4 layers and around 100.000 epochs.

Now the effect of the number of neurons is analyzed by performing the neural networks seen in Table 13. All of them are built with only 1 layer.

Neurons	Epochs	Batch size	MSE	Average prediction error	Time
8	1.000	200	51,42	34,42 %	6,38 s
20	1.000	200	57,32	34,39 %	5,97 s
50	1.000	200	53,37	33,20 %	6,06 s
100	1.000	200	52,28	31,74 %	6,63 s
200	1.000	200	51,19	31,21 %	6,71 s
500	1.000	200	48,23	31,33 %	7,56 s
1.000	1.000	200	46,06	30,68 %	8,72 s
2.000	1.000	200	44,41	30,59 %	10,19 s
10.000	1.000	200	38,21	29,37 %	28,34 s
8	10.000	2.000	52,50	32,30 %	18,34 s
20	10.000	2.000	56,31	35,24 %	17,55 s
50	10.000	2.000	47,54	30,06 %	18,11 s
100	10.000	2.000	43,42	32,50 %	21,89 s
200	10.000	2.000	37,14	30,92 %	22,12 s
500	10.000	2.000	29,05	38,13 %	28,94 s
1.000	10.000	2.000	25,12	47,46 %	36,93 s
2.000	10.000	2.000	23.23	41,63 %	1 min 6,34 s
10.000	10.000	2.000	19,28	46,54 %	4 min 11,73 s

Table 13: Trials to analyze the effect of the number of neurons of the neural network (Group 1)

The following two graphs are made with the results obtained:

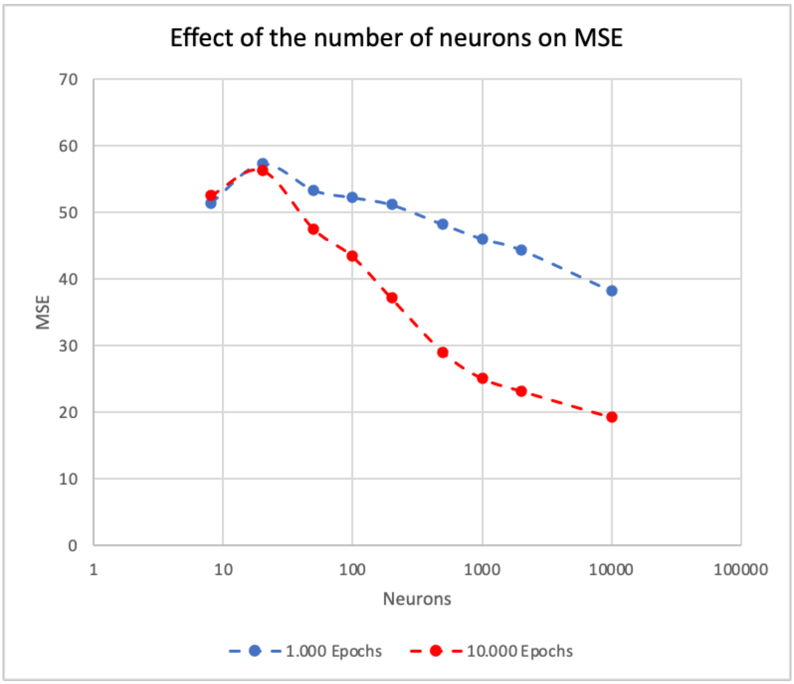

Figure 21: Relation between number of neurons and MSE (Group 1)

In general, the more neurons area added to the algorithm, the less error it has in predicting the values of the training data. And obviously the MSE also diminishes when the number of epochs increases.

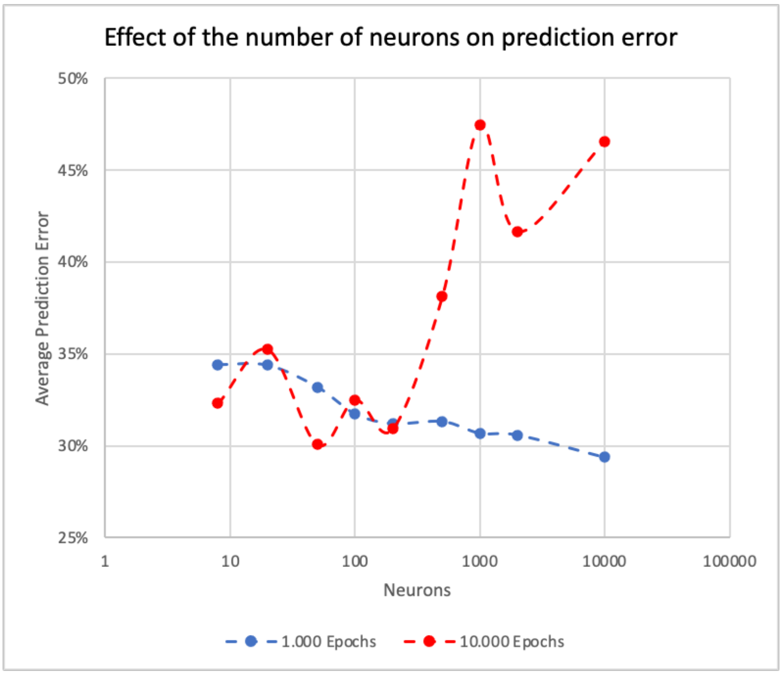

Figure 22: Relation between number of neurons and average prediction error (Group 1)

However, the smallest average prediction error is achieved using only 1.000 epochs around 10.000 neurons. Given the fact that it in this investigation is more important the prediction error because the objective is to predict the safety stock, it is more convenient to use this combination of parameters: 1.000 epochs and around 10.000 neurons.

In addition, the average prediction error accomplished with just 1 layer is less than the error obtained with any combination of 2 or more layers. Therefore, in this case the number of neurons is more significant the number the number of layers and only one layer will be used.

Finally, to find the best possible result, several trials are carried out around the best combination found:

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
1.000	1	1.000	200	46,06	30,68 %	8,72 s
5.000	1	1.000	200	47,30	31,57 %	14,54 s
10.000	1	1.000	200	38,21	29,37 %	28,34 s
25.000	1	1.000	200	41,35	30,17 %	1 min 23,36 s
50.000	1	1.000	200	38,69	29,96 %	4 min 7,25 s
100.000	1	1.000	200	46,57	33,39 %	4 min 47,65 s

Table 14: Trials of different neural networks to find the best combination of its parameters (Group 1)

As seen in the graph represented below, both values of MSE and average prediction error are minimized using 10.000 neurons.

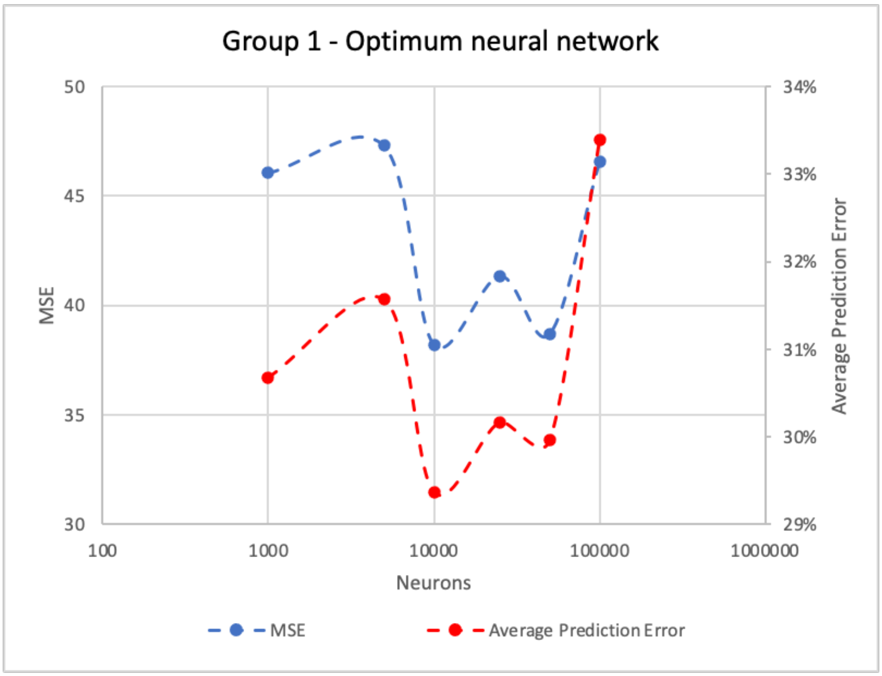

Figure 23: Neural networks with the best results (Group 1)

Therefore, the best neural network found for group 1 of materials is as follows:

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
10.000	1	1.000	200	38,21	29,37 %	28,34 s

Table 15: Parameters of the optimum neural network (Group 1)

6.3.2. Group 2

The second group is composed of 887 materials, which is 34% of the total. Note that not all data is used to train the neural network, the 20% of it (177 materials) is used to cross-validate the results obtained.

Thus, several trials are performed in order to analyze the effect of the number of hidden layers in the neural network to the results. All the neural networks are bult with only four neurons, the minimum recommended since there are four inputs. See all trials registered in the following table.

Layers	Epochs	Batch size	MSE	Average prediction error	Time
1	100	20	56,75	45,33 %	4,15 s
1	1.000	200	65,40	45,88 %	5,41 s
1	10.000	2.000	53,89	45,27 %	17,88 s
1	100.000	20.000	53,92	45,22 %	3 min 14,27 s
1	500.000	100.000	53,86	45,30 %	13 min 22,89 s
2	100	20	54,50	45,32 %	4,36 s
2	1.000	200	53,94	45,24 %	6,29 s
2	10.000	2.000	40,83	45,25 %	19,91 s
2	100.000	20.000	53,75	45,58 %	3 min 4,16 s
2	500.000	100.000	53,75	45,57 %	14 min 41,59 s
4	100	20	53,98	44,60 %	4,86 s
4	1.000	200	53,92	45,15 %	5,67 s
4	10.000	2.000	53,76	45,56 %	20,86 s
4	100.000	20.000	53,29	45,03 %	3 min 2,96 s
4	500.000	100.000	53,42	45,59 %	14 min 36,49 s
8	100	20	59,28	47,83 %	5,23 s
8	1.000	200	53,91	45,31 %	6,46 s
8	10.000	2.000	53,76	45,56 %	24,28 s
8	100.000	20.000	53,41	45,48 %	3 min 38,18 s
8	500.000	100.000	53,79	45,57 %	17 min 5,71 s

Table 16: Trials to analyze the effect of the number of layers of the neural network (Group 2)

From the results obtained in the table above, two graphs are made: one to examine how the MSE is altered, and the second one to analyze the fluctuation in the average prediction error.

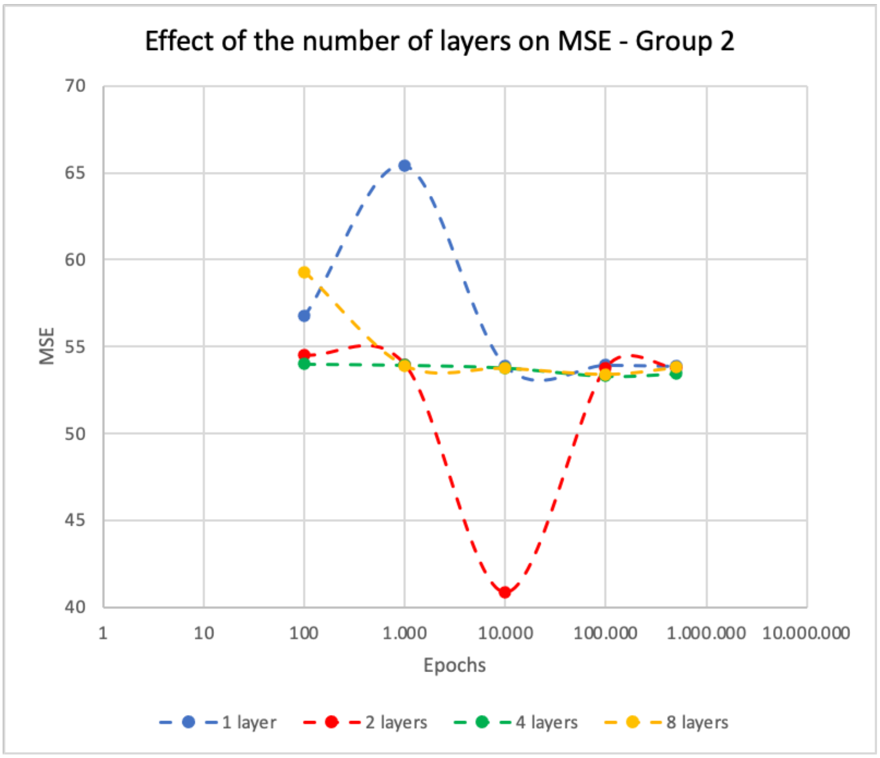

Figure 24: Relation between number of layers and MSE (Group 2)

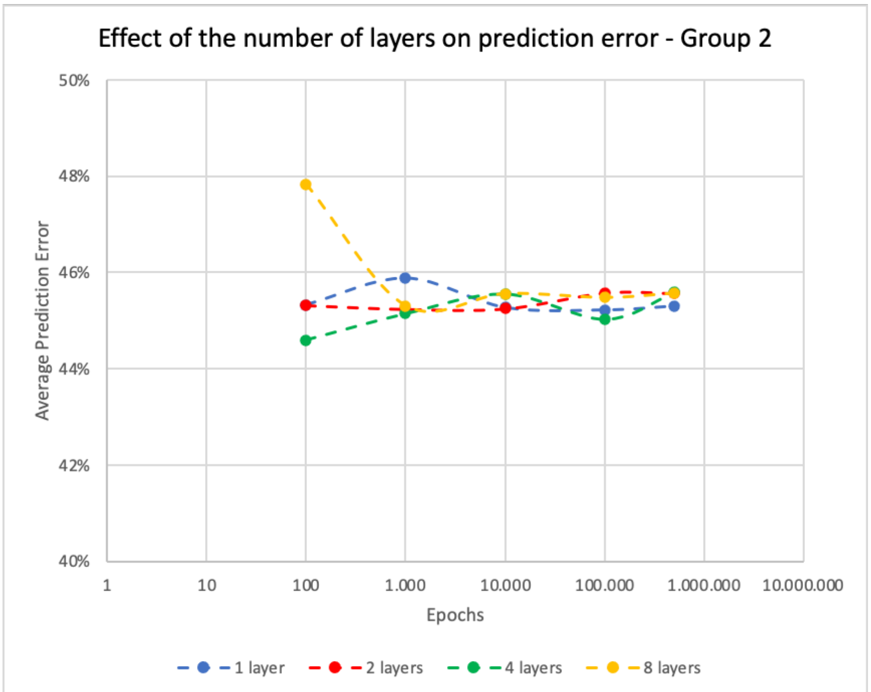

Figure 25: Relation between number of layers and average prediction error (Group 2)

As seen in both figures above, the consequences of modifying the number of hidden layers are not clear. The values in the MSE graph do not follow any pattern and all the values in the average prediction error are too similar.

Any conclusion from the number of layers can be drawn, therefore, only layer will be used to build the model in order to make easier its interpretation. Besides, there is practically no difference in implementing 1 or several layers since the solutions reaches are virtually the same.

Then, the following trials are performed to examine how the number of neurons affect to the results obtained, all of them are made with only layer.

Neurons	Epochs	Batch size	MSE	Average prediction error	Time
8	100	20	57,03	44,46 %	3,89 s
20	100	20	54,36	45,09 %	4,59 s
50	100	20	42,22	42,22 %	3,77 s
100	100	20	41,61	42,55 %	4,72 s
200	100	20	40,68	42,71 %	4,26 s
500	100	20	39,98	43,79 %	4,49 s
1.000	100	20	39,68	44,01 %	4,62 s
2.000	100	20	38,32	43,07 %	4,50 s
10.000	100	20	37,55	43,53 %	6,19 s
8	1.000	200	54,26	45,21 %	4,94 s
20	1.000	200	53,82	45,22 %	4,81 s
50	1.000	200	40,62	42,80 %	5,29 s
100	1.000	200	39,80	42,88 %	5,05 s
200	1.000	200	39,21	42,69 %	5,34 s
500	1.000	200	37,34	42,98 %	6,37 s
1.000	1.000	200	36,91	42,88 %	6,90 s
2.000	1.000	200	36,35	43,06 %	8,51 s
10.000	1.000	200	33,64	44,05 %	24,79 s
8	10.000	2.000	53,80	45,26 %	19,26 s
20	10.000	2.000	39,31	43,42 %	24,42 s
50	10.000	2.000	38,00	43,45 %	18,49 s
100	10.000	2.000	36,52	44,56 %	20,07 s
200	10.000	2.000	31,96	46,05 %	24,31 s
500	10.000	2.000	26,56	47,09 %	26,40 s
1.000	10.000	2.000	23,89	52,55 %	30,71 s
2.000	10.000	2.000	22,34	52,12 %	52,67 s
10.000	10.000	2.000	18,75	51,61 %	3 min 46,94 s

Table 17: Trials to analyze the effect of the number of neurons of the neural network (Group 2)

Using the results obtained, the values of MSE and average prediction are represented below in two separate plots.

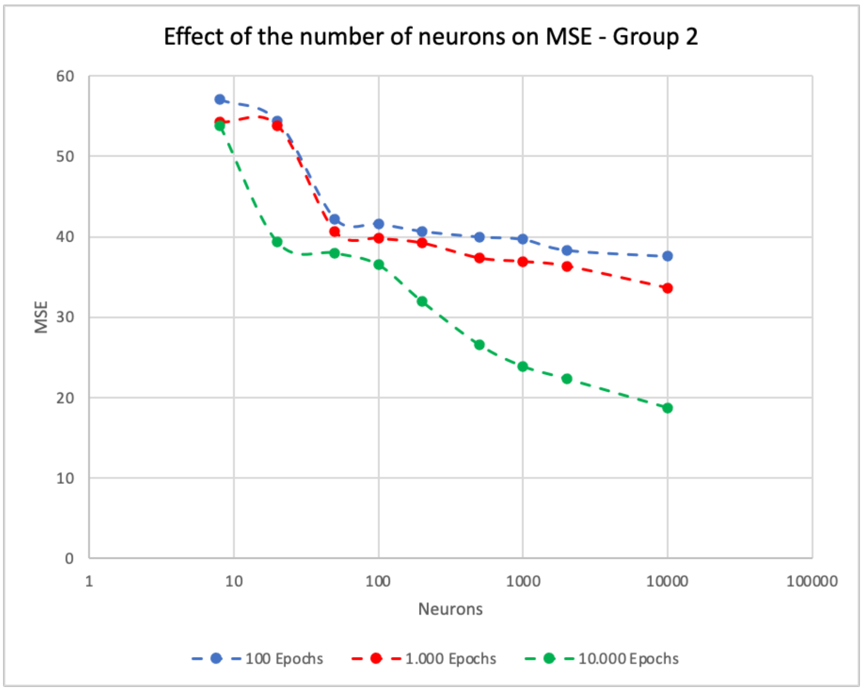

Figure 26: Relation between number of neurons and MSE (Group 2)

As seen in the graph above, the more neurons or more epochs, the lower the MSE is. This is logical since it means that the algorithm does more calculations, that is, the neural network is more trained.

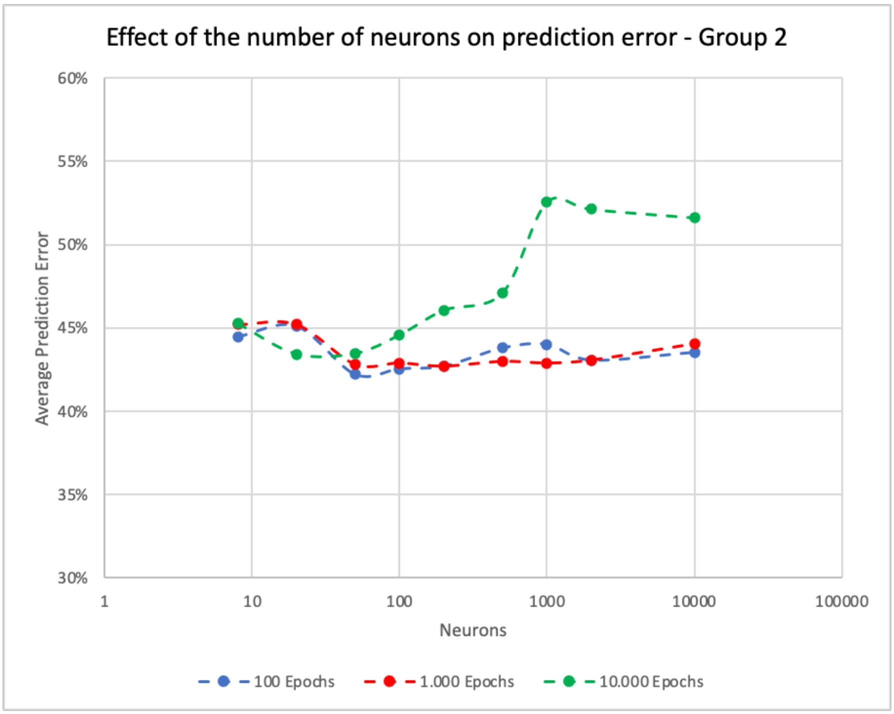

Figure 27 Relation between neurons and average prediction error (Group 2)

However, when implementing the neural network with 10.000 epochs, if more than 100 neurons are used, the algorithm overfits the neural network. That is the reason why the average prediction error grows so much from that combination.

As seen in Figure 27, the error obtained using 100 or 1.000 epochs is nearly identical, therefore, in this case 1.000 epochs will be used to perform the neural network as the MSE is lower with 1.000 epochs than with 100 epochs.

Thus, the combination that minimizes both MSE and average prediction error is achieved with 1.000 epochs and 1.000 neurons, with a MSE of 36,91 and an average prediction error of 42,88%.

With the conclusions obtained by carrying out all the trails explained above, several experiments are made to do a local optimization and find the best combination of the parameters (see Table 18).

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
500	1	1.000	200	37,34	42,98 %	6,37 s
600	1	1.000	200	37,47	42,86 %	6,49 s
700	1	1.000	200	37,16	42,71 %	7,30 s
800	1	1.000	200	37,04	42,79 %	7,13 s
900	1	1.000	200	36,85	43,14 %	7,11 s
1.000	1	1.000	200	36,91	42,88 %	6,90 s
1.100	1	1.000	200	36,85	43,38 %	7,46 s
1.200	1	1.000	200	36,64	43,17 %	7,14 s
1.500	1	1.000	200	36,55	43,02 %	8,66 s
2.000	1	1.000	200	36,35	43,06 %	8,51 s

Table 18: Trials of different neural networks to find the best combination of its parameters (Group 2)

The results obtained are summarized in the following graph:

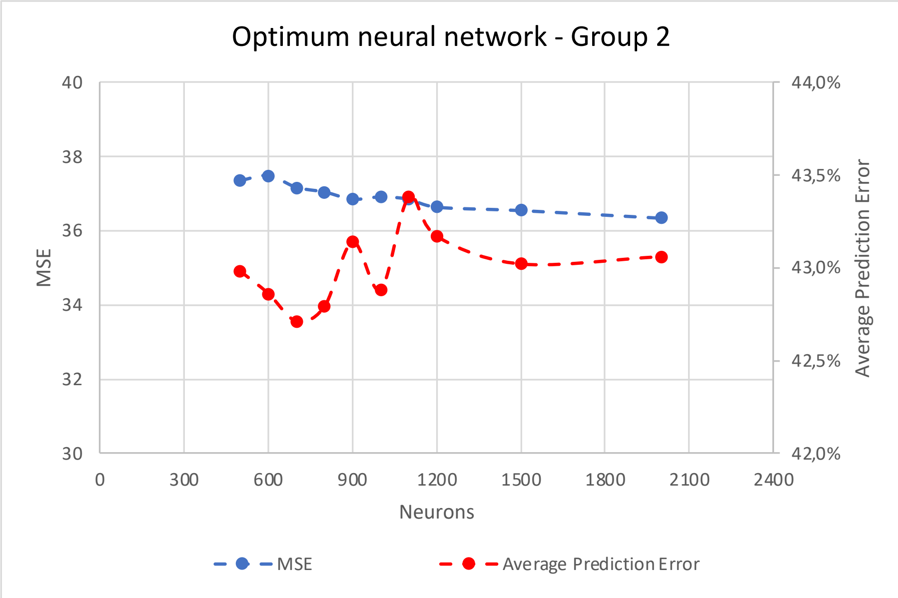

Figure 28: Neural networks with the best results (Group 2)

As expected, the MSE declines according to the number of neurons, since the training of the neural network is heavier, all the values are practically equal.

And the same happens with the average prediction error, all the values are virtually the same. Though obviously the minimum value is chosen as the optimum combination for the neural network of the materials classified as group 2, that is, 700 neurons, 1.000 epochs, a batch size of 200, and 1 layer.

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
700	1	1.000	200	37,16	42,71 %	7,30 s

Table 19: Parameters of the optimum neural network (Group 2)

6.3.3. Group 3

The third group of materials has a total of 629 materials, which is 24% of the total of the data of the study. As in the other two groups, the 20% of the subset is used to cross-validate the results of the neural network, instead of using them to train the neural network. That is, 126 materials are used in the cross-validation, and 503 materials are used to train the algorithm.

Thus, to examine the effect of the number of layers to this subset the trials seen in Table 20 are performed, all of them are carried out with only 4 neurons, the minimum recommended to implement a neural network with four inputs.

Layers	Epochs	Batch size	MSE	Average prediction error	Time
1	20	4	381,13	71,84 %	3,00 s
1	30	5	423,04	70,47 %	3,21 s
1	40	10	435,49	67,28 %	2,39 s
1	50	10	392,34	59,16 %	3,03 s
1	75	15	334,19	62,50 %	3,13 s
1	100	20	395,34	66,63 %	3,15 s
1	125	20	229,11	98,78 %	3,64 s
1	150	20	270,37	102,10 %	4,14 s
2	20	4	225,87	105,05 %	3,19 s
2	30	5	224,20	106,09 %	3,65 s
2	40	10	231,37	105,61 %	2,76 s
2	50	10	230,22	104,31 %	3,26 s
2	75	15	222,40	108,44 %	3,22 s
2	100	20	223,91	107,92 %	3,21 s
2	125	20	233,36	103,84 %	5,31 s
2	150	20	223,17	109,47 %	4,51 s
4	20	4	223,08	108,22 %	3,54 s
4	30	5	223,21	108,72 %	3,68 s
4	40	10	225,33	103,83 %	4,04 s
4	50	10	223,34	110,45 %	3,27 s
4	75	15	222,75	109,07 %	3,43 s
4	100	20	222,86	109,46 %	3,36 s
4	125	20	222,23	109,91 %	3,92 s
4	150	20	222,13	108,07 %	4,76 s

Table 20: Trials to analyze the effect of the number of layers of the neural network (Group 3)

One can observe better the results obtained regarding the MSE and the average prediction in Figure 29 and Figure 30.

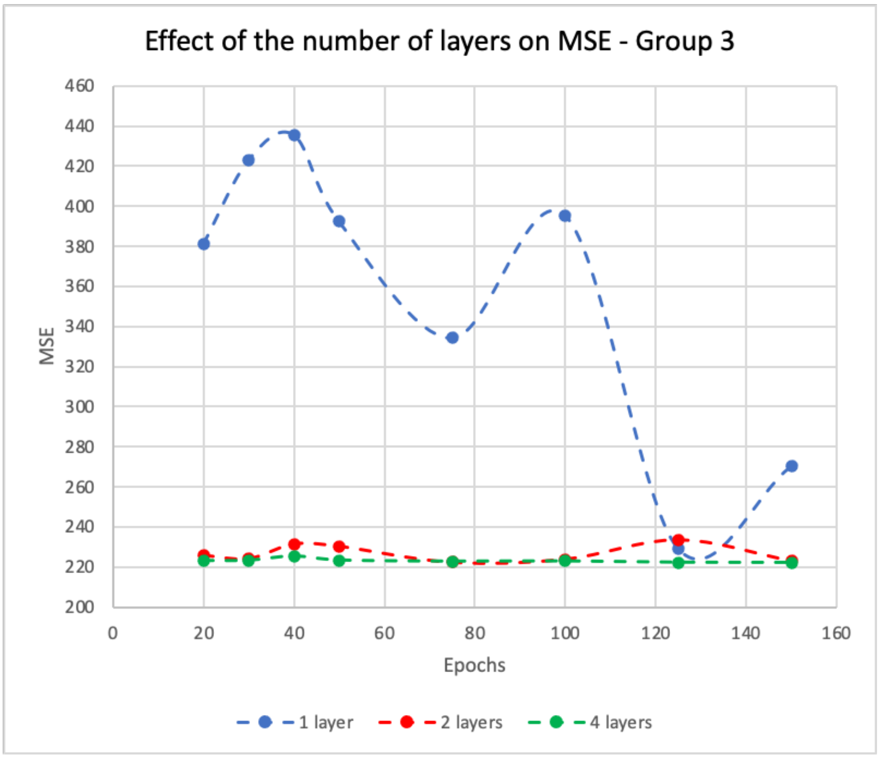

Figure 29: Relation between number of layers and MSE (Group 3)

Expectedly, the error obtained with 2 and 4 layers is lower than the error obtained with only 1 layer, even though the disparity between one layer and the others is extremely high.

On the other hand, the difference between two and four layers is almost inexistent, in fact, the error does not decrease as the number of epochs increases, as normally does. This is a sing that indicates that the neural network implemented using the subset of group 3 gets rapidly overfitted, since a very similar solution is reached using two or four layers.

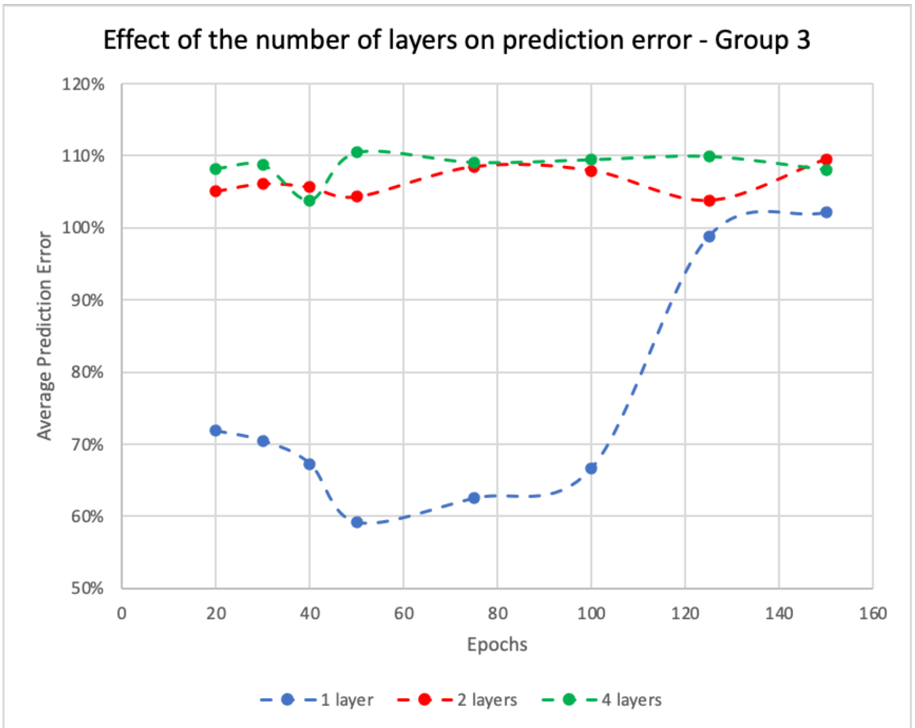

Figure 30: Relation between number of layers and the average prediction error (Group 3)

The average prediction error obtained using two or four layers are also very similar regardless of the number of epochs. In addition, this value of error is reached with only one layer when implementing in the algorithm 125 epochs or more.

This confirms that the neural network built with this subset is easily overfitted. Thus, to find the best neural network in this case it is better to execute the algorithm with only 1 layer, otherwise the neural network is overfitted and a very poor solution is obtained.

Unlike the other two groups, very few epochs are needed to find the neural network with least error, that is because of the overfitting of the neural network. Note that more trials were performed with larger number of epochs but the results are not included because the error obtained was exceedingly high, so it makes no sense to even consider them.

Next, several neural networks are carried out in order to analyze the effect of the number of neurons on the results. All neural networks are performed with just one layer, since better results are obtained as demonstrated above. Furthermore, very few epochs are implemented since in this case the overfitting of the neural network occurs very early.

Neurons	Epochs	Batch size	MSE	Average prediction error	Time
4	20	4	452,77	80,29 %	2,90 s
8	20	4	284,95	99,72 %	2,75 s
20	20	4	228,85	105,89 %	2,75 s
50	20	4	221,88	108,64 %	2,69 s
100	20	4	207,72	105,12 %	2,80 s
200	20	4	183,28	102,20 %	2,90 s
500	20	4	161,42	102,10 %	2,90 s
1.000	20	4	147,83	98,19 %	3,68 s
2.000	20	4	142,53	90,95 %	2,98 s
10.000	20	4	146,47	99,27 %	3,42 s
4	50	10	364,24	69,06 %	2,74 s
8	50	10	276,74	96,55 %	2,81 s
20	50	10	227,84	104,35 %	2,72 s
50	50	10	207,02	105,66 %	2,98 s
100	50	10	215,87	110,11 %	2,88 s
200	50	10	159,47	98,07 %	2,91 s
500	50	10	148,65	93,67 %	3,41 s
1.000	50	10	140,87	93,08 %	3,25 s
2.000	50	10	137,86	98,56 %	3,19 s
10.000	50	10	132,19	98,60 %	4,64 s
4	80	15	404,43	79,63 %	3,13 s
8	80	15	266,85	101,00 %	2,90 s
20	80	15	224,54	107,09 %	3,06 s
50	80	15	220,92	108,58 %	3,18 s
100	80	15	187,73	103,33 %	3,34 s
200	80	15	150,95	96,96 %	3,26 s
500	80	15	144,05	92,57 %	3,39 s
1.000	80	15	137,89	93,07 %	3,50 s
2.000	80	15	132,86	94,19 %	3,37 s
10.000	80	15	128,21	91,19 %	4,42 s

Table 21: Trials to analyze the effect of the number of neurons of the neural network (Group 3)

The results of the trials are summarized in Figure 31 and Figure 32.

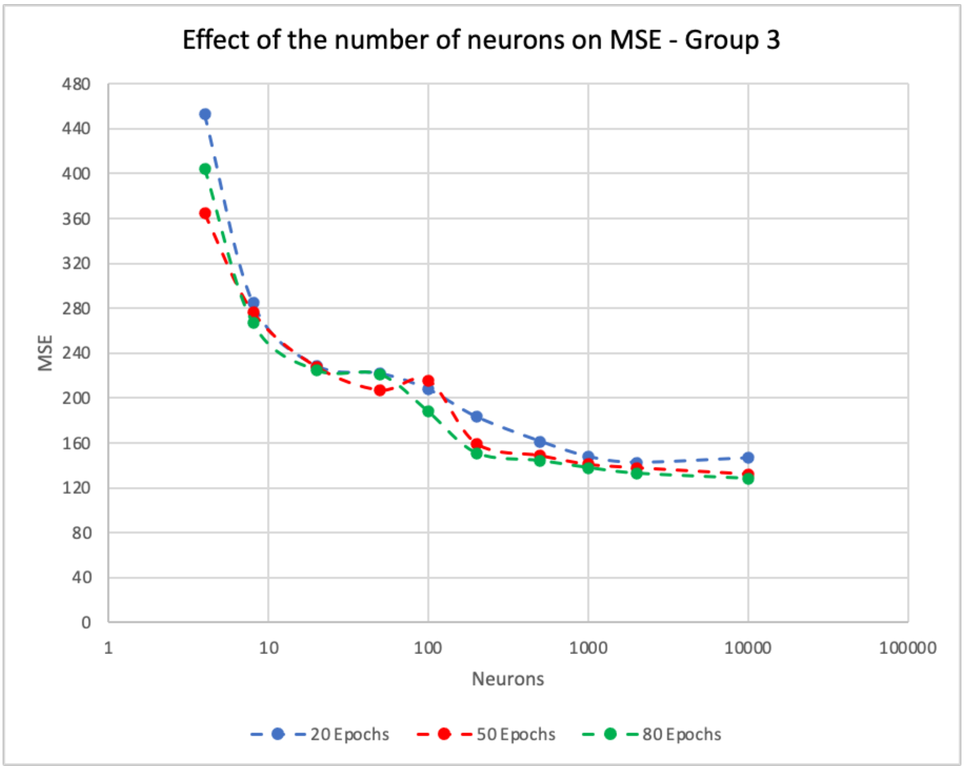

Figure 31: Relation between number of neurons and MSE (Group 3)

As expected, the MSE diminishes as the number of neurons and the number of epochs increases, since the algorithm spends more time in calculating the neural network. Even though the consequences of modifying the number of epochs are practically null.

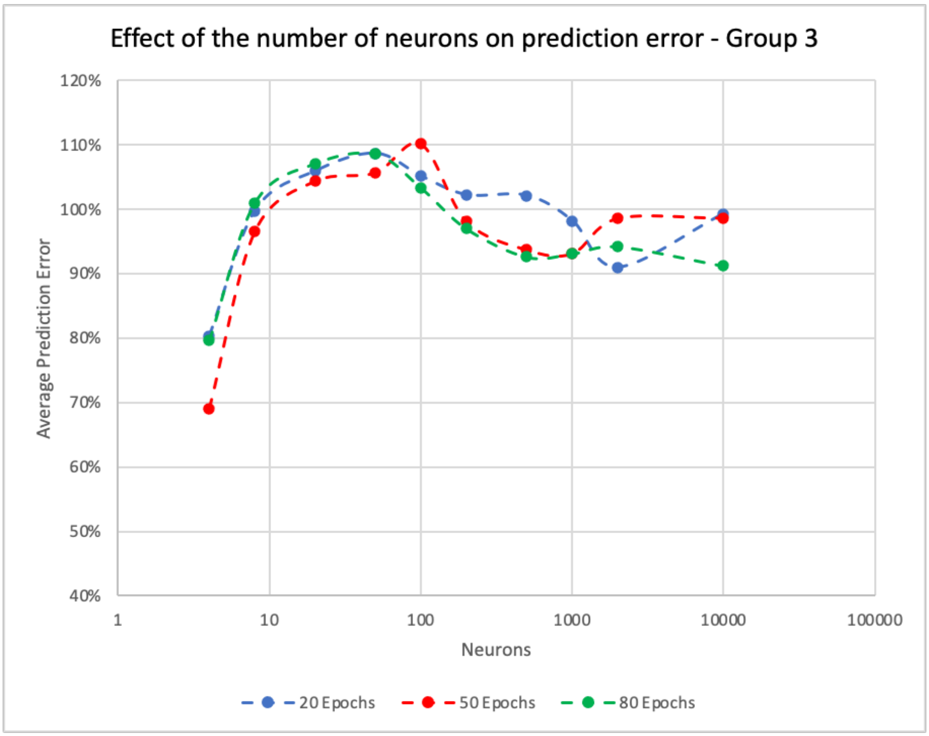

Figure 32: Relation between the number of neurons and the average prediction error (Group 3)

On the other hand, the average prediction error rapidly increases around 10 neurons and it remains around the same values until 10000 neurons. That is because the neural network found is overfitted and therefore the solution reached is very similar.

Again, the neural network of this group overfits very fast in comparison to the other groups, either increasing the number of neurons or the number of layers.

Thus, the least error is obtained around 50 epochs using 1 layer. Next several trials are performed around these values to locally optimize the neural network and fins the best combination possible. Since the overfit of the model occurs very fast, several neural networks below the recommended minimum number of neurons are built (as many neurons as inputs, which in this case are 4) to see whether better results are achieved.

Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
3	1	40	10	779,25	59,79 %	2,69 s
3	1	45	10	662,61	57,85 %	2,60 s
3	1	50	10	524,75	61,12 %	2,85 s
3	1	55	10	447,86	66,47 %	3,02 s
3	1	60	10	406,81	69,68 %	3,27 s
4	1	40	10	435,49	67,28 %	2,39 s
4	1	45	10	479,24	70,57 %	2,61 s
4	1	50	10	392,34	59,16 %	3,03 s
4	1	55	10	283,38	72,17 %	4,41 s
4	1	60	10	270,94	96,40 %	3,67 s
5	1	40	10	332,51	70,44 %	2,61 s
5	1	45	10	341,74	71,11 %	2,81 s
5	1	50	10	348,71	84,63 %	2,81 s
5	1	55	10	307,91	95,92 %	3,04 s
5	1	60	10	289,17	97,23 %	3,26 s

Table 22: Trials of different neural networks to find the best combination of its parameters (Group 3)

Conclusions are drawn from representing the results obtained in Figure 33 and Figure 34.

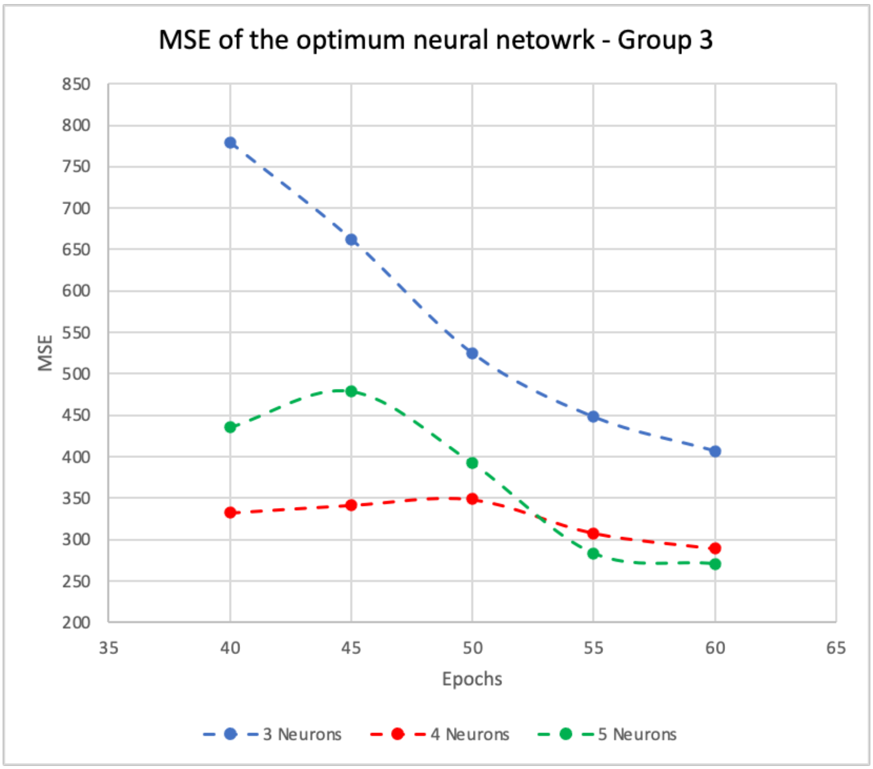

Figure 33: Neural networks found to minimize MSE (Group 3)

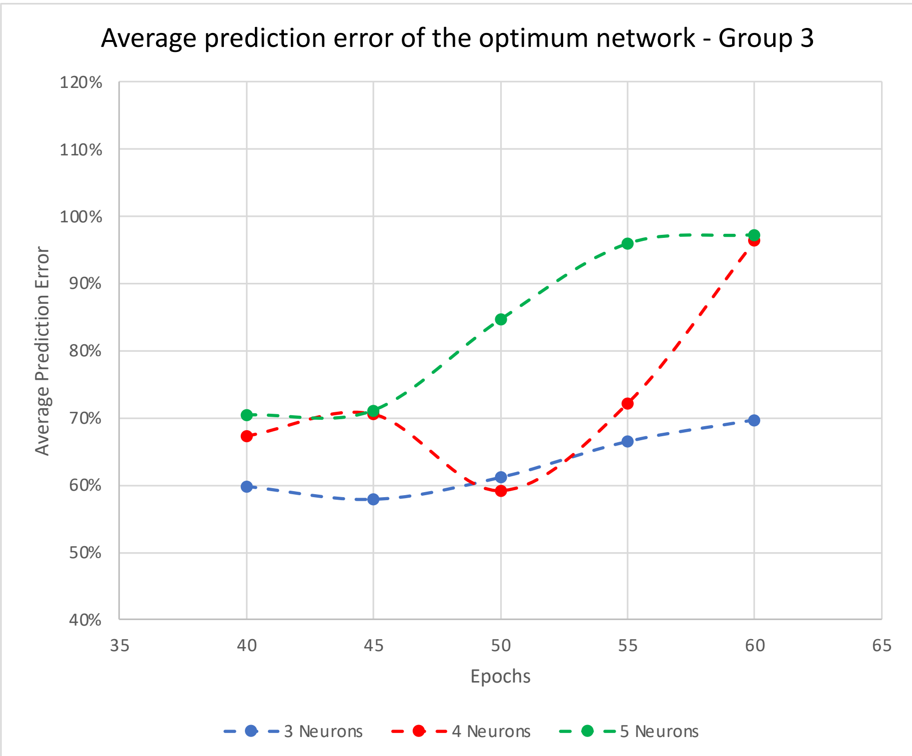

Figure 34: Neural networks found to minimize the average prediction error (Group 3)

The minimum average prediction error is accomplished with only 3 neurons (57,85%). However, by implementing neural networks with so few neurons, the MSE increases considerably, which means that the neural network is not trained properly.

Since a similar average prediction error is achieved using 4 neurons and 50 epochs (59,16%) and a markedly lower value of MSE is obtained, the combination taken as optimum is the neural network accomplished with 4 neurons, 50 epochs, 1 layer and a batch size of 10.

Neurons	**Layers**	**Epochs**	**Batch size**	**MSE**	**Average prediction error**	**Time**
4	1	50	10	392,34	59,16 %	3,03 s

Table 23: Parameters of the optimum neural network (Group 3)

6.4. Conclusions of the second trial

In this section the results of the second trial are analyzed. This second investigation consists in using as inputs of the neural network the variables that supply planners actually use to decide the safety stock of a material, also, the dataset is divided into three different groups so that a neural network for each group is studied.

After interviewing 10 supply planners (see Table 10), the parameters that they use the most to determine the safety stock of a material are the demand of the material (actual sales), the total replenishment lead time, the value resulting from the formula provided by the company and the demand forecasted of the material.

Neural network inputs of each group
Actual demand (sales)
Forecasted demand
Total Replenishment Lead Time (TRLT)
Value of the formula provided by the company

Table 24: Parameters used by supply planners to decide the safety stock of a material

Next, the materials are divided into three groups according their characteristics, so each group is studied independently. Moreover, not all data is used to train the algorithm, the 20% of each is used to cross-validate the results. Below is the detail of each group.

	Total number of materials	Percentage with respect to the total	Materials used in training	Materials used in cross-validation
Group 1	1107	42%	886	221
Group 2	887	34%	710	177
Group 3	629	24%	503	126
Total	**2623**	**100%**	**2099**	**524**

Table 25: Breakdown of the number of materials by group

Then, the four variables stated above are used to perform all the neural networks of this second examination. Thus, the best neural network found for each group of materials with its results is as follows:

	Neurons	Layers	Epochs	Batch size	MSE	Average prediction error	Time
Group 1	10.000	1	1.000	200	38,21	29,37 %	28,34 s
Group 2	700	1	1.000	200	37,16	42,71 %	7,30 s
Group 3	4	1	50	10	392,34	59,16 %	3,03 s

Table 26: Optimum neural network of each group

It is clear that the worst result is obtained with group 3, because both the MSE and the average prediction error are much higher than the neural networks of group 1 and 2.

This subset was very difficult to train, as a matter of fact, the optimum result is obtained with only 50 epochs and 4 neurons, which means that the neural network had much less training in comparison to the other two groups. In other words, it is very difficult for the algorithm to reach a decent solution.

Moreover, the result obtained with group 1 subset is notably better than the result of group 2. Although the MSE of group 1 is slightly higher, such difference is very small compared to the difference of the average prediction error. And, ultimately, the objective of the investigation is to predict the safety stock, that is, the average prediction error is more important than the

MSE obtained.

Also, the materials classified as group 1 are more similar between each other than the materials in group 2. And the similarity of materials in group 2 is greater than the similarity of materials in group 3. That is to say, the materials in group 1 are the most similar and the materials in group 3 have the most disparity.

Thus, it is concluded that the more similar the materials of the dataset, the better the outcome of the neural network.

However, none of the achieved neural networks is good enough to consider that it can predict the safety stock without the help of a human, since the average prediction error in all three cases is too high.

Another conclusion reached is that there is a relation between the size of the dataset and the load of training required for the neural network to get its optimum. Group 1 has more materials than group 2 and group 2 has more materials than group 3 (see Table 25). And the training needed for each neural network to yield the best possible result is directly related: group 1 needed more time than group 2, and group 2 took longer than group 3.

As seen in Figure 35, in all three groups the average prediction error most repeated is the one between the 0% and the 20%, in fact, this interval includes almost half of the materials of each group.

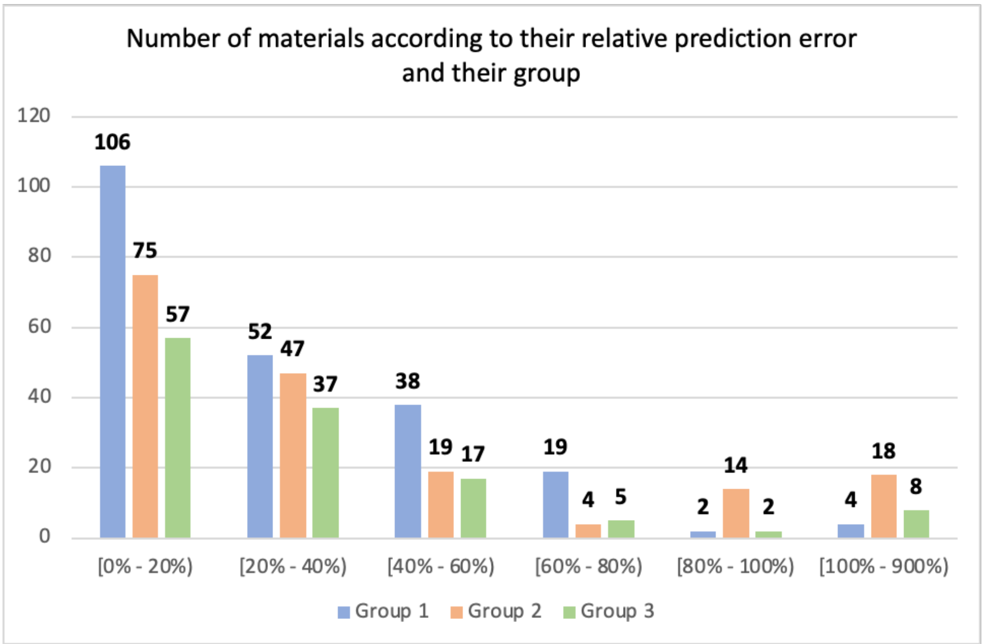

Figure 35: Number of materials according to their relative prediction error and their group (second trial)

In spite of that, the results obtained in all three cases are deficient because the average prediction error is too high. For example, every group has more than one material whose safety stock prediction has a relative error above 100%, therefore is totally unacceptable to consider any of the neural networks as a substitute for a real person.

7. Conclusions

In this section, the conclusions of the entire research are exposed together with possible further actions. In order to better understand the ideas reached, it must be taken into account that the main objective of the study is to find a neural network capable of substituting the decision-making of a supply planner regarding the safety stock of a material.

As seen in previous sections, the investigation is divided into two parts: first the dataset is studied by implementing a linear regression model followed by a neural network, and secondly, the dataset is separated in three groups and a neural network for each group is performed. Therefore, in this section the conclusions of each part of the research are presented together with a comparative analysis between the two studies.

In the first part of the investigation, the inputs of the neural network were chosen carrying out a linear regression model, thus the significant variables of the linear regression model were chosen as inputs of the neural network. On the other hand, in the second part of the investigation, to select the inputs several supply planners were asked how they plan the safety stock and their criteria were established as inputs.

	Linear regression	Criteria of supply planners
Make to strategy	✓	
Minimum Order Quantity (MOQ)		
Order lines	✓	
NON-OTIF order lines		
Product Activity (PA)	✓	
Total Replenishment Lead Time (TRLT)		✓
Standard Price		
Frequency of demand	✓	
Actual demand (sales)	✓	✓
Forecasted demand	✓	✓
Make to strategy * Order lines	✓	
Formula value		✓

Table 27: Comparison of the variables used as inputs in the neural networks of each part of the investigation

Note that the Make to strategy*Order lines input is the variable computed as the product of the binary variable representing the make to strategy and the continuous variable of the order lines. In other words, it is the parameter that represents the interaction term between the make to strategy and the order lines. Also, the formula value input consists in the result of a formula provided by the company of the study (the formula cannot be disclosed due to the privacy policy of the company).

Unexpectedly, the variables considered as relevant for the linear regression algorithm are very distant from the parameters that supply planners actually use to decide the safety stock of a material. The only common criteria are the actual demand and the forecasted demand, obviously two main factors involved in the decision making. This is a reason why the results obtained in the second trial are better than the results of the first trial, since logically the inputs of a neural network are a key element in its results.

Once the inputs are established, the next step is to perform the neural network and find the value of the parameters of the neural network that best fit to the dataset. Below are detailed the parameters of the optimum neural network of each part of the investigation with their outcome.

	Neural network with linear regression inputs	Neural network with criteria of supply planners as inputs		
		Group 1	Group 2	Group 3
Number of materials	2623	1107	887	629
Epochs	10.000	1.000	1.000	50
Batch size	200	200	200	10
Layers	1	1	1	1
Neurons	400	10.000	700	4
MSE	88,26	38,21	37,16	392,34
Average prediction error	45,76 %	29,37 %	42,71 %	59,16 %
Time	2 min 8,32 s	28,34 s	7,30 s	3,03 s

Table 28: Comparison of the best neural network found in each study

Regarding the neural networks of the second part of the research, whose inputs are the criteria that supply planners use to decide the safety stock, the best result is clearly obtained with the first group subset and the worst result is the group 3 subset, with an average prediction error of 29,37% and 59,16% respectively.

The materials in group 1 are the most similar between each other, and the materials in group 3 are the least alike, although they have several properties in common. Therefore, the more similar the materials are, the better predictions make the neural network, which makes sense because it is easier to identify the behavior of the same type of product than to determine the management of different materials simultaneously.

Moreover, the neural network found in group 1 subset is the best among all the neural networks, since its average prediction error is the lowest by far. Despite that, it is still a value too high (29,37%) to consider that this neural network can correctly determine the safety stock of a material. So the job of a person cannot be substituted by this neural network.

However, the second part of the research has a positive outcome. In general, the results obtained in the neural networks using as inputs the variables that supply planners actually use in their decision making are better than the neural network whose inputs were designated according to the results of a linear regression model.

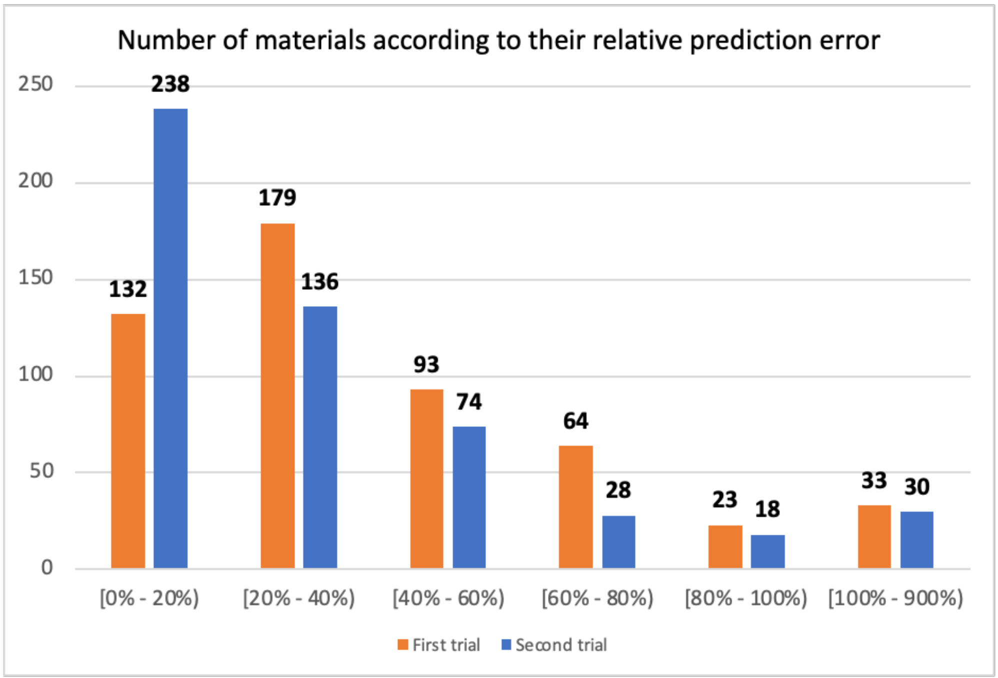

Table 29: Comparison of the number of materials according to their relative prediction error

As seen in the table above, the amount of materials whose safety stock prediction error is lower than the 20% is substantially higher in the second trial than in the first trial. In addition, the first trial has more materials in each interval with a relative error of 40% or greater.

Another conclusion of the research is that applying to much training to a neural network is inadequate, because it leads to overfitting and a poor outcome. Thus, a neural network should be designed implementing a trial-and-error strategy to find the combination of its parameters that best fits the dataset.

As further research, it could be analyzed the outcome of a neural network implemented only for one product, without grouping different goods. In this investigation it has been concluded that the more similar the data, the better results provide a neural network, thereby, performing a neural network only for a material it could possibly lead to better results. Thus, a neural network capable of substituting the task of a supply planner of determining the safety stock of a material may be found.

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